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Maize Price Relationships in a Changing International Market: Have Brazil and/or Ukraine Crossed a Threshold?

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Abstract

In this study we examine changing relationships among maize prices in four global markets. In doing so, we allow the quantity of exports to play a role in both price transmission and price response. That is, we adapt threshold cointegration methods to search for critical export volumes that enhance (or diminish) the role a region's price plays in the world market. We find that the short-run response of prices in both Argentina and Ukraine is influenced by the level of Ukraine's exports. However, the period when Ukraine's exports reached their threshold coincides with the period when Argentina imposed export restrictions on maize. We also find that there are numerous country-specific price thresholds that influence each market's short-run response to a price shock.

Introduction

Traditionally, the United States has dominated the international market for maize. In the past three decades the United States exported approximately 60% of the world's maize. Until recently, both analysts and market participants commonly assumed that international maize prices were determined by prices in the United States (Bredahl, M. and L Green (1983). Few analysts considered that any other country played a significant enough role to challenge United States price leadership role in the international maize market.

Confirming these views, both Mitchell and Duncan (1987) and Hellwinckel and Ugarte (2003) regressed maize exports on prices and import demand. By testing the significance of the import demand variable, these authors showed that the United States was the residual supplier in the world maize market. Adopting arguments made by analysts of international wheat markets (McCalla, 1966; Alaouze, Watson and Sturgess, 1987), the authors claimed residual suppliers were price leaders. In more recent work, Ghosay (2006) evaluated Argentina's competitive role in the international market by applying weak exogeneity tests to an error correction model (ECM) of Argentina and U.S. maize prices. He found that the United States was the price leader.

Today, it is questionable whether the United States has maintained a dominant role in determining the international price of maize. Trade patterns in international maize markets have changed significantly over the past decade. Creation of a much larger ethanol market in the United States (Westcott, 2007) diverted a significant amount of U.S. maize exports to domestic use. Until recently Argentina had imposed trade restrictions and trade taxes on many agricultural commodities including maize. Brazil expanded both the production and exports of maize, which, in turn, has influenced the timing of the South American maize harvest. And perhaps most surprising of all, Ukraine has emerged as a major exporter of maize.

The emergence of Brazil and Ukraine as a major exporters of maize coincides with the diminishing role that the United States plays in the international maize markets (see table 1). At the same time, Argentina's export taxes and quotas reduced Argentine production, competiveness, and contribution to the world maize market. Brazil's expansion of maize production has been rapid, resulting from the combined influences of changes in technology and locational shifts in area harvested, and has made the country the third largest global maize producer and the second largest maize exporter (Allen and Valdez, 2016).

Putting these factors together, it should be obvious that the international export market for maize has changed. For example, in 2004, the United States exported 72% of the maize of the four largest exporters, Argentina, 21%, Ukraine 4%, and Brazil 2%. By 2015, the share of U.S. exports had fallen to 40%, Brazil exported 31%, and Argentina and Ukraine exported 15% and 14%, respectively.

Yet, recent events may partially reverse the impact of this decade-old trend. A new Argentine government has lifted the bans and taxes on commodity exports, economic uncertainty has hit Ukraine's primary maize growing region, and political uncertainty may influence Brazil's agricultural economy. These changes warrant an investigation of the recent price relationships among the four major maize exporters. In particular, it may prove useful to test if the assumed price leadership role of the United States in the international maize market still holds.

This paper analyzes the relationships of maize prices for the top four exporting regions of the globe, (Argentina, Brazil, Black Sea, and the U.S.). We leave out two other exporting regions: China, whose exports briefly reached 10% of the world market (for 2 years over the period we cover) before dramatically falling to zero, and the European Union (EU) whose export share reached 3.5% of the market only once in the period covered in this study. And unlike the countries investigated in this study, the ratio of corn exports to production is extremely low in China and the EU.

Using both daily and weekly prices, we use threshold cointegration methods to evaluate price relationships among these four regions. We adopt the threshold concept, which typically tests for differences in price response to varying price threshold magnitudes to evaluate price response relative to the size of a country's exports. That is, we seek to determine if there are *export* thresholds which have changed price relationships among the four regions. We relate these findings to price discovery to determine whether each country's contribution to the price discovery process has changed over time.

We find that both price and export thresholds influence regional price interactions and price discovery. In particular, we find that the short run price response of Argentina and Ukraine alters when Ukraine's export quantities reach a critical threshold. We also find when price shocks are small, or very large, the market response to those changes is significantly diminished. To our knowledge this latter finding is unique to our study.

The next section introduces an error correction model and discusses our technique for identifying price and export thresholds that influence price relationships among these four markets. The following section discusses our data. The ensuing sections present our estimated model results; first using daily price data and second using weekly price data. Adjustment rates and price discovery weights, which measure each markets contribution to the price discovery process, are reported. This is followed by a conclusion and an appendix which discusses the method of calculating price discovery weights from adjustment rates in a four market model.

Price and Quantity Thresholds in an ECM Model

There are a wide number of studies that use threshold cointegration methods to analyze price relations among markets (Ghosay, 2006, Goodwin and Piggott, 2001, Gouveia and Rodrigues ,2004, Ghosay, 2006, Balcombe, Bailey, Brooks, 2007, Al-Albri and Goodwin 2009, Sephton, 2016). Underlying these studies is the proposition that prices must reach a certain magnitude to overcome transaction costs before price transmission takes place. In these instances, prices changes that lie below a critical magnitude do not transmit. Those above do transmit. Prices representing different markets may follow a common trend, but small changes in each market's price will be independent. Thus prices are cointegrated.

Given the extent of this literature, it is somewhat of a mystery why most threshold studies have focused only on prices. Economic theory suggests that it is the quantity produced (or traded) that influences the impact a region has on price determination. That is, underlying every price transmission is a real or implied (expected) quantity shipment (Grigsby and Arnade, 1985). And, the concept of market power emphasizes that shipment volume must reach a certain size before one market can influence another market's price (Deodhar and Sheldon, 1997).

This suggests that it may be useful to adopt threshold cointegration methods to evaluate the role export quantities play in price transmission. This could be particularly useful for evaluating the changing structure of the world maize market. For example, Brazil and Ukraine's emergence in world maize markets may or may not have allowed them to influence the formation of an international maize price. If either Brazil or Ukraine (or both) is (are) found to contribute to price discovery, one wants to know what *level of exports* allowed these countries to contribute to the discovery of the international maize price.

Our model is built up from standard error correction model of the form:

$$\Delta P_t^m = \gamma_m\left(P_{t-1}^m - \sum_i^3 \beta_i P_{t-1}^i - c\right) + \sum_{j=1}^{\bar{J}} . \sum_{i=1}^3 \eta_{i,j} \Delta P_{t-j}^i + \sum_{j=1}^{\bar{J}} \eta_{m,j} \Delta P_{t-j}^m + \varepsilon_{m,t} \quad (1a)$$

$$\Delta P_t^i = \gamma_i\left(P_{t-1}^m - \sum_i^3 \beta_i P_{t-1}^i - c\right) + \sum_{j=1}^{\bar{J}} . \sum_{i=1}^3 \eta_{i,j} \Delta P_{t-j}^i + \sum_{j=1}^{\bar{J}} \eta_{m,j} \Delta P_{t-j}^m + \varepsilon_{i,t} \quad (1b)$$

where P_t^m represents the maize price in market *m* at time *t* (Argentina in our case), and P_t^i represent the price in one of remaining 3 markets, representing either Brazil, Ukraine, or the United States. The subscript *j* represents the lag on the right hand side price (differenced) variables, which go up to $\bar{J}$.

The relation in parenthesis represents a single long-run cointegrating relationship. In contrast, there is one price difference equation for each market. This specification allows each market's adjustment rate parameter, γ_i, to be distinct.[1] Adjustment rate coefficients relate to short-run price transmissions and can be used to determine a market's contribution to the formation of prices (Schwartz and Szakmary, 1994; and Theissen, 2002).

Adjustment rates may follow a nonlinear process over a limited range and then suddenly jump in value (Chan, 1993). If jump points are related to the size of a price shock or price change, they can be viewed as thresholds. In this paper, we search for price and export thresholds that expose an adjustment rate break point. We define a quantity threshold as a specific export quantity, where adjustment rates are different above the threshold from what they are below the threshold. In contrast, price thresholds refer to the magnitude of a price *change*. Above a price threshold adjustment rates differ from rates below the threshold. Our model specification allows

[1] Argentina is the dependent variable (market *m*) in our long-run equation. Because of this, Argentina's adjustment rate should be negative, and the adjustment rates of other markets should be positive for prices to move towards their equilibrium values (Plato and Hoffman, 2011).

adjustment rate coefficients to change at data points where data are found to cross threshold categories. Thus, our model takes the form:

$$\Delta P_t^m = (D_{mql} * \gamma_{mql} + D_{mpl} * \gamma_{mpl} + \gamma_m) * \mu_{t-1} + \sum_{j=1}^{J} \sum_{i=1}^{3} \eta_{i,j}\, \Delta P_{t-j}^i + \sum_{j=1}^{J} \eta_{m,j}\, \Delta P_{,t-j}^m + \varepsilon_{m,t} \quad (2a)$$

$$\Delta P_t^i = (D_{iql} * \gamma_{iql} + D_{ipl} * \gamma_{ipl} + \gamma_i) * \mu_{t-1} + \sum_{j=1}^{J} \sum_{i=1}^{3} \eta_{i,j}\, \Delta P_{t-j}^i + \sum_{j=1}^{\bar{J}} \eta_{m,j}\, \Delta P_{,t-j}^m + \varepsilon_{i,t} \quad (2b)$$

where: $\mu_{t-1} = P_{t-1}^m - \sum_{=1}^{3} \beta_i P_i - c$ represents the error of the long run cointegrating relationship.

Dummy variables on the adjustment rate represent both price and quantity thresholds, so that

D_{mql} =1 if $Q_{mt} > \bar{Q}_{mk}$ and is zero otherwise.

D_{mpl} =1 if $|\Delta P_{mt}| > |\Delta \bar{P}_{mk}|$ and is zero otherwise.

where Q_{mt} is export quantity of country *m* in the year *t* and $\bar{Q}_{mk}$ is the *k*th export quantity threshold for that country; *k*=1,2 …, (that is a country can have multiple thresholds). A similar threshold condition applies to the 3 other countries. Countries may have no export thresholds or several.[2] Similarly $|\Delta \bar{P}_{mk}|$ represents the price threshold which is based on the size of a price change in market m; and which also applies to the other 3 markets.

As evident in equations 2a and 2b, thresholds represent critical magnitudes that alter how adjustment rates react to a market shock. As shown later, this change, in turn, influences the role each region plays in the price discovery process.

A distinguishing feature of threshold models is that thresholds are not set *a-priori* but are derived from the data itself. To find potential thresholds, Tsay (1989) estimates an autoregressive model

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[2] As written, both equations show one export and one price threshold for each market. However, each market may have several price and exports thresholds.

after ordering each market's data by magnitude. The recursive residuals from this estimated model (one step ahead forecast residuals) are then regressed on the lagged values of the series. Significant *F* tests indicate represent variable magnitudes where price response becomes nonlinear (Balke and Fomby, 1992). In another approach, Ghosay (2006) tests adjustment rate thresholds in an ECM model: by first ranking the *errors* from a long-run price equation (for maize) by their size. Standard statistical techniques are used to test for potential thresholds.

Other authors incrementally search for potential thresholds of interest (Goodwin and Piggot, 2001). Given the increasing power of computers, a grid search can be implemented at little cost. [3] We report threshold tests based on a grid search for both price and quantity thresholds.

Data: Argentina, Black Sea, Brazil, and the United States

The quality of our data varies by region, and readers should bear that in mind when evaluating our results. U.S. Gulf prices were obtained from the International Grains Council (2015). Argentine maize prices were obtained from both the International Grains Council and the Argentine government publication Bolsa De Cereales. These prices are tabulated at the inland port of Rosario (south of Buenos, Aires). Brazilian maize prices were obtained from the International Grains Council and Centro de Estudos Avancados em Economia Applicada and represent port prices in the State of Parana, a region south of Sao Paulo, and one of the main maize growing areas of Brazil. Ukraine prices were represented by Black Sea maize prices. Daily Black Sea data from 2011-15 were obtained from the International Grains Council. From 2004 to 2011, Black Sea maize prices were represented by weekly (offer) prices which were

[3] Dummy variables representing multiple thresholds can be created by looping over, a series of if/ then statements regarding the size of variable. These are used to create dummy threshold variables (or functions) that can be tested.

obtained from the USDA's Foreign Agricultural Service and the website (APK inform, 2015.) All port prices represent feed maize.

Thus the data set consisted of *daily* prices for 3 markets for the entire period (2004 to 2015), daily Black Sea prices from 2011 to 2015 and *weekly* Black Sea prices from 2004 to 2011. This led us to create two data sets. First we created a data set of weekly prices. Summary statistics for these data are reported in table 2, which is split between the period before the 2008 financial crisis and after. Export prices for all four countries (Argentina, Brazil, Ukraine, and the United States) represent the feed maize price.

Second, we used the Grain Council's daily price series for the 3 country markets over the whole period and daily Black Sea prices from 2011 to 2015. We then imputed daily Black Sea prices over the 2004-11 period from our weekly Black Sea data. We did this in two steps. First, we applied a 5-day linear interpolation of prices from weekly mean to weekly mean. Then assuming prices follow a normal distribution we took random draws from the daily interpolated data. We took five sets of random draws, creating five Black Sea price series from 2004 to 2011. It quickly became evident that more random draws would not greatly influence our results. In any case, these data were appended to the daily Black Sea price data which was available from 2011 to 2015. In the end, our data base contains 11 years of daily prices from 2004 to 2015.

While our daily data were not always precise, weekly data may skip over immediate price responses. Therefore, we estimated both daily and weekly models and compared results. Common results between daily and weekly models might be viewed as particularly useful.

Export thresholds were tested using annual export data. These data were obtained from the website "commodity basis" (2015) and from USDA's Foreign Agricultural Service. From this data we were able to create 6 Argentine thresholds, 11 Brazilian thresholds, 9 Ukrainian thresholds, and 6 United States export thresholds to be tested. That is, for both Argentina and the United States. there were several years where the quantity of exports were so similar (for example, for the United States 2006, 2007, and 2008, for Argentina 2009, 2010 and 2011), that only six distinct export-magnitude categories could be created from 11 years of data. The low frequency of export data relative to the price data insures that export thresholds were treated similar to dummy variables in our subsequent models.

Results

Dickey Fuller unit root tests indicate that we could not reject the nonstationary null hypothesis for each data series. We applied Johansen's (1992) eigenvalue tests which revealed, at a .05 confidence level, that there were three cointegrating vectors among the four maize prices. (Tests for one cointegrating vector was: r1=41.87, two vectors r2=21.83, for three vectors r3=21.37, for four vectors, r4=.434). Once determining that the data were nonstationary, we estimated our ECM model using Engle and Granger's (1987) two-step approach. The first step requires estimating an equation relating all 4 prices. This equation, which is defined by the term in parenthesis in equations 1a and 1b, represents the long-run equilibrium relationship among prices.

To account for the possibility that Ukraine's role in the international maize market was changing, we included dummy variables (representing 9 distinct Ukrainian export magnitudes) in the long-run equation. Two of these "threshold" variables were significant, indicating that long-run relationships differ according to Ukraine's role in the export market. Since our export data change on an annual basis (once every 365 days), we felt justified including quantity thresholds in the long run model. However, price changes occur on a daily basis, so we did not include or test price thresholds in the long-run model. We also applied unit root tests to the error term of the long-run equation, which was stationary- providing further indication that the four maize prices form a cointegrating relationship.

Having estimated a long-run equation, a system of four short-run disequilibrium (or adjustment) equations were estimated for each market; equations which include lagged values of the long run error (equation 2a and 2b). There were two countries, Ukraine and Brazil, where exports grew significantly over our period of analysis. Therefore, for each short-run price equation, we tested if there were Brazilian and Ukrainian export thresholds that influenced our model's adjustment rate coefficients. This is critical because price discovery weights are derived from estimated adjustment rates. If export thresholds influence adjustment rates then thresholds influence a country's contribution to the price discovery process.

To carry out this test, an ECM equation was estimated for each country, and a threshold dummy variable was interacted with the adjustment rate variable and tested. Initially, price equations were estimated separately for each country, and F tests were applied to potential threshold variables.[4] F tests revealed that once Ukraine's exports reached 17 million metric tons, which is above Ukraine's average export level of 9 million metric tons, Argentina's adjustment rate coefficient changed slightly. Ukraine's exports reached that threshold only in marketing years 2012/13 and 2013/14, a period when Ukraine's share of the 4-country maize exports rose above 18%. F tests also indicate that Ukraine's own price adjustment rate changed at two threshold

[4] Once threshold values were determined, a system of adjustment equations (2a and 2b) was jointly estimated. We then used system-based log likelihood ratio tests, to test if coefficients on threshold values were significant. These test produced results similar to those from single-equation-based *F* tests.

values: exports of 15 million metric tons and 20 million metric tons. Ukraine’s maize exports were above 15 million metric tons from 2011-15, a time when its export share was between 13.5% and 18% of the four-exporter market. Ukraine exports were above 20 million metric tons only in the marketing year 2013/14. In contrast, none of the Brazilian quantity thresholds were found to be significant in any of the equations. That is, the level of Brazil’s exports did not change any country’s adjustment rate.

Price thresholds tests are often defined by the magnitude of the long model error term (Balke and Fomby, 1992; Ghosay, 2006; Goodwin and Piggot, 2001), which can be viewed as an unexpected price shock. The average size (in absolute value) of the error of long-run price equation was 6.28 with a standard deviation of 5.66. The minimum size of the long-run error was .0038, and the maximum size was 41.9. There were few errors above 22 in absolute value. We chose to test price thresholds in increments of 0.5, starting with 0.5 as the first magnitude to be tested. Dummy variables were created for 45 possible thresholds; each representing a category for the size (absolute value) of the error of the long-run price equation.

For each country, the adjustment equation (2a-2b) was run 45 times over. F tests were used in each run to search for significant price thresholds. If a threshold was significant we included it in the model as a dummy variable interacting with the lagged long-run model error. This dummy/interaction variable then was included when testing for subsequent thresholds. In carrying out subsequent tests, the acceptance region for the null hypothesis was constantly adjusted upwards as our sequence of tests progressed (see Greene, 1993 page 524).

F tests revealed that a wide number of price thresholds were significant (see table 3). For Argentina, the first four thresholds tested (.5, 1, 1.5 and 2) were significant, as were the magnitudes of 3, 4, 5, and 15. In contrast, Ghoshay (2006), found just two threshold values in a two-price model between Argentine and U.S. maize. For Brazil (the U.S.), a magnitude of 18 (1) was significant. For Ukraine, the first tested threshold was significant (a change in the long run error equal to .5 in absolute value) as well as a series of higher thresholds (16, 18, 19, 21, 21.5). Each significant threshold indicates that the speed of adjustment to equilibrium is different for price shocks below and above the threshold value. As noted, this in turn, influences the role each market plays in the price discovery process.

Overall, our results indicate that in Argentina there appears to be a nonlinear response for small sized price shocks (from .5 to 5). For Ukraine, there is a nonlinear response for shocks (long-run errors) ranging from 18 to 22. Rather than try to include numerous dummy variables in our model we decided to specify a model, which allows adjustment rates to adjust continuously. We did so by including a quadratic error correction variable in each adjustment equation (Balcombe and Rapsomanikis, 2008). For example, the adjustment rates in equation 2b were specified as a combination of parameters and the long-run error or as:

$$adj = \gamma_i * \mu_{t-1} + \alpha_i * \mu_{t-1}^2 \tag{3}$$

The derivative of equation 3 with respect to μ_{t-1} produces an adjustment rate that changes from observation to observation.

Table 4 reports the average adjustment rate of each market over a period when no thresholds were reached and over the period when Ukraine had reached it first threshold level (15 million tons). This represents the years 2012/13 and 2013/14 and 2014/15. In marketing year 2013/14, Ukraine also reached the threshold level of 20 million metric tons. Table 4 also reports the number of days it takes for each market's price to adjust half-way to equilibrium. Based on the estimates from the daily data model, Ukraine is the fastest adjusting market taking 86 days to adjust halfway to equilibrium in most years. In the threshold years of 2013 and 2014, Ukraine's price takes 63 days to adjust halfway to its long-run equilibrium relationship with the prices of the other three markets. Countries whose price adjusts the fastest or furthest should be viewed as price followers.

In contrast, for most years, the U.S. maize price adjusts the least (thus forcing other markets to adapt to it), with an adjustment half-life lasting over a year and half. Finally, except for the years 2013-14, Argentina's price takes approximately a year to adjust halfway to equilibrium while Brazil's price takes approximately 8 months.

However, no market adjusts alone. Therefore, convergence rates, representing the sum of the absolute value of each market's rate of adjustment, are also reported along with the convergence half-life. The estimated convergence half-life, representing the time it takes for all market prices to converge to their long-run equilibrium relationship, is slightly under two months in the first period and slightly under a month in the second period.

<u>Price Discovery Weights</u>

Schwartz and Szakmary (1994) and Theissen (2002) provide a procedure for calculating price discovery weights from adjustment rates in a two-market model. The supplemental appendix (available from the authors) shows how price discovery weights can be derived from a 4-equation, 4-market model.

Five versions of the daily model were estimated using different data draws to represent the Ukrainian price. Adjustment rate coefficients did not differ appreciably among models. Table 5 reports PD weights calculated from estimated adjustment rate coefficients from the first draw.

Our model's quadratic adjustment rate term enabled us to calculate price discovery (PD) weights for each observation (see eq 3). When PD weights are calculated at the average level of a price shock (the average value of the long-run error) and below Ukraine's export threshold, the United States dominates short-run price discovery with a PD weight of .553. This reveals that the U. S. market contributes more than 55% to the price discovery process. Argentina follows with a weight of .328, Brazil with .086, and Ukraine with .032. However, in the 2013/14 marketing year, when Ukraine's export threshold of 20 million tons is met, the U.S. weight falls to .041, while Argentina rises to .929. And the contribution of Brazil and Ukraine to price discovery fall to very low levels.

The dramatic change in PD weights coincides with Ukraine's growth in exports in 2012-13 and 2013-14. This change also may reflect the impact of Argentina's trade restrictions and export taxes (see Brownstein, April 9, 2013). There are two ways to view such a situation. One, by being extremely slow to adjust, a country should no longer be viewed as part of the market. Another view is that reluctant players can force *other* markets to adjust, at least in the short run.[5] That is, price stickiness rather than price leadership slowed Argentina's adjustment rate. A key distinction between Argentina and the United States is that Argentina's slow adjustment only lasted a few years. In contrast, the relatively slow adjustment of U.S. prices was sustained over the 2004-11 period and appeared again in 2015. Thus, a more reliable indicator of price

[5] An analogy one can use is a hiker who wears out, slows down, and thus for a period, holds back the rest of the group.

leadership is a market that *consistently* adjusts slowly in the right direction over an *extended* period of time.

Price Thresholds

Price thresholds were defined by the size of the error (shocks) of the long run price equation. PD weights change slightly across different price thresholds. Table 5 reveals that U.S. domination was highest, with a PD weight of .617, when price shocks were below .5 in magnitude. As price shocks increase in magnitude, adjustment rates in Brazil, Ukraine, and the United States rise. This result fits findings in the adjustment rate literature. Large changes in prices or price shocks send unambiguous signals and overcome adjustment costs, allowing markets to react ((Balke and Fomby, 1992; Goodwin and Piggott, 2001). In any case, as price changes grow in magnitude, the PD weight of the United States. falls slightly while that of Argentina rises.

When the long-run error term was greater than 16 in magnitude, (approximately two standard deviations out from the average size of the price shock of 6.2), the maize prices of both Brazil and the United States did not adjust towards equilibrium. And the rate of adjustment of Argentina's and Ukraine's price slowed considerably. This final result highlights a point not addressed in the price threshold literature. Markets also may fail to adjust (or be slow to adjust) to abnormally *large* price changes. The reason for this should be obvious: markets may interpret large price changes as a possible structural break. Thus, market participants may take a wait-and-see approach before resuming normal trading relationships.

A Weekly Model

As pointed out earlier, daily Black Sea maize prices from 2004 to 2011 were generated by making random draws from daily interpolations of weekly data. Given the potential problems with making inferences from such data, we also used weekly data to estimate a four-price ECM. The drawback with this approach is that price information may spread so quickly that weekly data contain a blend of information from various sources. Thus, when using weekly data, it may not be possible to obtain a precise view of the price discovery process.

While both daily and weekly models have drawbacks, the shortcomings of using weekly data are distinct from the drawbacks of using daily data. Therefore, a comparison of daily and weekly models may be useful. Robust results across two distinct data bases would provide some indication that each model's results are not particular to the flaws inherent in the data.

Long-run and short-run models with weekly data are reported in an appendix available from the authors. The same quantity and price threshold tests were carried out in the weekly model as were carried out in the daily model. Tests revealed that 6 distinct Ukrainian-based quantity thresholds were significant in the long-run weekly equation.

The influence of quantity thresholds on the adjustment rate of the short-run model; (hence price transmission and price discovery) were somewhat similar to the daily model. As with the daily model, F tests revealed (at a .05 confidence level of significance) that once Ukraine's exports reached 17 million metric tons, Argentina's response to the long run-error changed. Here both weekly and daily models tend to agree. However, in the weekly model, exports of 17 million tons also influenced Ukraine's price response. And surprisingly, they also influenced the U.S. response. In contrast, in the daily model, two export thresholds, 15 million and 20 million tons, influenced Ukraine's own adjustment rates. As with the daily model, not one of the tested Brazilian export (quantity) thresholds was significant in any country equation.

Price thresholds were quite different for the weekly model than the daily model. In this paper price differences (or price shocks) are represented by the error of the long model which was smaller on average than the error in the long-run daily model. (This makes sense since daily prices are harder to forecast than weekly prices).

For two countries (Argentina and Ukraine), tests for adjustment rate changes to price shocks (the long-run error) above and below .5 in absolute value were significantly different (F test P values were .037 and .001 respectively). For Argentina and Brazil, price thresholds values equal to 1 in absolute value were significant (P values were .0018 and .038). And in Argentina, adjustment rates changed again at price shocks equal to 2 and 4 in magnitude (P values of .0018 and .015). The United States did not respond to any price thresholds. This later result makes sense, in that the United States has a more advanced market structure and more advanced information systems which may allow it to smoothly adapt to price changes at all levels.

Thus in two countries, (Brazil and Ukraine) a price threshold was found to be significant while in Argentina four price thresholds were found to be significant in the weekly model. Overall we found fewer price thresholds over a much shorter range in the weekly model than in the daily model. This was particularly so for Argentina and Ukraine. Despite this we chose to include a quadratic long run error term in the weekly model; which provides an opportunity for adjustment rates to constantly change throughout the entire time period of estimation. This allowed us to compare the adjustment rates and price discovery weights from the weekly model with a similarly specified daily model.

Table 6 reports estimated weekly adjustment and convergence rates. Argentina's weekly price failed to move towards equilibrium in 2013-14, and price discovery weights were not calculated for those years. In any case, adjustment rates are slightly faster in the weekly model than the daily model. For example, the convergence half-life is two and half weeks, where in the daily model it is slightly under two months. Notably in the weekly model, Argentina, rather than Ukraine, is the fastest adjusting market. Ukraine's adjustment is similar to that in the daily model (9.4 weeks versus 63 and 86 days in the two daily models).

Table 7 reports the price discovery rates for the weekly model. For all years but two (2013-14, when Ukraine had passed its quantity threshold), the United States strongly dominated price discovery. In the daily model, the United States led price discovery with a weight above 55% most of the time. In the weekly model the U.S. weight was above 90% all of the time. Also, the ranking of price discovery weights were different in weekly and daily models. In the daily model Argentina followed the United States in importance while Argentina contributed the least to price discovery in the weekly model with only a 1.3% weight. In the weekly model Brazil contributed 3.5% to price discovery, and Ukraine contributes 2.4% most of time in the weekly model.

PD weights vary considerably between categories in the daily model. In contrast, PD weights based on more predictable weekly data are stable across the different price threshold categories. While statistical tests revealed that there several price thresholds in the weekly model, changes in adjustment rates across the thresholds did not appreciably alter *relative* adjustment rates. One difference between daily and weekly models is that in the weekly model, Argentina adjusts in the wrong direction in 2013 and 2014. (the same years that Ukraine had crossed highest export threshold). In the daily model, Argentina did adjust in those years; although very slowly. This result is not that different and appears to indicate that the impact of Argentina's insular agricultural policies (export taxes and restrictions) peaked in influence in those years. These policies could have caused Argentina's price to adjust slowly (daily model) or the wrong way (weekly model).

In both models, the United States plays a small role in price discovery in marketing year 2013/14. This may have reflected the lagged impact of a severe 2012 drought in the maize growing regions of the United States. However, other factors may have played a role. For example, since 2007, the U.S. maize price has increasingly responded to changes in demand related to the expansion ethanol production (Fortenbery and Park, 2008; Westcott 2007). In light of this, by the period 2012-14 the U.S. maize price may have been viewed as less representative of international market conditions.

Conclusion

Over the past decade, Brazilian and Ukrainian exports of maize have increased while the global share of maize exports from the United States has declined. This raises the possibility that Brazil's and Ukraine's roles in the price discovery process have increased at the expense of the United States, the traditional price setter for maize. Using both daily and weekly maize prices, ECM were estimated. Price *and export* thresholds were tested, found to be significant, and shown to influence each market's role in the price discovery process.

Using *daily* data, we find that when Ukraine's maize exports were below its export threshold, the United States dominated the discovery of an international price for maize. However, when Ukraine's exports were above these thresholds, in 2013 and 2014, Argentina dominated price discovery. Similarly the model estimated with *weekly* data showed that Argentina's price did not adjust towards equilibrium in 2013 and 2014. This price stickiness can appear to be price leadership, particularly if other markets adjust to the market with sticky prices. More revealing is that in all other periods it was the United States that forced other markets to adjust to its pricing strategy.

The link between Ukraine's export growth and Argentine export restrictions could be a coincidence. Or the growth in Ukraine's maize exports could have been a *response* to policies which insulated the Argentine price. Ukraine's export growth also could have been a response to forces which diverted U.S. corn from the international market, such as drought and the growth of ethanol. Further research is needed to better understand the findings generated by our threshold tests.

When using daily data, we also uncovered a phenomena contrary to much of the threshold literature. Several markets, responded less (or did not respond) to extremely large price changes (shocks) than to smaller price changes. Past threshold literature has both presumed and verified that markets do not respond to price changes that are very small. Yet, it makes perfectly good sense that markets may not respond to a large price change in the short run. A large price change (shock) could be a warning that markets are about to change structurally. In this case, traders wait and see if a new equilibrium relationship is about to be established before responding. That we found this result using daily data but did not find it with weekly data suggests that responding markets may "wait and see" for only short periods of time.

Future research could investigate this issue as well as all other issues touched upon in this paper. This paper's results, particularly those produced with daily data, should not be taken as a final word on price relationships in the international market for maize. Future research could extend export threshold tests to data sets covering longer time periods. Future research also could continue to search for price thresholds in *both* tails of the price distribution. That is, market reaction to the size of a price change may follow an inverted u shape. Finally, more work needs to be done in comparing price transmission across data bases of different frequencies. Daily data, (as well as hourly or less) may contain so much random noise that a differenced based model may produce spurious results. On the other hand, a model based on weekly data may miss much of the action.

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Table 1. Maize Export Shares: 2004-15

	Argentina	Brazil	Ukraine	United States	Top 4/ World
2004	0.21	0.02	0.04	0.72	0.82
2005	0.15	0.04	0.03	0.78	0.87
2006	0.20	0.10	0.01	0.69	0.86
2007	0.19	0.09	0.02	0.70	0.88
2008	0.12	0.10	0.08	0.69	0.83
2009	0.21	0.11	0.06	0.62	0.86
2010	0.20	0.15	0.07	0.59	0.83
2011	0.19	0.15	0.18	0.46	0.82
2012	0.28	0.33	0.16	0.23	0.78
2013	0.12	0.21	0.19	0.48	0.81
2014	0.16	0.21	0.18	0.45	0.84
2015	0.15	0.31	0.14	0.40	0.84

1/ Shares report each countries' share of the four countries exports will be larger than shares of world exports. 2/ In 2012, there was a serious drought in the United States that significantly reduced the U.S. export share 3/ the last column reports the share of these top 4 countries of world exports 4/ Data source: commodity basis (2015). (https://www.commoditybasis.com/corn_prices)) and USDA FAS

Table 2: Summary Maize Price Statistics

Weekly Prices: August 2004 to August 2008

		Argentina	Brazil	Ukraine	US Dect	US Gulf
	Mean	231	263	238	226	255
	Coef-Var	0.18	0.14	0.11	0.19	0.19
	Last/First	111	167	146	109	122
	No Weeks					
Price	Up	121	114	66	122	118
Price	No Chg	0	2	107	1	0
Price	Down	89	94	37	87	92

Weekly Prices: Sept 2008 to November 2011

		Argen	Brazil	Ukraine	US Dect	US Gulf
	Mean	218	212	171	202	229
	Coef-Var	0.19	0.19	0.21	0.20	0.20
	Last/.First	-58	-100	-111	-72	-81
	No Weeks					
Price	Up	183	168	159	196	186
Price	No Chg			73	1	1
Price	Down	193	208	144	179	189

1/ US Dect represents Decatur Maize price.

2/ Mean Maize Prices are in dollars per metric ton, Coef-Var is the Coeff of Variation. Last/First is the difference in the last observed price and first observed price.

3/ No of Weeks is the number of weekly observations where the prices, rose, did not change, or fell.

4/ The time split represent the periods before and after the 2008 financial crisis.

Table 3: Tests for Price Thresholds, Daily Model

	Size	Argen F-Test	Brazil F-Test	Ukraine F-Test	Gulf F-Test
	LR. Error				
	0.5	33.00		6.33	
	1	49.49			12.09
	1.5	25.73			
	2	21.88			
	3.5	16.12			
	5	6.56			
	15	7.42			
	16			8.61	
	18		4.20	12.10	
	19			7.08	
	21			10.20	
	21.5			9.70	
Average	6.25				
STD	5.66				
Max/Min	41.9	.0038			

1/ For example column 1 reports those F statistics which were significant in the Argentina equation. Tests indicated that a price shocks (the long run error) above certain magnitude, could influence the rate of adjustment to equilibrium. For Argentina adjustment rates were different for price shocks above or below .5, (1, 1.5, 2, and 3.5 etc.) in magnitude.

2/ Forty five thresholds were tested. This table only reports those price thresholds where the F statistic was significant.

3) In a sequential series of hypothesis test, the significance level of F statistics vary and are conditional on the outcome of the previous tests (Greene Page 524). Small price, price changes were tested first starting with .5, and increasing in magnitude in increments of .5.

4/ Average, Std, Max/Min report the average magnitude of the long-run error, its standard deviation, and maximum and minimum value.

Table 4. Daily Adjustment Rates, Convergent Rates, and Half Life

Average Adjustment rates: Daily model

Q-Thresh	Argentina	Brazil	Ukraine	US	Converge rate
Q-none	-0.0082	0.012	0.034	0.005	0.0041
Q-7(Q-9)	-0.0013	0.037	0.047	0.027	0.0410

Days to reach half way to equilibrium

Q-Thresh	Argentina	Brazil	Ukraine	US	Converge
Q-none	366	248	86	597	49
Q7(Q-9)	2141	79	63	110	25

1/ The top half of the table reports average adjustment rates when there are no thresholds and in the marketing years 2013-14 and 2014-15 when threshold q7 or both q7 and q9 were reached. Thresholds are based on the quantity of Ukraine's exports.

2/ The half-life is the number of days it takes for each market price to adjust to the long run equilibrium relationship. When no threshold holds were attained Argentina's prices took on average 366 days to return halfway to equilibrium.

3) Argentina was the dependent variable in the long-run equation. To reach equilibrium requires adjustment rates must be negative for Argentina (the long run error is Argentina's) for Argentina and positive for other countries (see Plato and Hoffman).

4/ Convergence rates are derived from the sum of the absolute value of adjustment rates. Since all markets are adjusting at the same time, convergence of market prices to long equilibrium occurs over a much shorter period of time, than implied by individual adjustment rates. Using the daily model, market prices are estimated to converge to the long-run equilibrium relationship in slightly less than two months (one month).

Table 5: Price Discovery Weights: Daily Data [1]

	Average	$u_{-1} < .5$ [2]	$.5 < u_{-1} < 2$ [3]	$2 < u_{-1} < 16$	$u_{-1} > 16$
Q Below Thresholds					
US	0.553	0.617	0.575	0.535	0.No
Argentina	0.328	0.192	0.240	0.354	0.No
Brazil	0.088	0.099	0.106	0.085	0.no
Ukraine	0.032	0.093	0.079	0.027	0.no
Q-Above Threshold, Years 2013-14					
US	0.045	0.133	0.105	0.022	0.No
Argentina	0.929	0.884	0.883	0.971	0.No
Brazil	0.015	0.019	0.01	0.019	0.No
Ukraine	0.019	0.003	0.001	0.0033	0.No
Observations	2948	164	486	2100	198

1/ Price discovery rates are calculated from the relative adjustment rates of an ECM model. 2/ The first column represents discovery rates when the absolute value of price changes (the long error term, price change) is at that average of all price changes less 16. 2/ Different columns refer adjustment rate thresholds. Thresholds values are based on the absolute value of the long run error. For example, column 2, represents price discovery values for observations which the long-run error term was initial below .5 in absolute value, column 2, with it was between .5 and 2, column 4 when between 2 and 16, and column 5 when the long run error was above 16 in absolute value. 3/In Column 3 the United States contributes 57.5% to price discovery when, exports quantities are below threshold, 10.5% when Ukraine's export quantities are above either of its thresholds.

4. No refers to observations where prices did not move towards convergence and price discovery weights could not be calculated. The number of observations represent the no observations the landed in each price magnitude category

Table 6. Weekly Adjustment Rates, Convergent Rates, and Half Lifes

Average Adjustment rates: Weekly model

Q-Thresh	Argentina	Brazil	Ukraine	US	Converge rate
Q-none	-0.132	0.046	0.07	0.002	0.251

Weeks to reach half way to equilibrium

Q-Thresh	Argentina	Brazil	Ukraine	US	Converge
Q-none	5.6	14.6	9.4	398.2	2.4

1/ Adjustment rates are negative for Argentina since that country served as the dependent variable in the long-run model. Other countries adjustment rates, which were explanatory variables are expected to positively adjust to the long run model error.

2/ The convergence rate is the sum of the absolute value of adjustment rates.

3/ Equal to the number of days a market takes to adjust to halfway to equilibrium, when other markets are not adjusting at all. The convergence half-life represents the number of days to adjust to equilibrium when all markets are adjusting and is derived from the sum of the absolute value of adjustment rates.

Table 7: Price Discovery Weights: Weekly Data[1]

	Average	$u_{-1} <.5$[2]	$.5<u_{-1} <1$[3]	$u_{-1}>1$
Q Below Thresholds				
US	0.929	0.929	0.929	0.929
Argentina	0.013	0.013	0.013	0.013
Brazil	0.035	0.035	0.035	0.035
Ukraine	0.024	0.024	0.024	0.024
Above Threshold, Years 2013-214				
US	NA	NA	NA	NA
Argentina	NA	NA	NA	NA
Brazil	NA	NA	NA	NA
Ukraine	NA	NA	NA	NA
Observations	584	39	19	466

1/ Same interpretation as previous table (Three price threshold categories are listed. ie u<.5 means the price change was below .5 in magnitude) 2/ For the two years that Ukraine is above its threshold (2013-14), the Argentina price did not move towards convergence and price discovery weights could not be calculated. 3/ The number of observations represent the number of observations that belong to each price magnitude category,