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Spatial Price Efficiency in the Urea Market

Urea fertilizer is widely used in the U.S., however, most urea is not openly traded and formula pricing is common. This study measures the efficiency of spatial urea prices in the New Orleans-Arkansas River urea market and the New Orleans-Middle East urea market. The vector error correction model (VECM) and Baulch's (1997) parity bound model (PBM) are used. Nonlinearity testing finds no threshold effects. Thus, we do not include threshold values in our vector error correction models. Parameter estimates of vector error correction models show that violations of spatial price equilibrium are corrected faster in the Arkansas River-New Orleans urea market than the New Orleans-Middle East urea market. Results from the parity bound model show that in the New Orleans-Middle East urea market, price spreads are found greater than transportation costs in about 23% of the time. So, the New Orleans-Middle East market is a moderately inefficient market rather than a perfectly efficient market.

***Key words*:** Urea market, spatial price efficiency, error correction, switching regression.

Introduction:

In recent years, a number of researchers have investigated price efficiency in agricultural output markets like cheese, egg and cattle markets (Buschena and McNew, 2008; Peterson, 2005; Anderson et al., 2007). However, there is little research investigating fertilizer markets, which are the major agricultural input markets, perhaps because of low accessibility to data. Public fertilizer price data are only available monthly. Since the major traders in urea markets are big international companies and formula pricing is common, urea markets are likely thin markets. Thus, there are reasons to suspect the price efficiency of fertilizer markets may be low. The overall objective of this research is to measure the level of spatial price efficiency in U.S urea markets. Inefficiency of the current pricing system could suggest benefits from improving price transparency and data accuracy through public collection and publication of daily and/or weekly fertilizer prices.

When assessing spatial price efficiency, agriculture economists typically use the law of one price (LOP) as the criterion for spatial price efficiency. The law of one price states that the price difference for the same good at different locations should be no more than the transaction costs of trading the good between the two locations. Otherwise, an arbitrage opportunity occurs, which will reduce the price in the high-price market and increase the price in the low-price market until the LOP is met again.Thus, the extent of spatial price efficiency could not only be measured by how often violations of LOP occur, but also by the speed with which such violations are corrected.

One popular model that is based on the LOP for measuring spatial price efficiency is Baulch's (1997) Parity Bound Model (PBM). It was first introduced by Spiller and Huang (1986) and developed further by Sexton, Kling, and Carman (1991), Baulch (1997). Park et al. (2002) and Negassa and Myers (2007) also extended the PBM for testing whether changes in market policies can affect spatial efficiency between two spatial market. The PBM is a three-regime switching regression that accounts for nonstationary transfer costs and recognizes the existence of discontinuous trade patterns (Baulch, 1997; Barrett and Li, 2000; Barrett, 2001). This model allows estimating the probability of prices inside as well as outside the arbitrage bounds. Despite the advantages of the PBM, it has several shortcomings. First, results can be sensitive to the distributional assumptions such as independence between transportation cost data and commodity prices, half-normal error terms and no autocorrelation (Fackler 1996; Barrett and Li 2002). Second, the PBM does not identify the reasons for violations of spatial arbitrage conditions that indicate inefficiency. Third, the PBM estimates depend on transportation costs that are not always available.

When assessing spatial price efficiency, one problem that agriculture economists often meet is the lack of information on transaction costs. The vector error correction model (VECM) which only depends on price data is also based on the LOP. The VECM not only helps determine how fast violations of spatial equilibrium between two locations are corrected but also shows price dynamics. However, this model based on price data alone has been criticized because it neglects the role of transaction costs (Barrett, 2001; Meyer, 2004). To also incorporate effects of transaction costs into price transmission analysis, threshold vector error correction models (TVECMs) have been developed. In a TVECM, transaction cost from one market to another market can be estimated by a threshold estimator. TVECMs are extensions of the standard VECM, however, compared to the standard VECM, TVECMs not only show price dynamics between two spatial markets, but also measure the level of spatial price efficiency. A large number of studies have used threshold error correction models to analyze spatial price transmission as well as efficiency of spatial price. For example, Goodwin and Piggott (2001) used TVECMs for corn and soybean at four North Carolina terminal markets. Kaabia et al. (2007) used a threshold model to estimate price transmission in the Spanish lamb market. Meyer (2004) used the TVECM to investigate spatial price efficiency of the European pig market.

This paper begins with an extensive background of the urea market. Next, the justification and application of VECMs and TVECMs as well as underlying data analysis and testing will be conducted. Specifically, tests for threshold effects in the data will determine whether using a TVECM is appropriate for analyzing price transmission and spatial price efficiency. In addition, a PBM will be used for testing the spatial price efficiency when the transportation cost data are available. Results from tests and models will be used in order to assess the spatial price efficiency.

Urea Market Background

Urea is the most widely used dry nitrogen fertilizer in the United States (USDA, 2014). Compared to other nitrogen fertilizers, urea has a number of advantages. First, urea has the highest nitrogen content of all solid nitrogenous fertilizers and it can be used on virtually all crops. Second, it is easy and safe to ship and store urea because of its stable chemical and physical properties. Urea fertilizer is mostly marketed in solid form, either as prills or granules. The performance of granules during bulk storage, and use is generally considered superior to that of prills because granules are larger, harder, and more resistant to moisture than prills. Commercially, urea is produced from ammonia and carbon dioxide. In order to produce ammonia, steamed natural gas and steamed air are reacted with each other so that the hydrogen (from natural gas) is combined with nitrogen (from the air) to produce ammonia. And this synthesis gives an important by-product for manufacturing urea which is carbon dioxide. The ammonia and carbon dioxide are fed into a reactor at high temperature and pressure. After chemical synthesis, urea is produced.

The main urea exporters are gas-rich countries/regions including China (the largest exporter), Black Sea and Arab Gulf countries, while North America, Latin America and South and East Asia are the main importing regions. China has the largest capacity; however, most of its capacity is used to supply its large domestic market (Heffer and Prud'homme, 2013). Black Sea and Arab Gulf are two main hubs to follow in the urea trade market. As we can see from figure 1, Black Sea exports supply Europe and Latin America, while Middle East exports supply the U.S. and Asia. Yara (2012) argues that world urea prices are determined by these two flows. When demand is mainly driven from the U.S. and Asia, Arab Gulf will lead the price; otherwise, the Black Sea leads. According to the International Fertilizer Industry Association (IFA) (2012), Gulf Coast imports accounted for 63% of total urea imports in the United States. Urea shipped from the Middle East usually takes about 45 days to reach New Orleans, where it is then distributed along the entire length of the Mississippi River system, including the Ohio, Illinois and Arkansas Rivers.

Over the past ten years, urea price shows a dramatic increase and high volatility. According to Fertilizer Week, urea freight on board (FOB) granular bulk price at US New Orleans spot reached its peak of $620-650 per short ton on May 2012 then dropped to $310-320 per short ton on November 2013. On January 30, urea FOB granular bulk price at US New Orleans spot rose back to $390 per short ton. Ocean freight and barge prices have also been unstable over the last few years. According to Fertilizer Week, barge prices dropped from $91 in November 2007 per short ton to $30 per short ton in October 2013. The ocean freight from Middle East to New Orleans in Figure 3 shows the ocean freight is also very volatile from 2004 to 2012.

Table 1 shows U.S. solid urea capacity estimates for 2012. U.S. solid urea capacity is now only about 3.2 million short tons. The U.S. solid urea production is concentrated in the hands of a few large companies. Three companies account for 93% of the total, with CF Industries accounting for 53% of this total. Given the increase in U.S. natural gas production, new plants are being planned. For example, CF Industries is constructing new ammonia and urea plants at its Donaldsonville complex and Koch is building a new urea plant at its Enid, Oklahoma facility and undergoing a revamping process of its existing production facilities. The urea prices are mainly affected by natural gas prices (Huang, 2007). Natural gas prices were very unstable in the last decade, which makes Middle East urea prices volatile, as a result. In addition to feedstock cost, there is concern that urea prices are also affected by price manipulations. Under some protections in the major fertilizer export countries, manufacturer associations have a strong influence in setting the fertilizer prices in global markets, establishing a benchmark for the price of fertilizers sold in the United States (Huang, 2009). Kim et al. (2002) found that the U.S. nitrogen fertilizer market is an oligopoly market dominated by a few firms. Most urea fertilizer is transacted via formula prices. Previous research (Xia and Sexton, 2004; Zhang and Brorsen, 2010) shows that using formula pricing in thin markets can facilitate price manipulation and reduce competition. So there are reasons to suspect that spatial price efficiency in the urea market may be low.

Methodology

Vector Error Correction Model

The vector error correction model (VECM) which describes the dynamic equilibrium relationship of short-run and long-run in a system of equations is a popular model for spatial price analysis. It estimates price adjustment as the impact of a change in one price on another price. A specification of a general VECM is:

(1) $\Delta \boldsymbol{p_t} = \boldsymbol{\rho} \boldsymbol{\gamma}' \boldsymbol{p_{t-1}} + \boldsymbol{\theta} + \sum_{m=1}^{M} \boldsymbol{\Theta_m} \Delta \boldsymbol{p_{t-m}} + \boldsymbol{\varepsilon_t}$,

which is characterized by parameters $\boldsymbol{\rho}$, $\boldsymbol{\theta} \in \mathbb{R}^2$ and $\boldsymbol{\Theta_m} \in \mathbb{R}^{2\times 2}$ for $m = 1, \dots, M$; M is the number of lags included in the model; Observations $\boldsymbol{p_t} = (p_{1,t}, p_{2,t})'$, $t = 1, 2 \dots n$ where $p_{1,t}$ and $p_{2,t}$ are prices at location 1 and 2 at time t ; $\boldsymbol{\gamma} \in \mathbb{R}^2$ is a cointegrating vector; $\boldsymbol{\gamma}' \boldsymbol{p_{t-1}}$ is an error correction term and in the spatial equilibrium setting $\boldsymbol{\gamma}$ is often taken to equal $(1, -1)'$ so that $\boldsymbol{\gamma}' \boldsymbol{p_{t-1}}$ measures the price in location one minus the price in location 2; $\boldsymbol{\rho}$ estimates the adjustment speed at which violations of spatial equilibrium between two locations are corrected. So in a VECM, changes in prices of two different locations are explained by deviations from long term equilibrium (the error correction term $\boldsymbol{\gamma}' \boldsymbol{p_{t-1}}$), lagged short-term reactions to previous changes in prices ($\Delta \boldsymbol{p_{t-m}}$) and constant term θ. We assume the error term $\boldsymbol{\varepsilon_t}$ has zero expected value and covariance matrix $\operatorname{cov}(\boldsymbol{\varepsilon_t}) = \boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix} \in (\mathbb{R}^+)^{2\times 2}$. In matrix format, equation (1) can be written as:

$$(2) \qquad \begin{bmatrix} \Delta p_{1,t} \\ \Delta p_{2,t} \end{bmatrix} = \begin{bmatrix} \rho^1 \\ \rho^2 \end{bmatrix} \begin{bmatrix} p_{1,t-1} - p_{2,t-1} \end{bmatrix} + \begin{bmatrix} \theta^1 \\ \theta^2 \end{bmatrix} + \sum_{m=1}^{M} \begin{bmatrix} \Theta_m^{11} & \Theta_m^{12} \\ \Theta_m^{21} & \Theta_m^{22} \end{bmatrix} \begin{bmatrix} p_{1,t-m} \\ p_{2,t-m} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \end{bmatrix}.$$

If a VECM such as (1) is used to estimate price adjustment, one assumption must be noted. Price adjustment ($\Delta \boldsymbol{p_t}$) is assumed to be a continuous and linear function of the error correction term $\boldsymbol{\gamma}' \boldsymbol{p_t}$. Thus a deviation from the long-term equilibrium could lead to an adjustment process in each market (Meyer, 2004). However, if this function has a threshold effect which means it is discontinuous and non-linear, a threshold vector error correction model (TVECM) should be used instead of a general VECM. Previous studies on price transmission use either one threshold or two threshold vector error correction models. Usually, if price adjustment in the presence of significant transaction costs is expected to occur in only one direction, a TVECM with one threshold is likely more appropriate since the price adjustment in the other direction is insignificant (Meyer, 2004). In our case, trades are unidirectional, so we may need to use a one threshold vector error correction model to estimate price transmissions between different markets if a threshold effect is detected.

In estimating the VECM, we first check for stationarity properties of the data with the agumented Dickey Fuller (ADF) unit root tests in levels and first differences. In our study, data are in logarithmic form. ADF test lag lengths are determined using the Akaike information criterion(AIC). If level data are nonstationary, then the first differenced data are tested. If first differences are stationary, the data are said to be I(1).

Then the I(1) data are tested for cointegration. Johansen's cointegration test is used to determine the rank of cointegration between two prices. Trace and eigenvalue (max) test statistics are used. The null hypothesis for the trace test is the number of cointegrating price vectors is less than or equal to rank r, while the null hypothesis for the eigenvalue (max) test is that cointegration equals rank r. If prices series appear to be cointegrated, an error correction model needs to be used.

The next step in analyzing the urea data is to see causal relationship between variables. The Granger causality tests are used for this purpose. The Granger causality tests not only indicate the presence or absence of Granger-causality, but also show the direction of causality.

After confirming cointegration, we need to identify whether threshold effects are present. Hansen and Seo (2002) have developed an approach based on the Chow test to test the significance of threshold effects. This technique tests the null of linear cointegration against threshold cointegration. Failure to reject the null hypothesis of linearity indicates that no threshold value exists and a standard VECM is appropriate for the estimation. Otherwise, a TVECM should be used. Unit root, cointegration and causality tests are performed in SAS 9.3. Hansen's test is performed in statistical software R using 'tsDyn' package.

Threshold Vector Error Correction Model

Using the specification in (1), a one-threshold vector error correction model can be expressed as:

$$(3)\ \Delta \boldsymbol{p}_t = \begin{cases} \boldsymbol{\rho}_1 \boldsymbol{\gamma}' \boldsymbol{p}_{t\text{-}1} + \boldsymbol{\theta}_1 + \sum_{m=1}^{M} \boldsymbol{\Theta}_{1m} \Delta \boldsymbol{p}_{t-m} + \boldsymbol{\varepsilon}_t , \\ \qquad \boldsymbol{\gamma}' \boldsymbol{p}_{t\text{-}1} \leq \psi \quad \text{(Regime 1)} \\ \boldsymbol{\rho}_2 \boldsymbol{\gamma}' \boldsymbol{p}_{t\text{-}1} + \boldsymbol{\theta}_2 + \sum_{m=1}^{M} \boldsymbol{\Theta}_{2m} \Delta \boldsymbol{p}_{t-m} + \boldsymbol{\varepsilon}_t , \\ \qquad \psi < \boldsymbol{\gamma}' \boldsymbol{p}_{t\text{-}1} \ \text{(Regime 2)} \end{cases}$$

The TVECM (3) is a general VECM (1) delineated by a threshold value (ψ) into two regimes. All variables and parameters are defined as in (1). Like the standard VECM, this TVECM explains price changes by price adjustments in both short term and long term, but also conditionally on the magnitude of the deviation from the long term equilibrium. When deviations ($\boldsymbol{\gamma}' \boldsymbol{p}_{t\text{-}1}$) are below the threshold value (ψ), the price transmission process is defined by regime 1, and when deviations surpass the threshold value, the price transmission process is defined by regime 2. Regime 1 which is the "band of inaction" (Gred et al. 2013) represents spatial price efficiency and no adjustment is expected in this regime; regime 2 is the outer regime where spatial equilibrium is broken, and profitable arbitrage occurs;

To express the model in matrix notation, we use $I(\cdot)$ to denote the indicator function for each regime. For example, $I(\boldsymbol{\gamma}' \boldsymbol{p}_{t-1} \leq \psi)$ is the indicator function for regime 1 restricted as follows:

$$(4)\ I(\boldsymbol{\gamma}' \boldsymbol{p}_{t-1} \leq \psi) = \begin{cases} 1 & \text{if } \boldsymbol{\gamma}' \boldsymbol{p}_{t-1} \leq \psi \\ 0 & \text{otherwise} \end{cases}$$

Thus we can build two indicator functions $I(\boldsymbol{\gamma}'\boldsymbol{p}_{t-1} \leq \psi)$, and $I(\psi < \boldsymbol{\gamma}'\boldsymbol{p}_{t-1})$ for regime 1 and 2, respectively. $\boldsymbol{X}$ is an $n \times d$ matrix of observations at n time points which can be built by stacking $\boldsymbol{x}_t' = (\boldsymbol{\gamma}'\boldsymbol{p}_{t-1}, 1, \Delta\boldsymbol{p}_{t-1}', \ldots, \Delta\boldsymbol{p}_{t-M}')$ of length $d = 2M + 2$ where M is the number of lags in the model. We define $\boldsymbol{D_1}$and $\boldsymbol{D_2}$ as diagonal matrices of indicator functions for regime 1 and 2, respectively as:

(5) $\boldsymbol{D_1} = \text{diag}\{I(\boldsymbol{\gamma}'\boldsymbol{p^1}_{t-1} \leq \psi), I(\boldsymbol{\gamma}'\boldsymbol{p^2}_{t-1} \leq \psi) \ldots I(\boldsymbol{\gamma}'\boldsymbol{p^n}_{t-1} \leq \psi)\}$,

(6) $\boldsymbol{D_2} = \text{diag}\{I(\psi < \boldsymbol{\gamma}'\boldsymbol{p^1}_{t-1}), I(\psi < \boldsymbol{\gamma}'\boldsymbol{p^2}_{t-1}) \ldots I(\psi < \boldsymbol{\gamma}'\boldsymbol{p^n}_{t-1})\}$,

where n is the n is the number of observations. $\boldsymbol{D_1X}$ and $\boldsymbol{D_2X}$ represent the matrix for variables in Regime 1 and 2, respectively. We also define $\Delta\boldsymbol{p}_{i,t}$ and $\boldsymbol{\varepsilon}_{i,t}$ as vectors containing the *i*-th (*i*=1, 2) components of $\Delta\boldsymbol{p}_t$ and $\boldsymbol{\varepsilon}_t$, respectively. Thus, the TVECM can be written as:

$$
\begin{aligned}
(7)\ \Delta\boldsymbol{p}_{i,t} &= \boldsymbol{D_1X}\boldsymbol{\beta}_{i,1} + \boldsymbol{D_2X}\boldsymbol{\beta}_{i,2} + \boldsymbol{\varepsilon}_{it} \\
&= \boldsymbol{X_1}\boldsymbol{\beta}_{i,1} + \boldsymbol{X_2}\boldsymbol{\beta}_{i,2} + \boldsymbol{\varepsilon}_{it},
\end{aligned}
$$

where $\boldsymbol{X_1} = \boldsymbol{D_1X}$ and $\boldsymbol{X_2} = \boldsymbol{D_2X}$. $\boldsymbol{\beta}_{i,k}$ is the *i*-th column of the matrix $(\rho_k, \theta_k, \Theta_{k1,\ldots,}\Theta_{kM})'$, $i = 1{,}2$ and $k = 1{,}2$. A compact presentation of the TVECM can be written as:

$$(8)\ \Delta\boldsymbol{p}_t = \begin{pmatrix}\Delta p_{1,t} \\ \Delta p_{2,t}\end{pmatrix} = (\boldsymbol{I_2} \otimes \boldsymbol{X_1})\boldsymbol{\beta_1} + (\boldsymbol{I_2} \otimes \boldsymbol{X_2})\boldsymbol{\beta_2} + \boldsymbol{\varepsilon}_t,$$

where $\boldsymbol{\beta_k} = (\beta_{1,k}, \beta_{2,k})$ for $k = 1{,}2$, $\boldsymbol{I_2} \in \mathbb{R}^{2\times 2}$ denotes the identity matrix. In the next section, a reparameterized model of equation (7) will be used for the threshold estimation.

The Regularized Bayesian Estimator

A commonly used estimation of threshold parameters in threshold regression models is profile likelihood estimation which is performed by maximizing the corresponding profile likelihood function. However, some researchers (Lo and Zivot, 2011; Balcombe, Bailey, and Brooks, 2007) have acknowledged that in many cases, the profile likelihood estimator is biased and has a high variance. Bayesian estimators have also been developed and used (Chen, 1998; Chan and Kutoyants, 2010). A most recent development is that Greb et al. (2011) suggested an alternative regularized Bayesian estimator that circumvents the deficiencies of standard estimators. The regularized Bayesian estimator introduced by Greb et al. (2011) outperforms standard estimators (profile likelihood estimator and Bayesian estimator) especially when the threshold leaves only a few observations in one of the regimes or coefficients differ little between regimes. The regularized Bayesian estimator does not depend on trimming parameters. Second, in empirical applications the regularized Bayesian estimates of the adjustment parameters are more consistent with spatial equilibrium theory than profile likelihood estimates.

In order to get the regularized Bayesian estimators for the two thresholds, we first need to be reparameterize the model in equation (7) as:

$$(9)\ \Delta\boldsymbol{p} = (\boldsymbol{I_2} \otimes \mathbf{X_1})\boldsymbol{\beta_1} + (\boldsymbol{I_2} \otimes \mathbf{X_2})\boldsymbol{\beta_2} + \boldsymbol{\varepsilon_t}$$

$$= (\mathbf{I_2} \otimes \mathbf{X_1})\boldsymbol{\beta_1} + (\mathbf{I_2} \otimes \mathbf{X_2})\boldsymbol{\beta_1} + (\mathbf{I_2} \otimes \mathbf{X_2})\boldsymbol{\beta_2} - (\mathbf{I_2} \otimes \mathbf{X_2})\boldsymbol{\beta_1} + \boldsymbol{\varepsilon_t}$$

$$= (\mathbf{I_2} \otimes \mathbf{X_2})(\boldsymbol{\beta_2} - \boldsymbol{\beta_1}) + (\mathbf{I_2} \otimes \mathbf{X})\boldsymbol{\beta_1} + \boldsymbol{\varepsilon_t}$$

$$= (\mathbf{I_2} \otimes \mathbf{X_2})\boldsymbol{\delta} + (\mathbf{I_2} \otimes \mathbf{X})\boldsymbol{\beta_1} + \boldsymbol{\varepsilon_t},$$

with a normal prior $\boldsymbol{\delta} \sim \mathcal{N}\left(0, \sigma_\delta^2 \boldsymbol{I_{2d}}\right)$, where $d = 2M + 2$ with M the number of lags included in the model; a noninformative constant prior $\boldsymbol{\beta_1} \sim U(\mathbb{R}^{2d})$; and a uniform prior $\psi \sim U(\psi \in \Psi)$ where Ψ is the threshold parameter space. Then we aim to calculate the posterior density $\mathrm{P}_{rB}(\psi|\Delta\boldsymbol{p}, \boldsymbol{X})$ for model (9). Defining$\boldsymbol{Z} = \boldsymbol{I_2} \otimes \boldsymbol{X}$, $\boldsymbol{Z_1} = \boldsymbol{I_1} \otimes \boldsymbol{X_1}$, $\boldsymbol{Z_2} = \boldsymbol{I_2} \otimes \boldsymbol{X_2}$, and $\boldsymbol{V} = \boldsymbol{\Sigma} + \sigma_\delta^2 \boldsymbol{Z_2} \boldsymbol{Z_2'}$. Replacing $\boldsymbol{\Sigma}$ and σ_δ^2 by their maximum likelihood estimates $\widetilde{\boldsymbol{\Sigma}}$ and $\tilde{\sigma}_\delta^2$ respectively for $\boldsymbol{V}$, that is , $\widetilde{\boldsymbol{V}} = \widetilde{\boldsymbol{\Sigma}} + \tilde{\sigma}_\delta^2 \boldsymbol{Z_1} \boldsymbol{Z_1'}$ for $\boldsymbol{V}$, yields log posterior density (Greb et al, 2011):

$$(10)\quad \log P(\psi_{\boldsymbol{rB}}|\Delta\boldsymbol{p}, \boldsymbol{X}) \propto -\frac{1}{2}\{\log\left|\widetilde{\boldsymbol{V}}\right|\left|\boldsymbol{Z}'\widetilde{\boldsymbol{V}}^{-\mathbf{1}}\boldsymbol{Z}\right| + \left(\Delta\boldsymbol{p} - \boldsymbol{Z}\widetilde{\boldsymbol{\beta}}_{\mathbf{1}}\right)'\widetilde{\boldsymbol{V}}^{-\mathbf{1}}\left(\Delta\boldsymbol{p} - \boldsymbol{Z}\widetilde{\boldsymbol{\beta}}_{\mathbf{1}}\right)\},$$

with $\widetilde{\boldsymbol{\beta}}_{\mathbf{1}} = (\boldsymbol{Z}'\boldsymbol{V}^{-\mathbf{1}}\boldsymbol{Z})^{-\mathbf{1}}\boldsymbol{Z}'\boldsymbol{V}^{-\mathbf{1}}\Delta\boldsymbol{p}$. After the posterior density$\mathrm{P}(\psi_{rB}|\Delta\boldsymbol{p}, \boldsymbol{X})$ is obtained, we can get the regularized Bayesian threshold estimator $\widehat{\psi}_{\boldsymbol{rB}}$**.** Since the median of the posterior distribution is more robust than the mode and yields less biased estimates than the mean when the true threshold is located close to the boundary of the threshold parameter space (Greb et al, 2013), the regularized Bayesian threshold estimator $\widehat{\psi}_{rB}$ is used:

$$(11)\quad \int_{\min(\gamma' p_t)}^{\widehat{\psi}_{rB}} \mathrm{P}(\psi_{rB}|\Delta\boldsymbol{p}, \boldsymbol{X})\, d\psi_{rB} = 0.5, \quad i = 1{,}2,$$

assuming a prior $\mathrm{P}(\psi_{\boldsymbol{rB}}|\boldsymbol{X}) \propto I(\psi_{\boldsymbol{rB}} \in \Psi)$ for ψ_{rB}. The regularized Bayesian estimator can be computed by taking advantage of existing models in *nlme* package in statistical software R 3.0.1.

Parity Bounds Model

The parity bounds model can be a good complement for TVECM when transportation data are available. We use Baulch's parity bounds model (PBM) to determine spatial price efficiency in the Middle East-New Orleans urea market. The model requires estimating the probability of being in each trade regime, given transportation data and urea prices. Consider two markets i and j that trade the same good. Based on the relative size of price difference between two locations and transfer costs, three trade regimes can be divided as follows:

$$(12)\quad P_{it} - P_{jt} = TC_{jit} \text{ (Regime 1)}$$

$$(13)\quad P_{it} - P_{jt} < TC_{jit} \text{ (Regime 2)}$$

$$(14)\quad P_{it} - P_{jt} > TC_{jit} \text{ (Regime 3)},$$

where P_{it} and P_{jt} are prices in market *i* and *j* at time *t*, and TC_{jit} is the transportation cost from *j* to *i* at the same time *t*. According to the LOP, profitable arbitrage will occur when the price difference between two locations is higher than the transfer cost. Therefore, Regime I and Regime II are consistent with efficient spatial arbitrage and Regime III indicates spatial price inefficiency. To extend this, we model TC_{jit} as a random variable with constant mean T:

(15) $TC_{jit} = T + e_t$,

where $e_t \sim N(0, \sigma_e^2)$. Then we can define three regimes that can reflect all possible arbitrage conditions between export market *j* and import market *i* as:

(16) $P_{it} - P_{jt} = T + e_t$ with $prob\ \lambda_1$, (Regime 1)

(17) $P_{it} - P_{jt} = T + e_t - u_t$ with $prob\ \lambda_2$, (Regime 2)

(18) $P_{it} - P_{jt} = T + e_t + v_t$ with $prob\ 1 - \lambda_1 - \lambda_2$, (Regime 3)

where u and v are positive random variables, so that (16), (17) and (18) define regimes in which price in market *i* equals, falls below and exceeds price in market *j* plus transportation cost, respectively. Thus, the three equations together define a switching regression model with three regimes. To estimate the model, the likelihood function of the PBM is defined as (Baulch, 1997):

(19) $L = \prod_{t=1}^{T} [\lambda_1 f_1^t + \lambda_2 f_2^t + (1 - \lambda_1 - \lambda_2) f_3^t]$,

where parameters λ_1 and λ_2, are the probabilities of being in Regimes I and II. Thus, the probability for regime III when the price spread is beyond transfer costs is $1 - \lambda_1 - \lambda_2$. f_1^t, f_2^t and f_3^t, are respectively, the density functions of (16), (17) and (18). To specify these density functions, assume that u_t and v_t are distributed independently of e_t with a half normal distribution, i.e., $N(0, \sigma_u^2)$ and $N(0, \sigma_v^2)$ distribution truncated from below at zero (Sexton et al., 1991).

The function f_1^t is the density function for regime I defined as:

(20) $f_1^t = \frac{1}{\sigma_e} \phi(\frac{Y_t - K_t}{\sigma_e})$

The function f_2^t is the density function for regime II defined as:

(21) $f_2^t = \left(\frac{2}{(\sigma_e^2 + \sigma_u^2)^{1/2}}\right) \phi \left(\frac{Y_t - K_t}{(\sigma_e^2 + \sigma_u^2)^{1/2}}\right) \times \left[1 - \Phi \frac{-(Y_t - K_t)\sigma_u / \sigma_e}{(\sigma_e^2 + \sigma_u^2)^{1/2}}\right]$

and f_3^t is the density function for Regime III defined as:

(22) $f_3^t = \left(\frac{2}{(\sigma_e^2 + \sigma_v^2)^{1/2}}\right) \phi \left(\frac{Y_t - K_t}{(\sigma_e^2 + \sigma_v^2)^{1/2}}\right) \times \left[1 - \Phi \frac{(Y_t - K_t)\sigma_v / \sigma_e}{(\sigma_e^2 + \sigma_v^2)^{1/2}}\right]$

Y_t is the natural logarithm of the absolute value for price difference between location *i* and *j*; K_t is the logarithm of the transportation cost between market *i* and *j* in period *t*; e_t, u_t and v_t are the error terms; σ_e, σ_u and σ_v are standard deviations of these error terms; ϕ is the symbol of standard normal density function; Φ represents the standard normal distribution function. The estimates of parameters λ_1, λ_2, σ_e, σ_u and σ_v are obtained by maximizing the logarithm of likelihood function (19).

We focus on the magnitude of the sum of probabilities of Regime I and Regime II which could be interpreted as the frequency of market efficiency. In other worlds, a smaller probability for Regime III indicates better spatial price efficiency. Ten starting values of parameters were randomly selected from a uniform distribution, and then we chose the estimates from the likelihood function that has the highest value. We estimate parameters using *proc nlmixed* procedure in statistical software SAS 9.3.

Data

Most urea price data as well as other fertilizer price data are private and can only be purchased from professional fertilizer consulting companies like Fertilizer Week, Green Markets and ICIS. Public monthly average U.S urea farm price data and urea price index from 1960 to 2013 can be obtained from U.S. Department of Agriculture's Economic Research Service. Worldwide monthly urea price data can be found on International Fertilizer Industry Association website.

To estimate the described threshold model, two pairs of urea markets are analyzed (Middle East-New Orleans and New Orleans-Arkansas River). Urea is imported from Middle East to New Orleans markets then distributed to terminal markets along the Arkansas River. Weekly granular urea freight on board prices and transportation costs from the last week of August 2004 to the last week of January 2013 were purchased from Fertilizer Week, and Bery Maritime. Fertilizer Week is an online fertilizer market consulting service and Bery Maritime is a freight consultant with a particular focus on fertilizer. The urea price data includes Arkansas River prices (*AP*), New Orleans prices (*NP*), and Middle East prices (*MP*) which are collected by regular contact with all main contacts including producers, traders and end users. Arkansas River prices reflect trading activities in river terminals and inland warehouses in Arkansas, Western Kansas and Oklahoma where product is mostly barged from the US Gulf. New Orleans prices are prices of barged urea loaded from plants in US Gulf or prices of discharged urea along the lower Mississippi River in Louisiana. Middle East prices are collected from different countries including Qatar, Saudi Arabia, and Kuwait. Because of poor accessibility to transportation costs, we only have ocean freight (*OF*) from the Middle East to New Orleans. All the units are in dollars per short ton. Both urea prices and transportation costs have missing data. Most of these missing data could be found in holidays or at the end of the year when no trading occurred. Since only a small number of observations are missing, observations with any missing data (current or lagged) are not included in the estimation. In order to make the data stationary, we chose to use logarithmic form of the price data. Descriptive statistics of the data are provided in Table 2. Line graph representations of the data series may be seen in Figures 2 and 3.

Results

Unit Root Tests

The ADF test is used to test for unit roots. ADF tests are performed using the following three specifications: no intercept, intercept, and trend models. The lengths of lags for ADF test are determined using Akaike Information Criteria. All price data are in logarithmic form. ADF tests performed at the 5% significance level are reported in Table 3. For the price level data, ADF tests overall fail to reject the null hypothesis of nonstationarity, indicating the data may carry a unit root. Thus, first differences of the data are taken and tested. ADF tests for first differences of the data indicate rejection of the null hypothesis of nonstationarity. Thus, first differenced price data of all three markets are stationary. Therefore, level data are nonstationary, and first differenced logarithmic data are stationary for the three urea markets.

Cointegration Tests

Two pairs of prices in logarithmic form are tested for integration 1) New Orleans prices (*NP*) and Middle East prices (*MP*), 2) Arkansas River prices (*AP*) and New Orleans price. The Johansen trace test statistic is used. Table 4 shows trace statistics for the two price relationships. The hypothesis for the trace test is the number of cointegrating price vectors is equal to rank r against the alternative of greater than r. The null hypothesis that r=0 for both series of data is rejected, and we fail to reject the null hypothesis that r=1 for both series of data. All series indicate a cointegrated relationship between the price pairs. Lags (M) included in VECMs are determined by Akaike information criterion (AIC). Appropriate lag lenghth is 3 for *AP* and *NP* while an appropriate lag length is 4 for *NP* and *MP*.

Nonlinearity tests

Hansen's (2002) modification of Chow-type tests are used to verify nonlinearity and threshold effect in error correction terms. Hansen's test is conducted using the statistical software, R. The "HStest.TVECM" in the "tsDyn" library is used for Hansen's test. This test follows the implementation done by Hansen and Seo (2002). The lengths of lags are selected as we used in cointegration test and intercepts are included in our model. The cointegrating value is estimated from the linear VECM we specified in the previous section. Then, conditional on this value, the Lagrange Multiplier (LM) test is run for a range of different threshold values. The maximum of those LM test values is reported. Results for nonlinearities can be seen in Table 6. The results show that we fail to reject the null of linear cointegration for both pairs of price data. Thus, using standard VECMs should be more appropriate than using TVECMs.

Causality Tests

Granger causality tests based on VECMs are used to test pair-wise causal relationships. The lengths of lags for Granger Causality tests are the same as with Johansen cointegration tests. Results with first-differenced logarithmic data for both pairs of markets are reported in Table 5. All the four null hypotheses are rejected at the 5% significance level. Therefore, bidirectional causalities are found in the Arkansas River-New Orleans urea market and the New Orleans-Middle East urea market.

Parameter Estimates and Price Transmission

We specify a VECM for each pair of markets with $\Delta P_t^{AP-NP} = (\Delta AP_t, \Delta NP_t)'$ with $M = 3$ for Arkansas River to New Orleans and $\Delta P_t^{NP-MP} = (\Delta NP_t, \Delta MP_t)'$ with $M = 4$ for Middle East to New Orleans. The cointegrating vector $\boldsymbol{\gamma}'$ is normalized as $(1, -1)'$, so that the error correction term $\boldsymbol{\gamma}'\boldsymbol{p}_{t\text{-}1}$ is defined as the difference between the importer market and exporter market. Thus, $\gamma' P_t^{AP-NP} = \Delta AP_t - \Delta NP_t$ and $\gamma' P_t^{NP-MP} = \Delta NP_t - \Delta MP_t$. Coefficients for error correction terms are adjustment coefficients that measure the speed with which violations of spatial equilibrium between two locations are corrected in the long run. When prices deviate from equilibrium in the context of spatial arbitrage, trade restores equilibrium by causing the higher price to fall and the lower price to rise. Hence, we expect to see that $\rho^1 \leq 0$ and $\rho^2 \geq 0$.

A negative (positive) constant in a VECM estimates that the price in an importer market is higher (lower) than the price in an exporter market. In our case, prices in importer markets are mostly higher than prices in exporter markets, so we also expect $\theta^1 > 0$ and $\theta^2 < 0$.

Parameter estimates of the vector error correction models are presented in Table 7 and 8. For New Orleans-Arkansas River market, urea is transported from New Orleans to Arkansas River, so in general, urea prices in Arkansas Rivers are higher than urea prices in New Orleans. In table 7, both intercepts and adjustment coefficients have correct signs. Parameter estimates results show significant price adjustments to deviations from long term equilibrium. The estimated coefficients for the adjustment to deviations from the long term equilibrium indicate a stronger reaction of urea prices in New Orleans(0.19) to such deviations than in the Arkansas River (-0.08). Together, these price changes imply a total adjustment of 0.19+0.08=0.27 for the Arkansas River-New Orleans urea market. Lagged price changes in Arkansas River price (New Orleans price) have significant effects on the New Orleans price (Arkansas River price). This is consistent with what we found in causality tests, that New Orleans price and Arkansas River price influence each other.

In the New Orleans-Middle East urea market, urea is shipped from the Middle East to New Orleans. Urea prices in New Orleans are typically higher than urea prices in the Middle East. Estimates in Table 8 also have plausible signs, however, no significant adjustment is found in Middle East price. Only New Orleans price makes long term adjustment to deviations from spatial equilibrium. This result reflects the fact that Middle East price is the benchmark price of the global urea price. The total adjustment of this pair of markets equals the sum of absolute values of two adjustment coefficients. Results show that the total adjustment of New Orleans-Middle East (0.16) is smaller compared to the total adjustment of Arkansas River-New Orleans (0.27). So we may conclude the domestic market (Arkansas River-New Orleans) has faster adjustment than the international market (New Orleans-Middle East). New Orleans as the freight hub connecting the U.S. inland urea markets and overseas urea markets shows more adjustment than the other markets. Additionally, two prices have short term influence on each other in this pair of markets.

Parity Bound Model

To further investigate the extent of spatial price efficiency, we introduce Baulch's (1997) parity bound model (PBM). Since only the transportation costs between New Orleans and the Middle East are available, the degree of spatial price efficiency between New Orleans and the Middle East are studied. The estimates of the PBM using monthly urea prices and transportation costs between New Orleans and the Middle East are presented in table 9. As indicated by the sum of the probabilities of regime I and II (here regime I and II represent spatial price equilibrium), spatial arbitrage is efficient more than 76 % of the time between New Orleans and the Middle East. The probability of being in regime I is significant and equals 75.2%, while the probability of being in regime II is non-significant. Hence, the estimates indicate that most of the time, New Orleans urea price is equal to Middle East urea price plus the ocean freight. The probability of being in regime III is about 23%, which means 23% of the time, the price differences between New Orleans prices and Middle East prices are higher than the transportation costs between the two locations. In such a case, no trade happens between New Orleans and the Middle East and the market is not efficient. In fact, according to the IFA, about 22% (2010) of the total imported urea in New Orleans is from South America when the urea price in the Middle East is too high. Also, this proportion is close to the probability of being in regime III. So the New Orleans-Middle East urea market is a moderately inefficient market.

Conclusion

This study measures spatial price efficiency in the Arkansas River-New Orleans urea market and the New Orleans-Middle East urea market. Vector error correction models were used for estimating spatial price efficiency and price transmissions in both markets. The time-series properties of the data were considered using the Dickey-Fuller unit root testing procedures as well as by performing cointegration tests for pairwise price relationships. Unit root testing on first differenced logged data indicated stationary data, and cointegration tests in both pairwise price data yielded results showing cointegration in all pairwise vectors. Results from the Granger causality tests showed the bidirectional causalities in both pairwise price data. Nonlinearity tests confirmed linearity in error correction terms and rejection of a threshold. Thus, based on the nonlinearity tests results, we chose to use VECMs and instead of TVECMs.

Analysis of parameter estimates of VECMs allowed for a thorough investigation of spatial price transmissions and efficiencies. Three prices are found having short term influence on each other, which matches what we found in the Granger causality test. More importantly, price efficiency could be reflected by how fast the violation of spatial price efficiency is corrected . Results showed that the New Orleans urea price seems have more adjustment than the other urea prices. New Orleans, as the most important U.S. urea import port, has more urea trading activities. Thus, it is reasonable to see more adjustment in urea prices in New Orleans. The Middle East urea price, which is the benchmark urea price, does not have significant adjustment. Comparing the domestic market (the Arkansas River New Orleans market) and the international market (the New Orleans-Middle East market), we found that the domestic market has more adjustment than the international market.

Baulch's (1997) efficiency tests indicated a moderate inefficiency in the New Orleans-Middle East urea market. Price spreads between the Middle East and New Orleans are said higher than shipping costs between the two markets. Hence, the market inefficiency leads to a result that urea will be imported from elsewhere (usually from South America).

Over the last decades, because of the limited and stagnant U.S. production capacity of urea, the U.S. fertilizer industry is not able to supply the urea needed for agriculture production. So, the U.S. mainly depends on imports of urea to meet domestic demand. However, our study shows that the urea import market seems to lack perfect spatial price efficiency. Our study also shows that the domestic market is relatively more efficient. As more plants for producing urea are built in the U.S. inland markets will likely change future price dynamics.

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Tables and Figures

Table 1. U.S. Solid Urea Capacity Estimates (000'S S.T.) July 1, 2012

Company	Location	Total Annual Cap
Agrium	Borger, TX	109
	Kenai, AK	
Borden	Geismar, LA	0
CF Industries	Donaldsonville, LA	1710
	Blytheville, AR	
Dyno Nobel	Cheyenne, WY	105
	St. Helen's, OR	
Koch	Enid, OK	520
Mosaic	Faustina, LA	Na
PCS Groupe	Augusta, GA	771
	Geismar, LA	
	Lima, OH	
Rentech	East Dubuque, IL	11
Total		3226

A total annual capacity for MOSAIC in Faustina, LA is not available

Table 2. Summary Statistics of Urea Prices and Transportation Cost ($/Short ton)

Variable	Mean	Median	Std Dev	Minimum	Maximum
Arkansas River Price (*AP*)	421.37	383.05	144.40	241	929
New Orleans Price (*NP*)	378.53	341.72	138.17	205	838
Middle East Price (*MP*)	343.88	305.00	126.89	213	850
Ocean Freight (*OF*)	39.02	32.66	15.49	18	83

Note: 428 weekly data from Aug 2004 to Jan 2013

Table 3. Augmented Dickey-Fuller Unit-Root Testing Results

Model	Arkansas River	New Orleans	Middle East
Level Data			
Intercept	-2.57	-2.19	-2.20
Intercept with Trend	-3.19	-2.91	-3.58*
No Intercept	0.31	0.36	0.40
First Differenced Data			
Intercept	-9.12*	-6.93*	-7.12*
Intercept with Trend	-9.11*	-6.92*	-7.11*
No Intercept	-9.12*	-6.92*	-7.11*

Note: ADF test values are reported varying on optimal lag lengths determined by AIC.
* Indicates significance at the 5 % level.
Test hypothesis:
H_0: Unit root, H_1: No unit root.

Table 4. Results of Johansen Co-integration Tests with Logged Level Data

Pair of Prices	H_0: *r*	Trace	5% Critical Value
AP-NP (3)	0	54.74*	19.99
	1	8.36	9.13
NP-MP (4)	0	31.14*	19.99
	1	8.31	9.13

Note: *r* is the number of cointegrating vectors.
* Indicates significance at the 5 % level.
All numbers are from restricted models.
Lags are in parentheses.
Trace hypothesis:
H_0: cointegrating vectors $\leq r$, H_1: cointegrating vectors $> r$

Table 5. Results of the Granger Causality Tests with Logged Level Data

Null hypothesis (H_0)	DF	Chi-Square	Pr>ChiSq
AP does not cause *NP*	3	64.49	<.001
NP does not cause *AP*	3	37.55	<.001
NP does not cause *MP*	4	105.44	<.001
MP does not cause *NP*	4	16.07	0.003

Table 6. Hansen's Threshold Testing Results for Error Correction Terms

Error Correction Term	Lag	Test Statistic	P-Value
lnAP-lnNP	3	25.98	0.24
lnNP-lnMP	4	30.82	0.25

Note: Test hypothesis:

H_0: linear conintegration, H_1: threshold cointegration

Arkansas River-New Orleans Relationship, Vector Error Correction Model

Variables	Parameter Estimates	Standard Error
Arkansas River Equation		
Intercept	0.01*	0.02
Error Correction Term	-0.08*	0.02
$\Delta lnAP_{t-1}$	0.21*	0.00
$\Delta lnNP_{t-1}$	0.17*	0.00
$\Delta lnAP_{t-2}$	0.10	0.11
$\Delta lnNP_{t-2}$	0.13*	0.01
$\Delta lnAP_{t-3}$	-0.10*	0.08
$\Delta lnNP_{t-3}$	0.03	0.59
New Orleans Equation		
Intercept	-0.02*	0.00
Error Correction Term	0.19*	0.00
$\Delta lnAP_{t-1}$	0.20*	0.00
$\Delta lnNP_{t-1}$	0.27*	0.00
$\Delta lnAP_{t-2}$	0.14*	0.02
$\Delta lnNP_{t-2}$	0.02	0.67
$\Delta lnAP_{t-3}$	0.03	0.64
$\Delta lnNP_{t-3}$	0.11*	0.03

Note: * Indicates significance at the 5 % level.

Table 8. New Orleans-Middle East Relationship, Vector Error Correction Model

Variables	Parameter Estimates	Standard Error
New Orleans Equation		
Intercept	0.01*	0.00
Error Correction Term	-0.14*	0.00
$\Delta lnNP_{t-1}$	0.09	0.11
$\Delta lnMP_{t-1}$	0.44*	0.00
$\Delta lnNP_{t-2}$	-0.06	0.27
$\Delta lnMP_{t-2}$	0.20*	0.00
$\Delta lnNP_{t-3}$	0.14*	0.01
$\Delta lnMP_{t-3}$	0.08	0.22
$\Delta lnNP_{t-4}$	-0.06	0.24
$\Delta lnMP_{t-4}$	-0.14*	0.02
Middle East Equation		
Intercept	0.00	0.69
Error Correction Term	0.02	0.50
$\Delta lnNP_{t-1}$	0.14*	0.01
$\Delta lnMP_{t-1}$	0.12*	0.06
$\Delta lnNP_{t-2}$	0.02	0.77
$\Delta lnMP_{t-2}$	0.13*	0.04
$\Delta lnNP_{t-3}$	0.10*	0.06
$\Delta lnMP_{t-3}$	0.14*	0.03
$\Delta lnNP_{t-4}$	-0.04	0.39
$\Delta lnMP_{t-4}$	-0.07	0.26

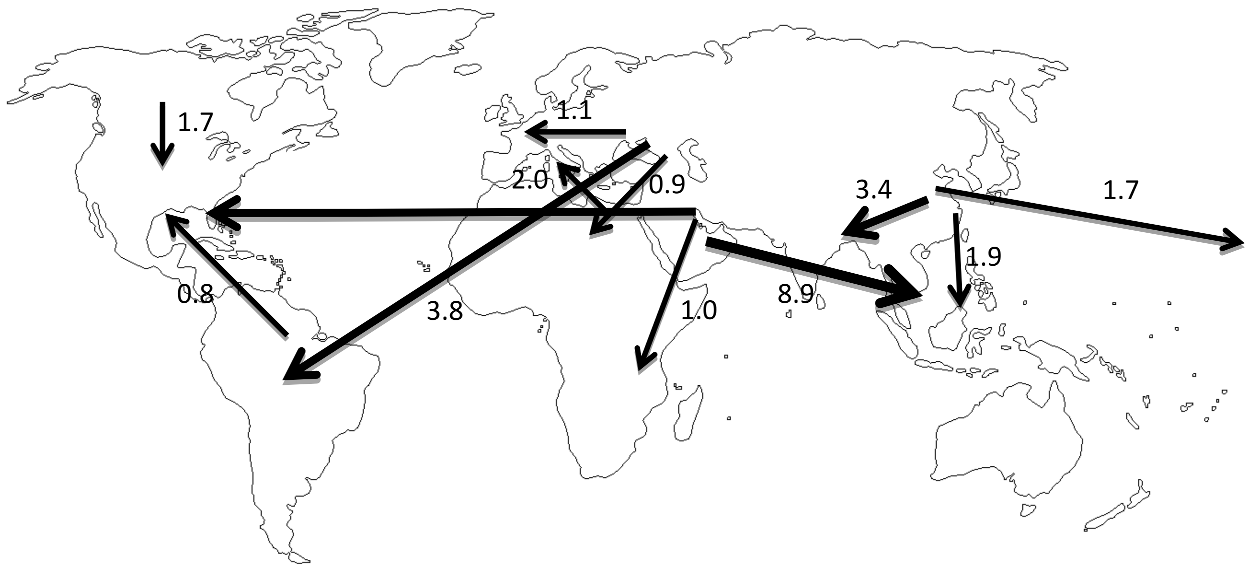
Note: * Indicates significance at the 5 % level.

Table 9. Estimates of the PBM Regime Probabilities for Middle East-New Orleans

Market	Probability		
	Regime I	Regime II	Regime III
Middle East→ New Orleans	0.752	0.016	0.232
	(0.049)	(0.022)	(0.056)

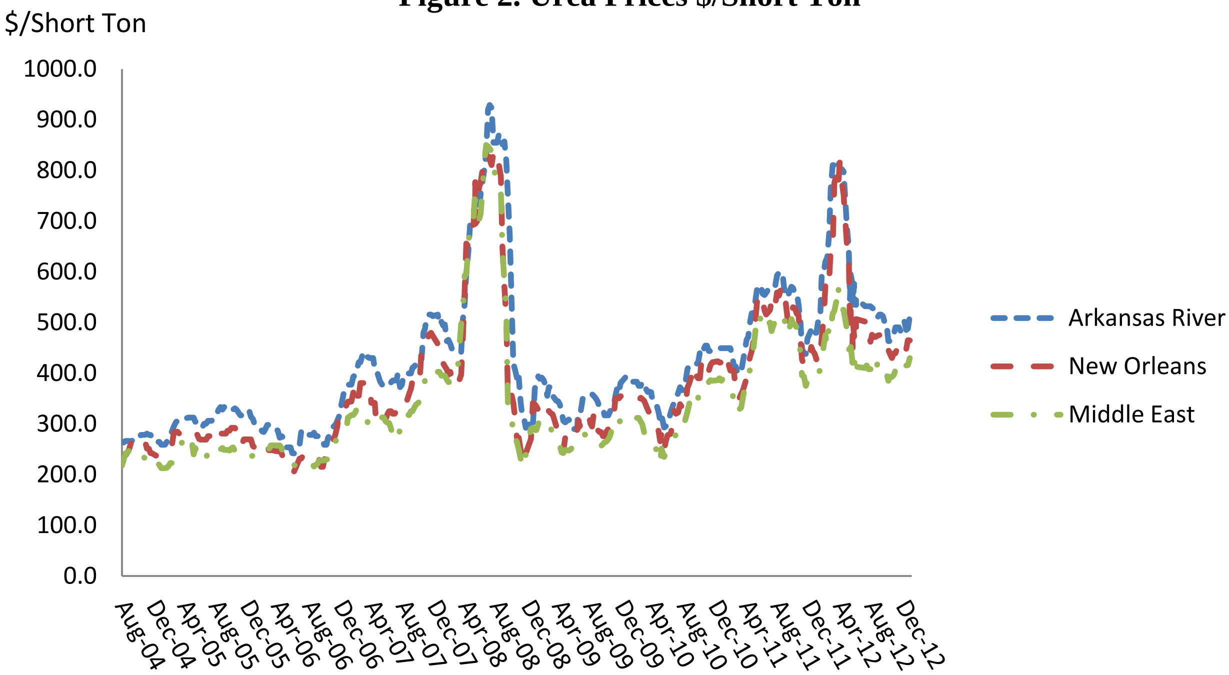
Note:Regime I, II, and III are defined respectively when price spreads equal, fall below, and exceed transfer cost. Standard errors are in parentheses.

Figure 1. Main Urea Trade Flows 2010/million tons



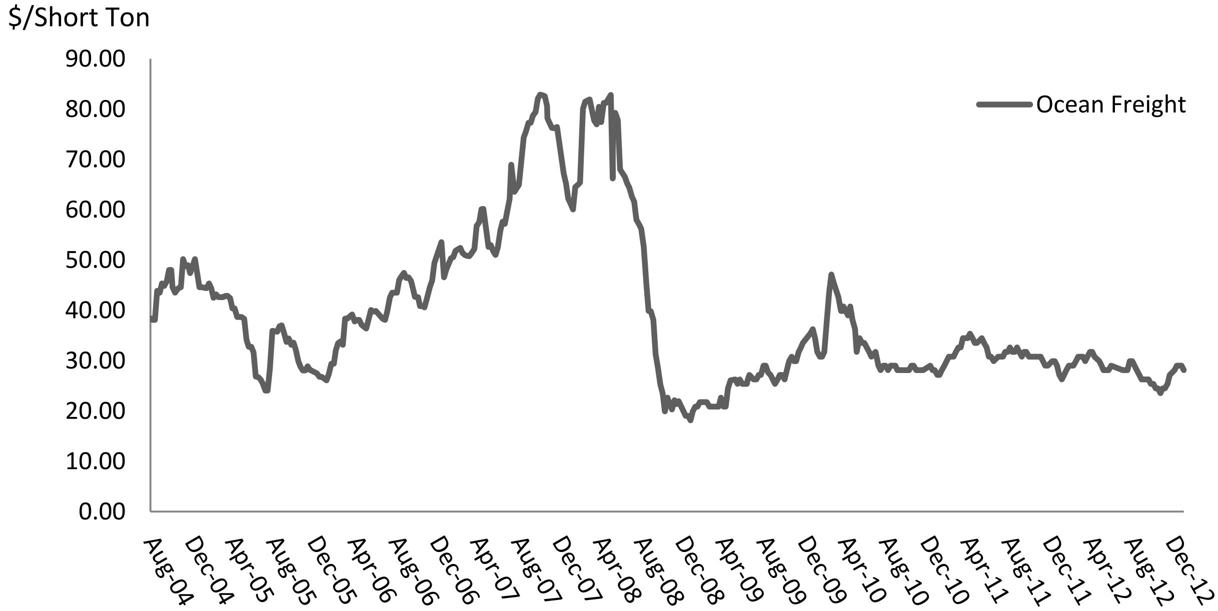
Source: International Fertilizer Industry Association, 2010
Note: The width of the arrows indicates the relative size of trade flow.
The arrows' positions of origin and destination do not indicate the ports location

Figure 2. Urea Prices $/Short Ton



Source: Fertilizer Week

Figure 3. Ocean Freight $/Short Ton (Middle East to New Orleans)



Source: Bery Maritime