**Dynamic and Spatial Relationships in US Rice Markets**

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## Abstract

Spatial market integration refers to the smooth transmission of price signals and information across spatially separated markets. This paper investigates whether US rice markets are spatially integrated and whether these markets are integrated across rice varieties. Understanding dynamic and spatial relationships across regions and varieties provides important insights for policy making. Rice is among the top seven US major crops in terms of harvested acres – covering over 2.6 million acres – and sixth in terms of sales, with annual cash receipts around 3.1 billion dollars. Of the four major producing regions, three are in the South – Arkansas-Missouri, Louisiana-Mississippi, and Texas, and the other is California. The varieties are different associated with the production region. California mainly produces short and medium grain; while Arkansas, Texas, and Louisiana produces mostly long also medium grain. We investigate the potential market integration of these rice markets by applying a Vector Error Correction Model to monthly f.o.b. milling price data from 1980 to 2014. Arkansas-Missouri region is identified as the leading price in the variety of long grain also medium grain markets. Interestingly, Arkansas-Missouri medium grain plays an additional important role in the long grain market. California short grain market seems to move somewhat independently (weakly exogenous) in the short run, but its price movement is affected by Arkansas-Missouri medium grain in the longer term.



**Keywords**: Rice markets, Cointegration, Impulse response functions

**JEL Classification**: Q11, Q13, C32

## Introduction

Rice is a staple commodity in both the U.S. and world markets – especially Asia, Africa and Latin America. Although US rice is produced in four distinct regions, i.e. Arkansas-Missouri, Mississippi Delta (parts of Mississippi, Missouri, Louisiana and Arkansas), Texas-Southwest Louisiana, and California (mainly Sacramento Valley), it still plays a major role in US agriculture. It is among the top seven US crops in terms of harvested acres, covering over 2.6 million acres in 2013 to 2015, and sixth in terms of sales (cash receipts) with annual transactions of over 3.1 billion dollars (ERS - USDA). In addition, U.S. is a major rice exporter, accounting for more than 10 percent of the annual volume of global rice trade (ERS, 2015).

There are three varieties of rice in the U.S., classified according to the length of grain - long, medium and short. The long grain is almost entirely produced in the southern regions, covering about 70% of the total US rice production. Arkansas produces about 65% of all long grain rice. The medium grain is produced in Arkansas and California, accounting for over 25% of the total US rice production, while remaining less than 2% of short grain is produced in California. (Childs, 2012). Figure 1 presents the time trend of rice production over varieties across regions. More than 200 million cwt of rice being produced in 2000s. The blue and light blue area together indicates the long grain production from Arkansas-Missouri, Louisiana-Mississippi, and Texas. The combined brown and light brown areas present the medium grain production across Arkansas-Missouri, Louisiana-Mississippi, and California. The area in green refers to short grain production in California.

Spatial price analysis of agricultural commodities in the United States has been widely studied in the literature (e.g. Fackler and Goodwin, 2001; Serra and Goodwin, 2004; Yu, Bessler and Fuller, 2007; Stockton, Bessler and Wilson, 2010). However, it is surprising that the spatial and dynamic relationships among U.S. rice prices is still lacking given its economic value. Taylor et al. (1996) has investigated the relationships between US and Thai rice prices but spatial price dynamics within US rice markets was not covered in their study. The analysis of spatial price dynamics is important to understand the US rice market structure and, in turn, helpful for improving price transparency in the markets. Thus, the objective of this study is to investigate and identify the dynamic relationships of the prices of three rice varieties, i.e. short, medium and long grain, among major domestic markets. The analysis will provide insights in the price discovery process among separate US rice markets. Relevant findings have potential risk management effects for producers, as well as price discovery effects having policy implications.

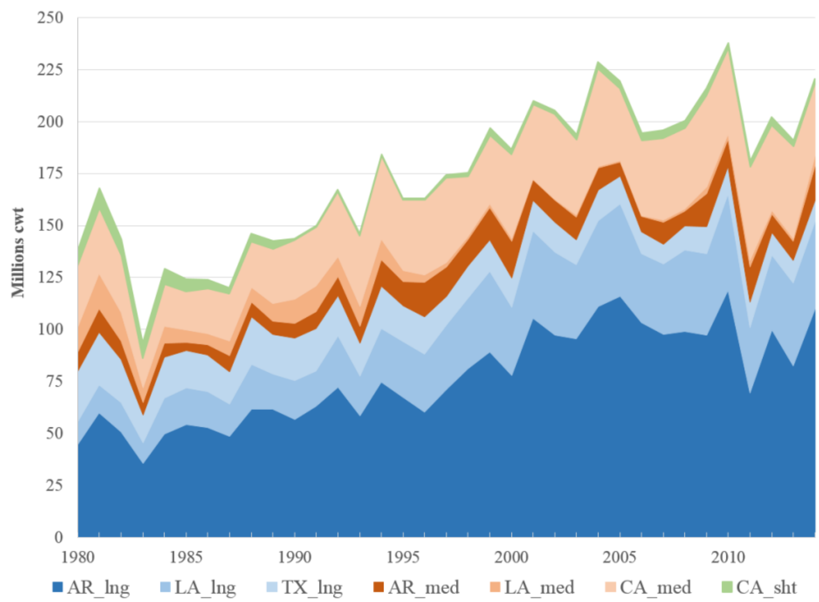


**Figure 1: US Rice Production of Different Varieties and Regions**

Source: USDA NASS

Note: AR_lng = AR-MO long grain, LA_lng = LA-MS long grain, TX_lng = Texas long grain, AR_med = AR-MO medium grain, LA_med = LA-MS medium grain, CA_med = CA medium grain, and CA_sht = CA short grain

We employ a structural multivariate time series Vector Autoregression model with an error correction term (VECM). Multivariate time series such as a VECM has been commonly used in the literature of spatial price analysis. To formulate a structural VECM, a Directed Acyclic Graphs (DAG) from Pearl (1995 and 2000) and Spirtes, Glymour and Scheines (2000) have been utilized to sort-out the instantaneous causal flows among the innovations from the VECM (Hoover, 2005) and used to construct the structural decomposition of the VECM residuals (Swanson and Granger, 1997).

## Data

We use average monthly f.o.b. prices in $/cwt from major milling centers located in each specific region. In particular, we use price data for grain varieties of Arkansas long (ar_lng), Arkansas medium (ar_med), Louisiana long (la_lng), Louisiana medium (la_med), Texas long (tx_lng), California medium (ca_med) and California short (ca_sht) obtained from the Agricultural Markets Service – USDA (Table 17, [www.ers.usda.gov/data-products/rice-yearbook-2015.aspx](www.ers.usda.gov/data-products/rice-yearbook-2015.aspx)). Prices are considered from January 1980 to July 2015. Figure 2 depicts these prices over the study period. The spike of rice prices between 2008 and 2010 is related to price movement of other crops over the same period. After 2010 California short grain (green line) is generally the most expensive and long grains from Arkansas, Texas, and Louisiana (blue-light blue lines) are lower than the short grain and medium rice varieties. Descriptive statistics of the data are reported in Table 1.

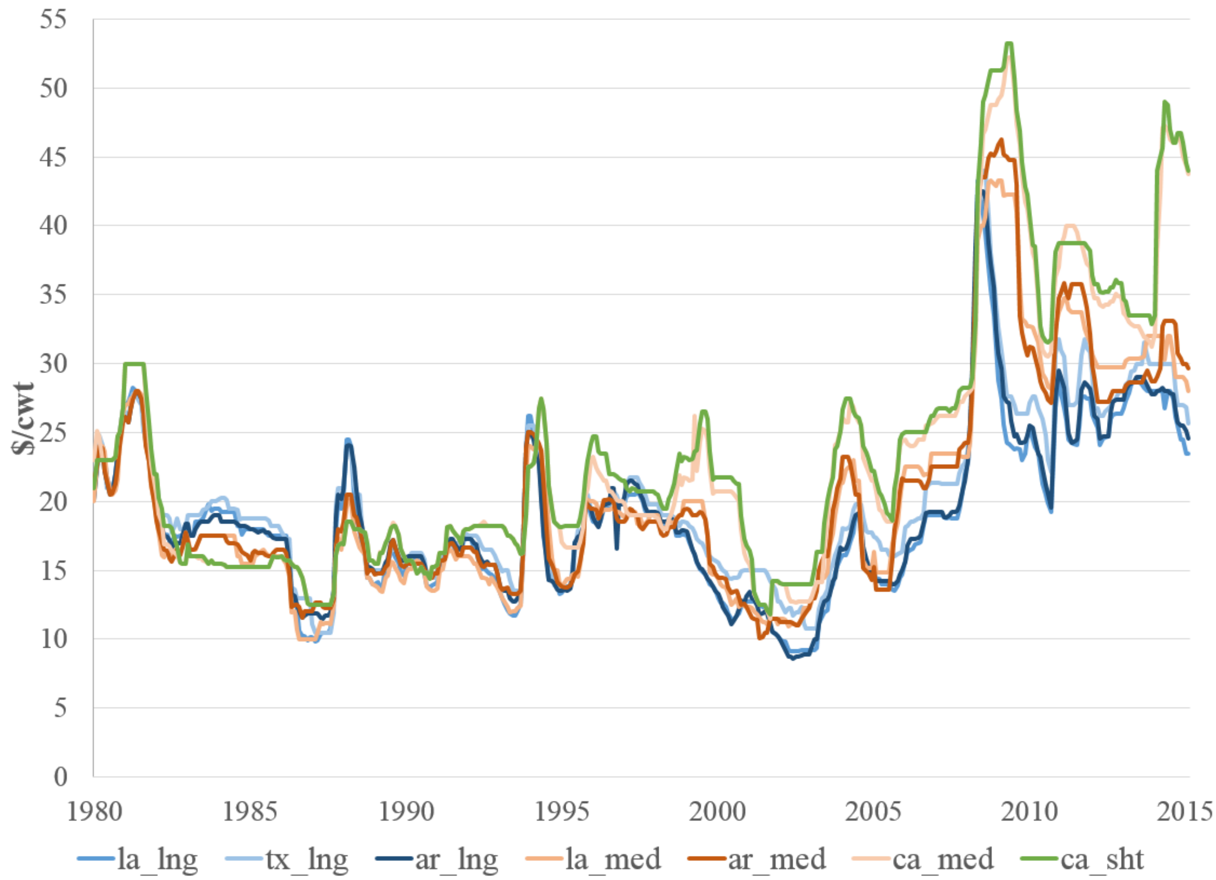


**Figure 2: U.S. Rice Prices of Grain Size and Major Producing States**

Source: Table 17, Rice Yearbook 2015, Agricultural Markets Service – USDA

Note: AR_lng = AR-MO long grain, LA_lng = LA-MS long grain, TX_lng = Texas long grain, AR_med = AR-MO medium grain, LA_med = LA-MS medium grain, CA_med = CA medium grain, and CA_sht = CA short grain

**Table 1.** Descriptive Statistics of Data ($/cwt), August 1979 – February 2015 (427 observations)

| | Variables | Mean | Std. Dev | CV | Min | Max | Autorcorr. |
|---|---|---|---|---|---|---|---|
| Arkansas long grain | ar_lng | 19.06 | 5.94 | 31.17 | 8.56 | 42.50 | 0.9829 |
| Louisiana long grain | la_lng | 18.74 | 5.82 | 31.03 | 9.13 | 43.25 | 0.9818 |
| Texas long grain | tx_lng | 20.11 | 5.96 | 29.62 | 10.50 | 44.00 | 0.9823 |
| Arkansas medium grain | ar_med | 20.44 | 7.71 | 37.73 | 10.06 | 46.25 | 0.9896 |
| Louisiana medium grain | la_med | 20.28 | 7.71 | 37.73 | 10.00 | 43.25 | 0.9916 |
| California medium grain | ca_med | 23.09 | 9.44 | 40.89 | 11.50 | 52.25 | 0.9929 |
| California short grain | ca_sht | 23.66 | 9.68 | 40.93 | 11.81 | 53.25 | 0.9929 |

Note: Price data are not deflated
Source: Table 17, Rice Yearbook 2015, Agricultural Markets Service – USDA

**Methods**

We employ the framework used by Bessler and Yang (2003) and Stockton, Bessler and Wilson (2010), which combines the DAG method and multivariate time series modeling, to explore the spatial price dynamics of rice markets. Given the non-stationarity nature of the data, we specify a vector error correction model (VECM) of the U.S. rice market with the seven selected prices. After the VECM is estimated, the contemporaneous innovations (residuals) are obtained. The DAG analysis then identifies the contemporaneous causal relationships among these innovations. This enables to address our matter of interest, that is, the dynamics of the variables are investigated by innovation accounting (impulse response functions and forecast error variance decompositions).

First, the data series are tested for non-stationarity using the Augmented Dickey-Fuller (ADF) test and Phillip-Perron (PP) test (Dickey and Fuller, 1979; Phillips and Perron, 1988) considering a constant and constant with trend. For the ADF test, the optimal lag length for the augmented terms was determined by minimizing the Schwarz-loss statistics (SL in Table 2). A unit root was found in five out of seven price series based on the ADF test (Table 2). The PP test suggested all series are not stationary. The unit root test for the data in first difference in the second half of Table 2 to confirm that we have I(1), i.e., the first difference is stationary.

**Table 2. Non-Stationarity Tests**

| ***Raw data*** | ADF test with time trend | | | | | | |
|---|---|---|---|---|---|---|---|
| | ar_lng | ar_med | ca_med | ca_sht | la_lng | la_med | tx_lng |
| Test statistics | -3.37 | -3.27 | -3.06 | -2.80 | -3.60 | -3.12 | -3.57 |
| Lag using SL | 1 | 1 | 2 | 1 | 1 | 1 | 1 |
| 5% critical value | -3.41 | -3.41 | -3.41 | -3.41 | -3.41 | -3.41 | -3.41 |
| Decision[a] | NS | NS | NS | NS | S | NS | S |
| | Phillips Perron test with time trend | | | | | | |
| | ar_lng | ar_med | ca_med | ca_sht | la_lng | la_med | tx_lng |
| Z(t) stat | -2.86 | -2.73 | -2.65 | -2.57 | -3.01 | -2.73 | -3.12 |
| Lags[b] | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| 5% critical value | -3.42 | -3.42 | -3.42 | -3.42 | -3.42 | -3.42 | -3.42 |
| Decision | NS | NS | NS | NS | NS | NS | NS |
| ***First difference*** | ADF test | | | | | | |
| | Δar_lng | Δar_med | Δca_med | Δca_sht | Δla_lng | Δla_med | Δtx_lng |
| Test statistics | -12.15 | -12.20 | -13.28 | -12.76 | -11.11 | -11.93 | -12.63 |
| Lag using SL | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 5% critical value | -2.86 | -2.86 | -2.86 | -2.86 | -2.86 | -2.86 | -2.86 |
| Decision[a] | S | S | S | S | S | S | S |
| | Phillips Perron test | | | | | | |
| | Δar_lng | Δar_med | Δca_med | Δca_sht | Δla_lng | Δla_med | Δtx_lng |
| Z(t) stat | -12.23 | -12.27 | -13.61 | -12.94 | -11.06 | -11.96 | -12.60 |
| Lags[b] | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| 5% critical value | -2.87 | -2.87 | -2.87 | -2.87 | -2.87 | -2.87 | -2.87 |
| Decision | S | S | S | S | S | S | S |

[a] NS = nonstationary, S = stationary; [b] The number of Newey-West lags, $\{4(T/100)^{\frac{2}{9}}\}$ lags

After confirming the presence of unit roots, the Johansen's Trace test for co-integration (Johansen, 1991) was applied in order to determine the possible presence of any long-run stationary relationships among the prices. To determine the optimal lag of the VECM, we first determine the optimal lag of the corresponding level VAR since the optimal lag length of the VECM is one less than that of the corresponding level VAR. The optimal lag of the level VAR is determined based on the Schwarz Loss metric. The optimal number of lags in the series was determined as three. Thus, for the VECM, the optimal lag length is two.

The Johansen trace test provides the information on the cointegrating vectors. The results are reported in Table 3. Based on the trace-test statistics regarding the rank hypothesis, the number $(r)$ of cointegrating vectors was determined to be six. Trace* and C* refer to the values of the trace statistic and the critical values at the 5% significance level considering an intercept, while Trace and C refer to the values of the trace statistic and the critical values at the 5% significance level considering a trend and intercept.

**Table 3. Trace Test on Order of Cointegration**

| Rank | Trace*[a] | C*[a] | Decision | Trace[b] | C[b] | Decision |
|---|---|---|---|---|---|---|
| r = 0 | 237.33 | 134.54 | Reject | 276.56 | 150.35 | Reject |
| r ≤ 1 | 166.10 | 103.68 | Reject | 186.77 | 117.45 | Reject |
| r ≤ 2 | 103.32 | 76.81 | Reject | 122.75 | 88.55 | Reject |
| r ≤ 3 | 69.12 | 53.94 | Reject | 87.78 | 63.66 | Reject |
| r ≤ 4 | 42.98 | 35.07 | Reject | 59.06 | 42.77 | Reject |
| r ≤ 5 | 20.76 | 20.16 | Reject | 33.15 | 25.73 | Reject |
| r ≤ 6 | 3.20 | 9.14 | Fail[c] | 10.98 | 12.45 | Fail |

[a] Trace* and C* refer to the values of trace statistic and critical values at the 5% significance level with an intercept.
[b] Trace and C refer to the values of trace statistic and critical values at the 5% significance level with a time trend and an intercept
[c] The first "fail to reject" the null hypothesis occurs for r ≤ 6. Thus, there are 6 cointegrating vectors.

Given these prior results, we apply the vector error correction model (VECM) to our series of prices based on the procedure described in Lütkepohl and Krätzig (2004). Let $\mathbf{y}_t$ denote the vector of variables under consideration, $\mathbf{y}_t' = [y_{1t}, \cdots, y_{7t}]$, where the subscript 1 represents ar_lng, subscript 2 represents la_lng and so on. The VECM model with two lags is noted as:

$$\Delta\mathbf{y}_t = \mathbf{\Pi}\mathbf{y}_{t-1} + \sum_{i=1}^{2}\mathbf{\Gamma}_i\Delta\mathbf{y}_{t-i} + \mu + \mathbf{e}_t \qquad (t = 1, \dots \dots . . T) \qquad (1)$$

where $\Delta$ is the first difference operator (e.g. $\Delta\mathbf{y}_t = \mathbf{y}_t - \mathbf{y}_{t-1}$); $\mathbf{y}_t$ is a (7× 1) vector of prices; $\mathbf{\Pi}$ is a 7×7 coefficient matrix of rank $r$, i.e., number of co-integration vectors such that $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$. The 7×6 matrix $\boldsymbol{\alpha}$ is a matrix of weights knows as the speed of adjustment parameters and the 6×7 matrix $\boldsymbol{\beta}$ is the matrix of cointegrating parameters. $\mathbf{\Gamma}_i$ is a 7×7 matrix of short-run dynamic coefficients; and $\mathbf{e}_t$ is a 7×1 vector of innovations.

After estimating the VECM of 2 lags in equation (1), we identify the contemporaneous structure of the innovations through the DAG analysis of the correlation matrix of the $\hat{\mathbf{e}}_t$. The DAG method, as described by Pearl (1995, 2000) and Spirtes, Glymour and Scheines (2000), considers a non-time sequence asymmetry in causal relations among variables and is an illustration using arrows and vertices (variables) to represent the causal flow among a set of variables (Pearl, 2000). Directed acyclic graphs represent a conditional independence relationship as given by the recursive decomposition:

$$\Pr(v_1, v_2, \dots \dots \dots . . , v_n) = \prod_{i=1}^{n}\Pr(v_i|pr_i) \qquad (2)$$

where Pr (.) is the joint probability of variables $v_1, v_2, \cdots, v_n$ and $pr_i$ represents parents of $v_i$, the minimal set of predecessors (the variables that come before in a causal sense) that renders $v_i$ independent of all its other predecessors (Pearl, 2000, p.14-15). Geiger, Verma, and Pearl (1990) have shown that there is a one-to-one correspondence between the set of conditional independencies among variables implied by (2) and the graphical expression of variables in a directed acyclic graph.

The PC Algorithm marketed as TETRAD V (www.phil.cmu.edu/tetrad/current.html) is used to compute the directed acyclic graph. The process of causal determination begins with a completely undirected graph which shows an undirected edge between every pair of variables in the system. Then, the PC algorithm proceeds step-wise to remove edges based on correlation relationships among the variables. Finally, the PC Algorithm determines causal flows using conditional independence relationships on the remaining edges. See Spirtes, Glymour and Scheines (2000) for more about the PC algorithm.

After obtaining the DAG results, we estimate structural innovations directly from the reduced form residuals by applying the additional (obtained) contemporaneous restrictions (Lütkepohl, 2005, p. 362). We then use standard innovation accounting techniques to obtain inferences with respect to the dynamic adjustments in each of the variables from unexpected shocks in the series. The forecast error variance decomposition (FEVD) consists of when the innovations/shocks to each variable is decomposed, permitting the identification of the relative proportion of the movements in a sequence due to its own shock, over the other shocks to the variable. In the case that own shocks explain mostly all of the forecast error variance of a specific series, this variable may be considered (weakly) exogenous with respect to the other variables in the system.

Conversely, if a large proportion of the FEVD from a variable's sequence can be explained by shocks to one or more of the other variables, then this variable is considered endogenous to the system. The FEVD approach likewise permits to draw inferences with respect to the magnitude and degree of influence during the sequence, among the variables in the system. In addition, impulse response functions (IRF) are likewise determined through standard innovation accounting. IRFs permit to identify the dynamic adjustments, in terms of direction and magnitude, for each variable in the system in response to unit shocks in a particular system's variable. The IRFs are generated by separately shocking innovations for each of the variables by one standard deviation.

**Results**

*Contemporaneous Causal Structure*

Figure 3 displays the contemporaneous causal relationships among the variables, where each line is an edge indicating a relationship between the connected markets. As shown in Figure 3, CA market is separated from other markets in the contemporaneous period. California short grain price concurrently leads California medium grain price. Likewise, Arkansas medium grain concurrently leads Arkansas long grain as well as Louisiana medium grain. Arkansas long grain concurrently leads both Texas long grain and Louisiana long grain. This latter also concurrently leads Louisiana medium. As seen in Figure 3 the California markets are contemporaneously segregated.  Based on Figure 3, we may conclude that Arkansas medium is the price concurrent leader in the southern regions and Louisiana medium is the “sink of the price dynamics.

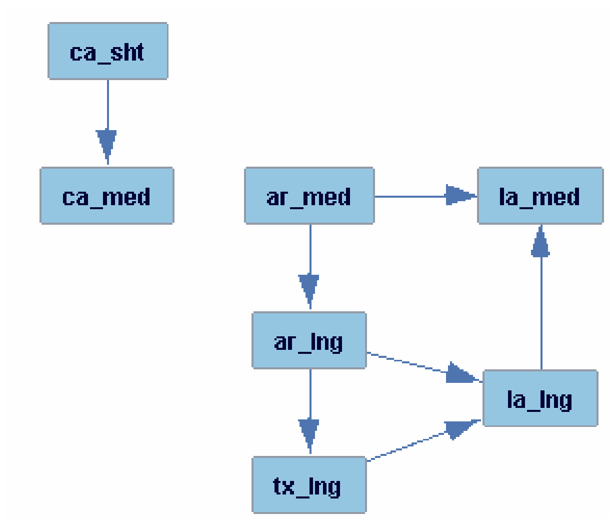


**Figure 3: Directed Acyclic Graph of Seven Rice Markets using PC Algorithm**
ar_lng = Arkansas long grain, ar_med = Arkansas medium, ca_med = California medium, ca_sht = California short, la_lng = Louisiana long, la_med = Louisiana medium, and tx_lng = Texas long, respectively

It is relevant to re-emphasize that the DAG results from Figure 3 show only the contemporaneous causal structure. The contemporaneous period here refers to the actual period in which a disturbance to the system (the US rice market) may occur; for example, a one-time-only shock to Arkansas medium grain and its effects. It is also noted that the causal structure in Figure 3 only shows the direction of causal flows among the variables and does not say anything about the magnitude or the sign (positive or negative) of the effect. These latter are determined by the innovation accounting.

*Innovation Accounting*

Impulse responses in Figure 4 depicts the response of all variables to a one-time-shock in the innovation of one variable when other variables' innovations remain constant. The (one-time) shock is positive and of a magnitude equal to one standard deviation of the innovation of the particular factor (variable), applied at a contemporaneous period (month zero), and leaving all other factor's innovations constant for all dates (Hamilton, 1994, pg. 318).

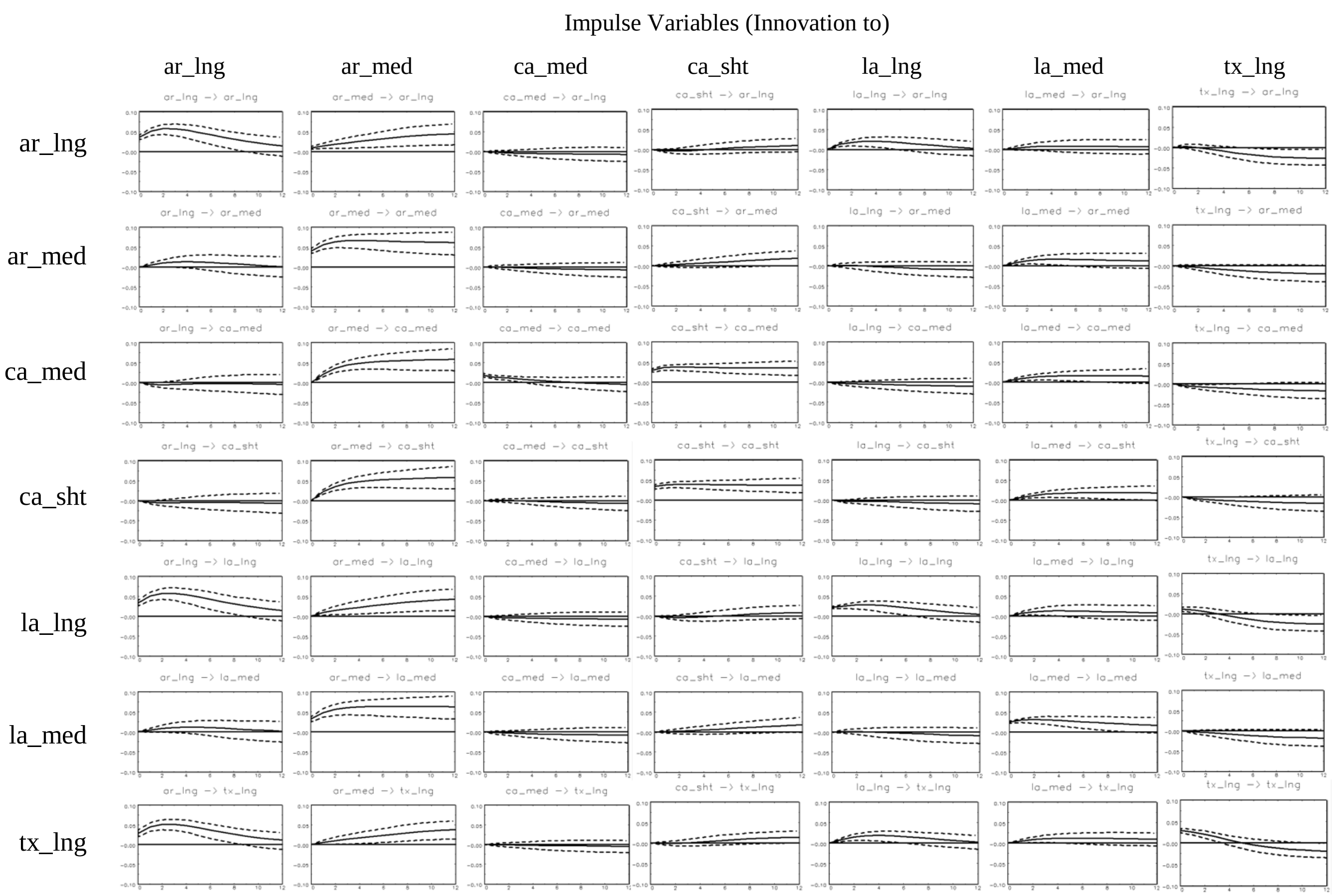


**Figure 4: Impulse Response Functions**

ar_lng = Arkansas long grain, ar_med = Arkansas medium, ca_med = California medium, ca_sht = California short, la_lng = Louisiana long, la_med = Louisiana medium, and tx_lng = Texas long, respectively

In the first column in Figure 4, Arkansas long grain market's shock only affects the other long grain markets in a significant manner; i.e. Louisiana long and Texas long. This significant positive impact, of up to five to six percent on Louisiana and Texas long grain subsides after about eight months. Similarly, Louisiana long grain's shock significantly affects only Arkansas long and Texas long grain, but at a briefer impact of up to six months. The shock from Texas long grain only produces a very minor effect on Louisiana long grain and it's negligible on Arkansas long grain. Thus even though all markets are co-integrated, Arkansas long grain has a sizeable effect on the other long grain markets and not upon its own local (Arkansas) medium grain market. Thus it appears that grain markets are not spatially segregated but actually set apart by varieties. In addition, Arkansas dominance among long grain markets may respond to its larger volume in comparison to the other producing states.

The second column illustrates the effect from a shock to Arkansas medium grain. In this case, there is a significant positive effect of about five percent in both California's medium and short grain markets. In addition, this effect is persistent through time and appears to be permanent. There is also a significant positive impact on Louisiana medium grain, in the order of six to seven percent, and again seems like it maybe a permanent effect given its persistence through time. Finally, there likewise exists an increasing effect on Texas long, which also remains permanent. Thus Arkansas medium grain market affects not only the other medium markets, but also other variety markets (e.g. California short and Texas long) in other regions. In addition, its impact on these markets shows certain steady persistence.

California medium grain does not have any effect on the other markets (column three). However, California short grain (column four) does have a significant positive impact of about four percent on California medium grain. Once again this effect is appears to be permanent. Thus the effect from California markets seem to be spatially segregated from other markets, and just impacting from short to medium grain. Shocks on Louisiana medium grain (column six) only have a minor substantial impact on the other markets, at around two percent; however, this impact becomes insignificant after six months.

The Forecast Error Variance Decomposition (FEVD) considering up to 18 months for the Arkansas long and medium grain are shown in Table 4, which is grouped across varieties. Arkansas long grain's price variation, first row, is impacted mostly by itself but also a bit by Arkansas medium, as well as much less by Texas long grain.

**Table 4. Forecast Error Variance Decompositions**

Accounted for by →

| Months | Variation in ↓ | ar_lng | la_lng | tx_lng | ar_med | la_med | ca_med | ca_sht |
|---|---|---|---|---|---|---|---|---|
| 1 | ar_lng | 0.94 | 0.00 | 0.00 | 0.06 | 0.00 | 0.00 | 0.00 |
| 2 | | 0.89 | 0.04 | 0.00 | 0.06 | 0.00 | 0.00 | 0.00 |
| 6 | | 0.76 | 0.08 | 0.01 | 0.13 | 0.01 | 0.00 | 0.00 |
| 12 | | 0.53 | 0.06 | 0.09 | 0.29 | 0.01 | 0.01 | 0.01 |
| 18 | | 0.37 | 0.04 | 0.12 | 0.42 | 0.01 | 0.01 | 0.02 |
| 1 | la_lng | 0.65 | 0.27 | 0.08 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | | 0.71 | 0.21 | 0.04 | 0.02 | 0.01 | 0.00 | 0.00 |
| 6 | | 0.69 | 0.18 | 0.02 | 0.08 | 0.03 | 0.00 | 0.00 |
| 12 | | 0.51 | 0.13 | 0.07 | 0.24 | 0.03 | 0.01 | 0.01 |
| 18 | | 0.37 | 0.09 | 0.11 | 0.37 | 0.03 | 0.01 | 0.02 |
| 1 | tx_lng | 0.48 | 0.00 | 0.52 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | | 0.64 | 0.02 | 0.34 | 0.01 | 0.01 | 0.00 | 0.00 |
| 6 | | 0.71 | 0.07 | 0.13 | 0.06 | 0.03 | 0.00 | 0.00 |
| 12 | | 0.54 | 0.07 | 0.11 | 0.22 | 0.04 | 0.00 | 0.02 |
| 18 | | 0.37 | 0.05 | 0.12 | 0.37 | 0.04 | 0.01 | 0.05 |
| 1 | ar_med | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 |
| 2 | | 0.01 | 0.00 | 0.00 | 0.98 | 0.01 | 0.00 | 0.00 |
| 6 | | 0.03 | 0.00 | 0.01 | 0.91 | 0.04 | 0.00 | 0.01 |
| 12 | | 0.02 | 0.01 | 0.04 | 0.87 | 0.04 | 0.00 | 0.03 |
| 18 | | 0.01 | 0.01 | 0.05 | 0.83 | 0.04 | 0.01 | 0.05 |
| 1 | la_med | 0.00 | 0.00 | 0.00 | 0.62 | 0.38 | 0.00 | 0.00 |
| 2 | | 0.00 | 0.00 | 0.00 | 0.68 | 0.31 | 0.00 | 0.00 |
| 6 | | 0.02 | 0.00 | 0.01 | 0.75 | 0.21 | 0.00 | 0.00 |
| 12 | | 0.02 | 0.00 | 0.03 | 0.78 | 0.15 | 0.01 | 0.02 |
| 18 | | 0.01 | 0.01 | 0.04 | 0.77 | 0.11 | 0.01 | 0.04 |
| 1 | ca_med | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.27 | 0.73 |
| 2 | | 0.01 | 0.00 | 0.01 | 0.14 | 0.01 | 0.15 | 0.68 |
| 6 | | 0.01 | 0.01 | 0.02 | 0.47 | 0.04 | 0.04 | 0.41 |
| 12 | | 0.00 | 0.01 | 0.03 | 0.57 | 0.05 | 0.02 | 0.32 |
| 18 | | 0.00 | 0.02 | 0.04 | 0.60 | 0.05 | 0.01 | 0.28 |
| 1 | ca_sht | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| 2 | | 0.01 | 0.01 | 0.01 | 0.16 | 0.02 | 0.00 | 0.81 |
| 6 | | 0.01 | 0.00 | 0.02 | 0.45 | 0.05 | 0.00 | 0.46 |
| 12 | | 0.01 | 0.01 | 0.03 | 0.55 | 0.06 | 0.00 | 0.35 |
| 18 | | 0.01 | 0.01 | 0.04 | 0.58 | 0.06 | 0.01 | 0.30 |

ar_lng = Arkansas long grain, ar_med = Arkansas medium, ca_med = California medium, ca_sht = California short, la_lng = Louisiana long, la_med = Louisiana medium, and tx_lng = Texas long, respectively

However, in the case of Arkansas medium grain's price variation, fourth row, it is almost completely due to itself (i.e. weakly exogenous). In case of California, both medium and short grain markets move a bit independently in the short term, but are likewise affected by Arkansas medium after half a year. Also, Louisiana long's price variations, second row, is mostly affected by Arkansas long, and then after a year it is also affected by Arkansas medium. However, Arkansas medium substantially affects the majority of Louisiana medium grain's price variations, fifth row. Finally, Texas long, third row, is again mostly impacted by Arkansas long after the 1st month, and also after a year by Arkansas medium, thus in a similar way as Louisiana long grain is affected.

**Conclusions**

Rice is a staple commodity in the US and world markets. Although U.S. rice is produced in four distinct regions, i.e. Arkansas, Mississippi Delta, Texas and Southwest Louisiana, and California, it still plays a major role in US agriculture. Rice is among the top seven US crops in terms of harvested acres and sixth in terms of cash receipt. The U.S. exports about half of its rice production to overseas markets and accounting for over ten percent of the annual volume of global rice trade. Thus understanding the dynamic and spatial domestic market integration is of significant relevance. Dynamic and spatial market integration refers to the smooth transmission of price signals and information across spatially separated markets. We investigate whether there is dynamic and spatial market integration among US rice markets. More specifically, this paper attempt to unveil whether the US rice markets are spatially integrated and investigate whether integrated across rice varieties, long, medium and short grain.

In this study, we applied the DAG approach to compute the contemporaneous causality among seven US f.o.b. mill prices in the context of the multivariate time series modeling, a Vector Error Correction Model. Results suggest that, in the contemporaneous period, Arkansas medium price is the leading reference among Arkansas, Louisiana and Texas long and medium grain. California medium and short grains are segregated. From IRFs and FEDV, we conclude that Arkansas long grain price is a leading reference in the markets for the long grain. Arkansas medium price is also identified as a leading reference in markets for medium grains. Interestingly, Arkansas medium grain plays an important role in long grain markets, medium grains markets itself, and also California short grain even though California short grain seems to move somewhat independently in the short run. The findings of this research are in general agreement with the size of regional rice production, in terms of long grain (and Arkansas) being the sizeable major player. Except the considerable influence of price from Arkansas medium grain is not immediately apparent, and is left for future analysis.

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