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U.S. milled rice markets and integration across regions and types

RESEARCH ARTICLE

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Abstract

Rice is among the top seven U.S. 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. This paper investigates whether U.S. milled rice markets are integrated across regions and whether these markets are integrated by rice types. Understanding dynamic relationships across regions and types provides important insights for risk management and policy making. Of the four major producing regions, three are in the South – Arkansas-Missouri, Louisiana-Mississippi, and Texas – and the other is California. There are different rice types associated with a production region. California mainly produces short and medium grain; while Arkansas, Texas, and Louisiana primarily produce long and also m6edium grains. We determine the potential market integration of these rice markets by applying a Vector Error Correction Model and Directed Acyclic Graphs to monthly free on board milled rice price data from August 1986 to December 2015. Results suggest that Arkansas-Missouri region is the leading price reference in the long grain markets. Arkansas-Missouri medium grain also plays an important role in the medium grain markets. California medium grain markets are weakly exogenous in the short run, but affected by Arkansas-Missouri medium grain in the longer term. As anticipated, Arkansas-Missouri long grain milled rice markets are driven by rough rice futures price in the longer term. Interestingly, Arkansas-Missouri medium grain market has a sizable impact on long grain markets even though long and medium grains are not substitutes. This may be due to land competition to long grain rice production in Arkansas, a major area of long grain rice production.

Keywords: rice markets, cointegration, impulse response functions
JEL code: Q11, Q13, C32

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1. Introduction

Rice is considered as a staple commodity in major world markets – especially Asia, Africa and Latin America. About 20% of the caloric intake of the world population is from rice (Giraud, 2013). Rice also plays a major role in U.S. agriculture and 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 is among the top seven U.S. crops in terms of harvested acres, covering over 2.6 million acres in 2013 to 2015,[1] and sixth in terms of sales (cash receipts) with annual transactions of over 3.1 billion dollars. In addition, U.S. is a major rice exporter, accounting for about 8 to 9% of the annual volume of global rice trade (ERS, 2015).

There are three types of rice grown in the U.S., classified according to the length of grain as long, medium and short grain. Moreover, several varieties of each type are produced each year. Long grain type of rice is almost entirely produced in the southern regions; i.e. Arkansas, Louisiana, Mississippi, Missouri and Texas; and long grain covers about 70% of the total U.S. rice production. Also, Arkansas produces about 65% of all long grain rice. The medium grain is mainly produced in California, while a much smaller production is located in the southern regions – mostly in Arkansas and far behind in Louisiana. Medium grain production accounts for over 25% of the total U.S. rice production. Less than 2% of total rice production is short grain and nearly all U.S. short grain rice is grown in California (Childs, 2012). Figure 1 presents the time trend of rice production over types across regions between 1980 and 2015. More than 200 million cwt (centum or hundred weight equivalent to 100 pounds) of rice were annually produced on average during the 2000s decade. The blue and light blue areas together indicate long grain production from Arkansas-Missouri,

[1] These years include periods of severe drought in California and Texas that resulted in reduced plantings; i.e. the size of industry may be quite larger than that of the data during these years.

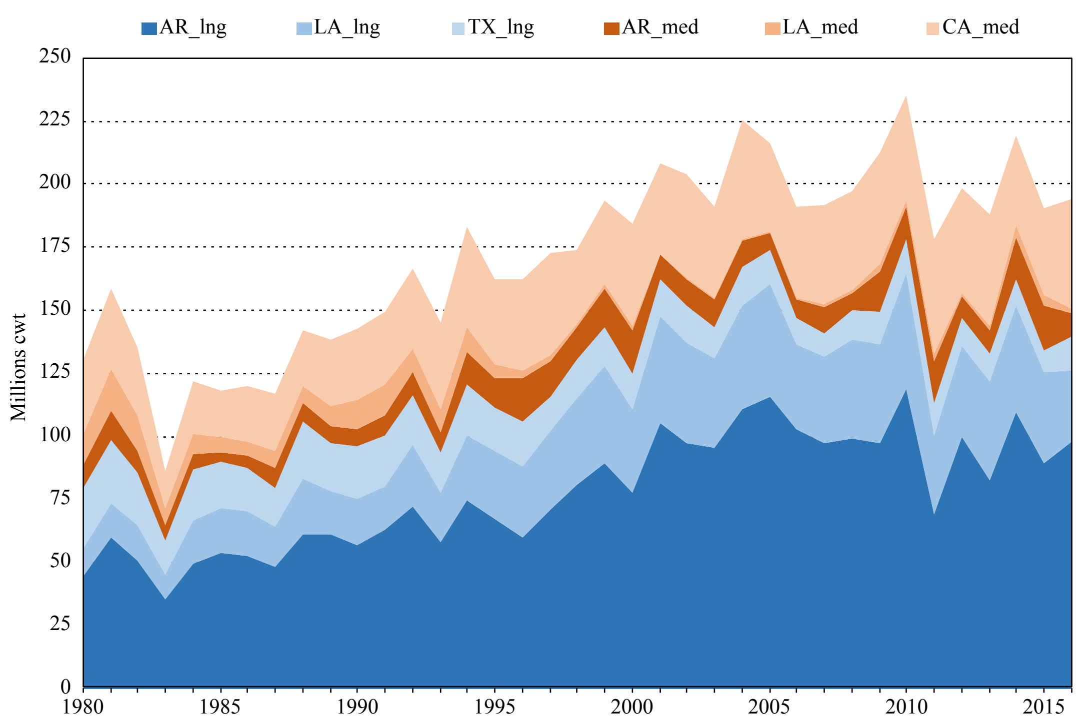

Figure 1. U.S. rice production of different varieties and regions (USDA NASS; https://www.nass.usda.gov). AR_lng = AR-MO long grain; LA_lng = LA-MS long grain; TX_lng = Texas long grain; AR_med = AR-MO medium grain; LA_med = LA-MS medium grain; CA_med = CA medium grain.

Louisiana-Mississippi, and Texas. The combined brown and light brown areas represent the medium grain production across Arkansas, Louisiana, and California.

Global rice markets have very little substitution between types of long-grain and medium-grain rice. Japan, Korea and other Northeast Asian countries – the largest export markets for U.S. medium- and short-grain rice – consumes only 'higher quality' medium and short grain rice from California. Note that almost all U.S. rice purchased by Northeast Asia is from California. Conversely, Southern medium-grain export sales are much smaller and limited to North Africa and the Middle East. In the U.S. domestic market, substitution between grain types hardly occurs and only in case of processed food products, where mostly southern medium-grain is used.[2]

Price analysis of agricultural commodities in the U.S. has been studied extensively in the literature (e.g. Fackler and Goodwin, 2001; Serra and Goodwin, 2004; Stockton *et al.,* 2010; Yu *et al.,* 2007). However, it is surprising – given its economic value – that dynamic relationships among U.S. rice prices is still limited. Taylor *et al.* (1996) investigated the dynamic relationships between U.S. and Thai rice prices but price dynamics within U.S. rice markets was not addressed in their study. Djunaidi *et al.* (2001) study long-run relationships between long grain rice markets from Southern states and California, finding only existing for Southern states and not with the California rice market. In addition, McKenzie *et al.* (2002) study the efficiency of the U.S. long-grain rough rice futures market and find evidence in favor of it, concluding that rice futures market should be considered useful as a price risk management and forecasting tool. The analysis of price dynamics across regions and types is important to understand the U.S. 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 two U.S. rice types, i.e. medium and long grain, among major domestic producing markets. The analysis will provide insights in the price discovery process among separate U.S. rice markets. Findings on price discovery among rice markets and types can potentially mitigate marketing risk for producers and wholesales, also assist policy makers to stabilize the market through policy tools.

We employ a structural multivariate Vector Autoregression model with an error correction term (VECM). Multivariate time series models such as the VECM have been commonly used in the literature of price analysis across regions. To formulate a structural VECM, a Directed Acyclic Graphs (DAG) from Pearl (1995, 2000) and Spirtes *et al.* (2000) is 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).

2. Data

We use average monthly f.o.b. (free on board)[3] milled prices in $/cwt from major milling centers located in each specific region. We are interested in f.o.b. milled prices because the bulk of U.S. rice is sold as milled. In addition there is no prior study addressing price discovery of these milled rice markets. Based on product-weight, about 50% of rice exports is in the milled form (USDA, 2015: Tables 12-13); however, actually about two-thirds of U.S. rice exports are classified as milled rice (milled and brown rice on a rough-basis). 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), and California medium (CA_med) obtained from the Agricultural Markets Service – USDA (USDA, 2017: Table 17). Prices considered are from August 1986 to December 2015. Figure 2 illustrates these prices for the study period. The spike of prices between 2008 and 2010 is related to global rice price movements over the same period (Childs and Kiawu, 2009). After 2010 long grains in Arkansas, Texas, and Louisiana (blue-light blue solid lines) are lower prices than the medium rice varieties (dotted lines). Descriptive statistics of the data are reported in Table 1.

[2] We thank an anonymous referee for pointing this out.

[3] Shipping terminology that means price of product includes loading on top of truck, rail cargo, vessel, or other.

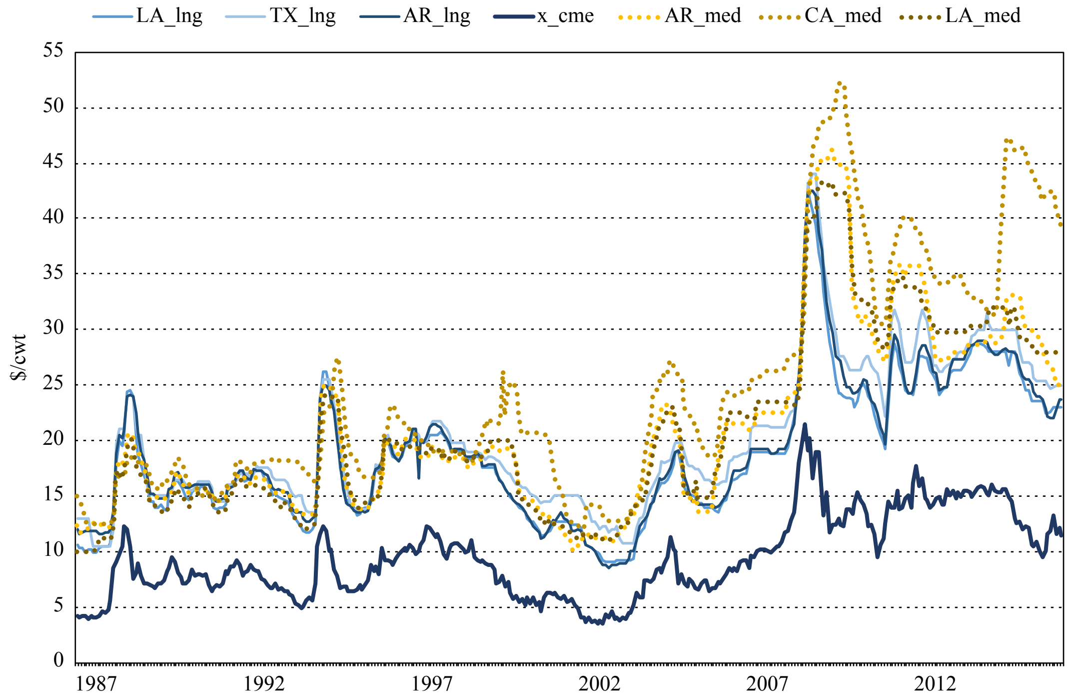

Figure 2. U.S. (milled) rice prices of grain size and milling states (Aug. 1986 ~ Dec. 2015) (adapted from USDA, 2017: Table 17). AR_lng = AR-MO long grain; LA_lng = LA-MS long grain; TX_lng = Texas long grain; AR_med = AR-MO medium grain; LA_med = LA-MS medium grain; CA_med = CA medium grain; x_cme = rough rice futures price from CME Group Inc. (Chicago Mercantile Exchange and Chicago Board of Trade).

Table 1. Descriptive statistics of data ($/cwt), August 1986-December 2015 (353 observations) (adapted from USDA, 2017: Table 17).[1]

		Mean	Std. Dev.	CV(%)	Min.	Max.	Autocorr.
Arkansas long grain	AR_lng	18.99	6.34	33.40	8.56	42.50	0.984
Louisiana long grain	LA_lng	18.57	6.18	33.27	9.13	43.25	0.983
Texas long grain	TX_lng	20.18	6.43	31.89	10.50	44.00	0.984
Arkansas medium grain	AR_med	20.98	8.30	39.57	10.06	46.25	0.990
Louisiana medium grain	LA_med	20.86	8.23	39.43	10.00	43.25	0.993
California medium grain	CA_med	24.54	10.30	41.95	11.50	52.25	0.993
CME rough rice futures	x_cme	9.44	3.68	38.99	3.51	21.48	0.971

[1] Price data are not deflated.

Rough rice futures price is also included in the analysis. Incorporating rough rice futures price in the analysis can help us investigate whether it provides information in the price discovery of the U.S. milled rice markets since rough rice is a major input of milling facilities. Taylor *et al.* (1996) point out that rough rice futures markets provide market participants with information regarding local, national and international rice market as well as serving as a primary discovery mechanism. Rough rice futures prices are compiled from CME available from Quandl; http://tinyurl.com/ycy7s9u8.

3. Methods

We employ the framework used by Bessler and Akleman (1998), Bessler and Yang (2003) and Stockton *et al.* (2010), which combines the DAG method and multivariate time series modeling, to explore the price dynamics of rice markets. Given the non-stationarity nature of the data, we specify a 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 which are investigated by using innovation accounting (impulse response functions (IRF) and forecast error variance decompositions (FEVD)).

First, the data series are tested for non-stationarity using the Augmented Dickey-Fuller (ADF) test considering a constant (Dickey and Fuller, 1979) and Kwiatkowski-Phillps-Schmidt-Shin (KPSS) test (Kwiatkowski *et al.,* 1992). For the ADF test, the optimal lag length for the augmented terms was determined by minimizing the Schwarz-loss statistics (SL). A unit root was found in five out of seven price series based on the ADF test (Table 2). The KPSS test suggested all series are not stationary. The unit root test for the data in first difference is in the second half of Table 2 and suggests that those price series are integrated of order one, or I(1), given test results for the first difference is stationary.

Table 2. Non-stationarity tests.[1]

Raw data	**Long grain**				**Medium grain**		
	AR_lng	**LA_lng**	**TX_lng**	**x_cme**	**AR_med**	**CA_med**	**LA_med**
ADF test (non-zero mean)							
Test statistics	-2.82	-3.25	-2.97	-2.77	-2.50	-1.69	-2.40
Lag using SL	1	1	1	1	1	1	1
5% critical value	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86
Decision[2]	NS	S	S	NS	NS	NS	NS
KPSS test (level stationary)							
Test statistics	2.15	2.26	2.96	2.34	3.18	3.98	3.56
Lags[3]	5	5	5	5	5	5	5
5% critical value	0.463	0.463	0.463	0.463	0.463	0.463	0.463
Decision	NS	NS	NS	NS	NS	NS	NS
First difference	**ΔAR_lng**	**ΔLA_lng**	**ΔTX_lng**	**Δx_cme**	**ΔAR_med**	**ΔCA_med**	**ΔLA_med**
ADF test (non-zero mean)							
Test statistics	-7.92	-8.52	-8.35	-9.92	-8.02	-8.18	-8.14
Lag using SL	0	0	0	1	0	0	0
5% critical value	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86	-2.86
Decision	S	S	S	S	S	S	S
KPSS test (level stationary)							
Test statistics	0.034	0.064	0.025	0.050	0.042	0.034	0.045
Lags	5	5	5	5	5	5	5
5% critical value	0.463	0.463	0.463	0.463	0.463	0.463	0.463
Decision	S	S	S	S	S	S	S

[1] 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; x_cme = CME rough rice futures; ADF = Augmented Dickey-Fuller test; SL = Schwarz-loss statistics; KPSS = Kwiatkowski-Phillps-Schmidt-Shin test.

[2] NS = nonstationary; S = stationary.

[3] The number of Newey-West lags, $\{4(T/100)^{\frac{2}{9}})\}$lags where T is the number of observations.

After confirming the presence of unit roots, the Johansen's Trace test for co-integration (Johansen, 1991) was applied to determine the possible presence of any long-run stationary relationships among the prices. In addition, to determine the optimal lag of the VECM, we first determine the optimal lag of the corresponding level vector autoregression (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 two. Thus, for the VECM, the optimal lag length is one.

The Johansen trace test provides the information on the cointegrating vectors and 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 five. 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.

Given these results, we apply the 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, $\mathbf{y}'_t=[y_{1t}, ..., y_{7t}]$, where the subscript 1 represents the prices series of AR_lng, subscript 2 represents the price series of LA_lng and so on. The VECM model with one lags is represented as:

$$\Delta\mathbf{y}_t = \mathbf{\Pi}\mathbf{y}_{t-1} + \mathbf{\Gamma}\Delta\mathbf{y}_{t-1} + \boldsymbol{\mu} + \mathbf{e}_t \ (t = 1,........T) \tag{1}$$

where Δ 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 $\mathbf{\Pi}=\boldsymbol{\alpha\beta}'$. $\boldsymbol{\alpha}$ is a 7×5 matrix of weights knows as the speed of adjustment parameters and $\boldsymbol{\beta}$ is the 5×7 matrix of cointegrating vectors. $\mathbf{\Gamma}$ 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 1 lag in Equation (1), we identify the contemporaneous structure of the innovations through the DAG analysis of the correlation matrix of residuals, $\hat{\mathbf{e}}_t$. The DAG method, as described by Pearl (1995, 2000) and Spirtes *et al.* (2000), considers a non-time sequence asymmetry in causal relations among variables resulting in an illustration using arrows and vertices (variables) to represent the causal flow among a set of variables (Pearl, 2000). DAG represent a conditional independence relationship as shown by the recursive decomposition:

$$\Pr(v_1,v_2,... ... ...,v_n) = \Pi_{i=1}^{n} \Pr(v_i \mid pr_i) \tag{2}$$

where Pr (.) is the joint probability of variables $v_1,v_2,...,v_n$ and pr_i represents 'parents' of v_i, a minimal set of predecessors (variables that come before in a causal sense) that renders v_i independent of all its other

Table 3. Trace test on order of cointegration.

Rank	Trace*[1]	C*[1]	Decision	Trace[2]	C[2]	Decision
r=0	280.52	134.54	Reject	324.00	150.35	Reject
r≤1	172.71	103.68	Reject	216.00	117.45	Reject
r≤2	108.36	76.81	Reject	142.51	88.55	Reject
r≤3	65.36	53.94	Reject	93.50	63.66	Reject
r≤4	38.57	35.07	Reject	52.25	42.77	Reject
r≤5	20.13	20.16	Fail[3]	27.37	25.73	Reject
r≤6	5.16	9.14	Fail[3]	8.97	12.45	Fail

[1] Trace* and C* refer to the values of trace statistic and critical values at the 5% significance level with an intercept.

[2] 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.

[3] The first 'fail to reject' the null hypothesis occurs for r≤5. Thus, there are 5 cointegrating vectors.

predecessors (Pearl, 2000: 14-15). Geiger *et al.* (1990) have shown that there is a one-to-one correspondence between the set of conditional independencies among variables implied by Equation 2 and the graphical expression of variables in a directed acyclic graph. For example, consider four variables, v_1, v_2, v_3, and v_4. If there is causal relationship such as v_1, v_2 cause v_3 and v_3 causes v_4, then the directed graphs that represents in this causal relationship can be represented in Figure 3. The directed graph is expressed as the probability distribution product by:

$$\Pr(v_1,v_2,v_3,v_4) = \Pr(v_1)\Pr(v_2)\Pr(v_3 \mid v_1,v_2)\Pr(v_4|v_3) \tag{3}$$

A Linear Non-Gaussian Acyclic Model (LiNGAM) algorithm, developed by Shimizu *et al*. (2006a), identifies the causal patterns in the case of non-normal data (Shimizu and Kano, 2008). Our study applies LiNGAM following a recent study by Lai and Bessler (2015). This algorithm determines the causal directionality based on functional composition (Pearl, 2009) by making use of independent component analysis (ICA). In effect, and as noted by Lai and Bessler (2015), the Central Limit Theorem (CLT) affirms that any mixture of independent variables generally has a distribution that is closer to a normal distribution than that of any of the original variables (Stone, 2004). Assuming we observe the mixtures, $\mathbf{x}=(x_1,\ldots,x_n)$ from the independent (unobserved) variables $\mathbf{v}=(v_1,\ldots,v_n)$, then $\mathbf{x}=\mathbf{Av}$ where $\mathbf{v}$ are mutually independent components. From CLT, any of the $\mathbf{v}$ is less Gaussian than the (mixture) variables $\mathbf{x}$. ICA's main goal is to determine the 'de-mixing' matrix $\mathbf{W}$, such that $\mathbf{W}$ maximizes the sum of the non-normal, mutually statistical independent components of $\tilde{\mathbf{v}}$ where $\tilde{\mathbf{v}}=\tilde{\mathbf{W}}\mathbf{x}$ and $\mathbf{x}=\mathbf{A}^{-1}$ (Shimizu *et al.*, 2006b). In the case of LiNGAM (Lai and Bessler, 2015; Shimizu *et al.*, 2006a), we assume existing causal relationships among the vector $\mathbf{x}=(x_1,\ldots,x_\mathrm{n})$ characterized by the linear equation model:

$$x_i = \textstyle\sum_{k(j)<k(i)} b_{ij}x_j + e_i \tag{4}$$

where $k(i)$ denotes a causal order of x_i and x_j is a direct cause of x_i. The disturbances e_i are mutually independent and non-Gaussian distributed with non-zero variances. Assuming each x_i has a zero mean, we have:

$$\mathbf{x}=\mathbf{Bx}+\mathbf{e} \tag{5}$$

where $\mathbf{B}=[b_{ij}]$ is the coefficient matrix of the model. Solving for $\mathbf{x}$, we obtain:

$$\mathbf{x}=(\mathbf{I}-\mathbf{B})^{-1}\,\mathbf{e}=\mathbf{Ae} \tag{6}$$

From Equation 5 and non-Gaussian disturbances, we obtain the classical linear ICA model. Equation 5 may be rewritten as:

$$\mathbf{e}=(\mathbf{I}-\mathbf{B})\mathbf{x}=\tilde{\mathbf{W}}\mathbf{x} \tag{7}$$

The LiNGAM algorithm operates by initially conducting ICA estimation to obtain the matrix $\mathbf{A}$ and the permuting and normalizing it before computing $\mathbf{B}$. It is important to remark that some estimated edges between variables may be weak and are most likely zero in the generating model. The Wald test is appropriately used to determine if some remaining connection(s), such as these weak estimated edges, are to be 'pruned' as noted by Shimizu *et al.* (2006a) and Lai and Bessler (2015).

$$\begin{tikzcd}
v_2 \arrow[r] & v_3 & v_4 \arrow[l] \\
& v_1 \arrow[u] &
\end{tikzcd}$$

Figure 3. Example of directed acyclic graph.

After obtaining the DAG results, we estimate structural innovations directly from the reduced form residuals by applying the additional (obtained) contemporaneous restrictions (Lütkepohl, 2005: 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 FEVD consists of when the variance of each variable's forecasted error is decomposed, permitting the identification of the relative proportion of the movements in that sequence due to its own shocks, over shocks to the other variables.

In the case that own shocks explain mostly all of the forecasted error's 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 on the sequence, among the variables in the system. In addition, IRFs 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.

4. Results

4.1 Contemporaneous causal structure

Figure 4 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 4, milled rice markets are segregated by types and regions in the contemporaneous period. Arkansas, Louisiana, and Texas long grain prices and rough rice futures prices are connected. Median grain is segregated and only Arkansas and Louisiana markets are connected. California median grain price moves independently, perhaps because California medium grain is exported to East Asia, and Arkansas/Louisiana medium grain is exported mostly Mexico, Central America, the Caribbean, and the Middle East. Note that large amounts of U.S. southern medium grain rice is exported to Libya. Median grain rice in both markets are different in terms of quality and export destinations. Arkansas long grain appears to be the source of price discovery in the long grain markets, which is expected because of its size of production. Also, Arkansas medium grain is the source of information in the median grain markets. Based on Figure 4, we may conclude that Arkansas long grain and medium grain is the milled rice price reference in the southern regions and California medium market is exogenous in the contemporaneous period.

It is relevant to re-emphasize that the DAG results in Figure 4 show only the contemporaneous (i.e. non-time) causal structure. The contemporaneous period here refers to the actual period in which a disturbance to the U.S. milled rice market may occur, e.g. a one-time-only shock to Louisiana long grain. It is also noted that

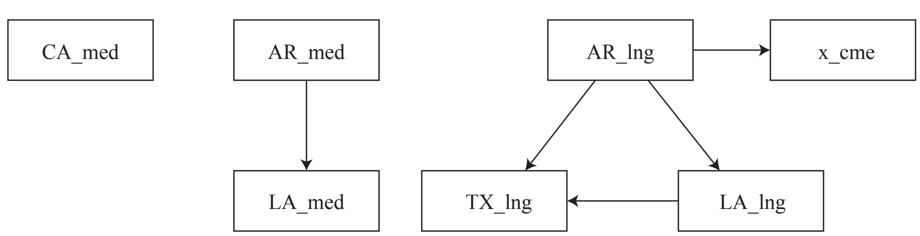

Figure 4. Directed acyclic graph of milled rice markets using LiNGAM algorithm. LiNGAM = Linear Non-Gaussian Acyclic Model. AR_lng = AR-MO long grain; LA_lng = LA-MS long grain; TX_lng = TX long grain; AR_med = AR-MO medium grain; LA_med = LA-MS medium grain; CA_med = CA medium grain; and x_cme = CME rough rice (long grain) futures price.

the causal structure in Figure 4 shows the direction of instantaneous causal flows among the variables and does not suggest the magnitude or the sign (positive or negative) of the effect.

4.2 Innovation accounting

Impulse responses shown in Figure 5 depict the responses of all variables to a one-time-shock in the innovation of one variable – when the 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 throughout the period (Hamilton, 1994: 318).

In the first column in Figure 5, Arkansas long grain market's shock affects all the long milled rice markets, including futures market, and has stronger impacts on the long grain markets in the first few months. This significant positive impact is up to 5 to 6% on Louisiana and Texas long grain and then diminishes after six months. Similarly, in the second column, Louisiana long grain positively affects Arkansas long and Texas long grain markets initially, while it has a negative effect on these two markets in the long run, which is similar to the findings in Djunaidi *et al.* (2001). The impacts of shock in Texas long grain market on Arkansas and Louisiana long grains is very limited (third column). Thus, even though markets are co-integrated, Arkansas long grain has a sizably larger effect on the other long grain markets. This appears to indicate that grain markets are not segregated regionally but actually more set apart by types. In addition, Arkansas dominance among long grain markets may respond to its larger volume of production in comparison to the other producing states.

The fifth column illustrates the effect from a shock to Arkansas medium grain. In this case, there is a significant positive effect of about 2-3% in both Louisiana and California's medium grain markets. In addition, this effect appears to be rather permanent. It is anticipated that Arkansas medium affects Louisiana medium as both these grains are mainly used for processed foods (e.g. cereals); however, California medium is of high

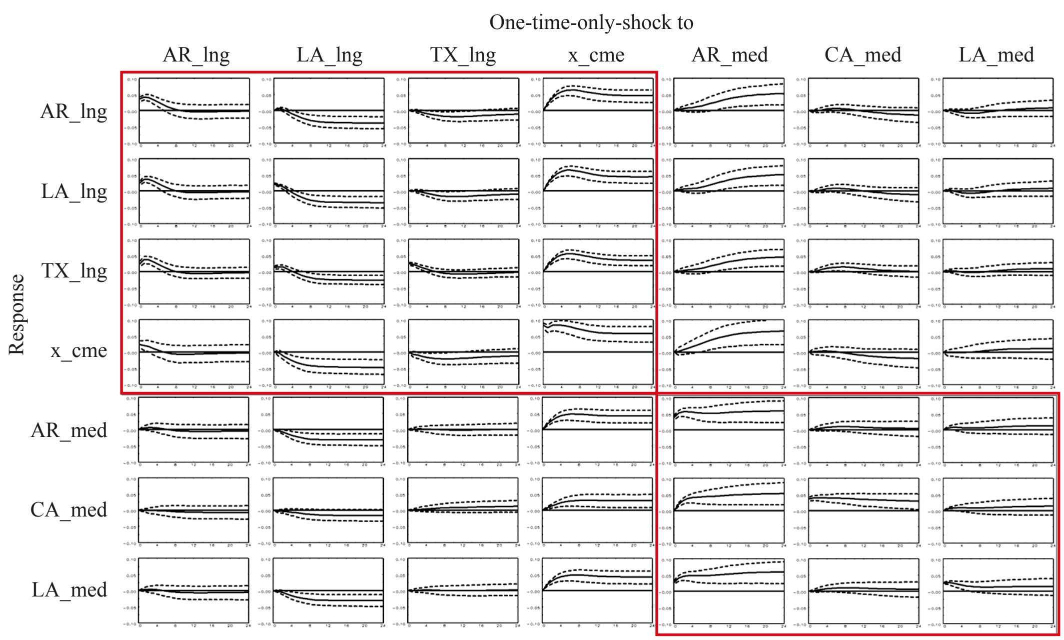

Figure 5. Impulse response functions. Red boxes represent long grain and medium grain markets, respectively. AR_lng = AR-MO long grain; LA_lng = LA-MS long grain; TX_lng = TX long grain; and x_cme = CME rough rice (long grain) futures price; AR_med = AR-MO medium grain; LA_med = LA-MS medium grain; and CA_med = CA medium grain.

quality serving mainly high-end markets and exports (Baldwin *et al.*, 2011). Moreover, the production size of California medium grain is more than four times that of Arkansas. We conjecture that given that California medium holds a premium over Arkansas medium grain, it has to hold that premium when the Arkansas grain (of lower quality) increases its prices. Thus California medium grain 'maintaining' a premium price over the southern states' less quality grain may be seen in the permanent effect from the positive shock coming from Arkansas medium.

In addition to the impact of Arkansas medium grain on other medium grain markets, it also present positive impacts on the long grain markets for over one year. The substitution between long-, medium-, and short-grain rice is generally lacking, given that they are demanded by different markets – according to particular tastes and preferences (Childs and Burdett, 2000). However, the positive effect of Arkansas medium grain price may be due to land competition to long grain rice production in Arkansas, a major area of long grain rice production. As a result, price in domestic long grain rice markets increases in the long run given anticipated competition for land in the major supply region. A shock to California medium grain does not have any significant effect on the other markets (column six), responding to its 'high quality' characteristics. Thus the effect from shocks to California market seems to be segregated from other markets. Shocks on Louisiana medium grain (column seven) have no significant impacts on other medium grain markets.

The FEVD series considering up to 18 months for the long, and medium grains are shown in Table 4, and grouped across varieties. The long grain's variations of its prices' forecasted errors, first three rows, are explained mostly by shocks from Arkansas long grain market as well as by shocks from its own regional long grain markets. Again may respond to milled rice major producer is Arkansas and a smaller later effect from Louisiana, the outbound shipping port. In the case of variation of Arkansas medium grain's forecasted errors, fourth row, it is mostly explained by shocks to itself. For the case of unexpected changes to California's forecasted errors (sixth row), the medium grain is affected by shocks to itself but mostly from shocks to Arkansas medium, corroborating findings from the IRFs. Regarding Louisiana's variations in its forecasted errors, seventh row, it is mostly explained by shocks from Arkansas medium and a bit by its own shocks.

As shown in the fourth column of Figure 5, futures price (x_cme) is the most important variable in the system, given that a shock to it produces a substantial significant positive effect in all markets. This is anticipated given that futures markets act as price discovery for cash markets (Leuthold *et al.*, 1989). As shown in the fourth row of Table 4 the variation in forecasted errors of the futures markets seems that mainly shocks to futures market has effects on them, though also a bit of Arkansas long markets minimal initial effects and Louisiana long and Arkansas medium has effects after six months and a year, respectively. Conversely, variations in futures explains much of the variation in long grain prices after the second month, which is anticipated given that this is the primary type of grain market served by futures prices. In addition, CME futures has a smaller effect from variations in its prices on the medium grain markets in latter months, perhaps as a spillover information effect.

Table 4. Forecast error variance decompositions.[1]

Variation in	Months	Accounted for by						
		AR_lng	LA_lng	TX_lng	x_cme	AR_med	CA_med	LA_med
AR_lng	1	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	0.84	0.01	0.00	0.14	0.00	0.00	0.00
	4	0.54	0.01	0.00	0.43	0.01	0.00	0.00
	6	0.34	0.02	0.01	0.60	0.02	0.00	0.01
	12	0.13	0.12	0.04	0.62	0.08	0.00	0.01
	18	0.08	0.16	0.04	0.53	0.17	0.00	0.00
LA_lng	1	0.56	0.44	0.00	0.00	0.00	0.00	0.00
	2	0.57	0.24	0.00	0.17	0.01	0.00	0.00
	4	0.40	0.09	0.00	0.49	0.01	0.00	0.00
	6	0.25	0.06	0.01	0.66	0.01	0.01	0.00
	12	0.10	0.12	0.03	0.67	0.07	0.01	0.00
	18	0.06	0.16	0.04	0.56	0.16	0.01	0.00
TX_lng	1	0.41	0.12	0.47	0.00	0.00	0.00	0.00
	2	0.50	0.10	0.30	0.10	0.00	0.00	0.00
	4	0.41	0.06	0.16	0.36	0.00	0.01	0.00
	6	0.29	0.04	0.10	0.54	0.01	0.02	0.00
	12	0.13	0.08	0.05	0.63	0.07	0.04	0.00
	18	0.09	0.12	0.04	0.55	0.18	0.03	0.01
x_cme	1	0.08	0.00	0.00	0.92	0.00	0.00	0.00
	2	0.07	0.00	0.00	0.92	0.00	0.00	0.00
	4	0.05	0.02	0.01	0.91	0.01	0.00	0.00
	6	0.03	0.05	0.02	0.87	0.02	0.00	0.00
	12	0.02	0.13	0.04	0.70	0.11	0.00	0.00
	18	0.01	0.17	0.03	0.58	0.20	0.01	0.00
AR_med	1	0.00	0.00	0.00	0.00	1.00	0.00	0.00
	2	0.00	0.00	0.00	0.06	0.92	0.00	0.01
	4	0.01	0.01	0.00	0.18	0.78	0.00	0.01
	6	0.01	0.04	0.00	0.26	0.67	0.01	0.01
	12	0.00	0.10	0.00	0.33	0.55	0.01	0.01
	18	0.00	0.13	0.00	0.32	0.53	0.01	0.01
CA_med	1	0.00	0.00	0.00	0.00	0.00	1.00	0.00
	2	0.00	0.00	0.00	0.01	0.11	0.86	0.01
	4	0.00	0.00	0.00	0.06	0.29	0.64	0.02
	6	0.00	0.01	0.00	0.10	0.35	0.52	0.02
	12	0.00	0.03	0.01	0.16	0.40	0.39	0.02
	18	0.01	0.04	0.01	0.16	0.44	0.32	0.02
LA_med	1	0.00	0.00	0.00	0.00	0.56	0.00	0.44
	2	0.00	0.00	0.00	0.08	0.59	0.00	0.32
	4	0.00	0.01	0.00	0.21	0.57	0.00	0.20
	6	0.00	0.03	0.00	0.30	0.52	0.01	0.14
	12	0.00	0.09	0.00	0.35	0.46	0.01	0.07
	18	0.00	0.12	0.00	0.33	0.48	0.01	0.06

[1] ar_lng = AR-MO long grain; la_lng = LA-MS long grain; tx_lng = TX long grain; x_cme = CME rough rice (long grain) futures price; ar_med = AR-MO medium grain; la_med = LA-MS medium grain; ca_med = CA medium grain.

5. Conclusions

Rice is among the top seven U.S. crops in terms of harvested acres and sixth in terms of cash receipt. The U.S. exports about half of its rice production to international markets and accounts for over 10% of the annual volume of global rice trade. U.S. rice is produced in four distinct regions, i.e. Arkansas, Mississippi Delta, Texas and Southwest Louisiana, and California. There are different types of rice associated with a production region and there are different varieties produced within each type. California produces almost exclusively short and medium type of grain; while Arkansas, Texas, and Louisiana produce mostly long types of grain and also small amount of medium types of grain. Thus, understanding the dynamic integration of domestic markets is of significant relevance. In this study, we determine whether the U.S. rice markets are integrated across regions and whether these markets are integrated across its grain types.

We applied the Directed Acyclic Graph approach to investigate the contemporaneous structure among seven U.S. f.o.b. milled rice prices and rough rice futures price in the context of multivariate time series modeling. Results are summarized as follows:

- Milled rice markets are segregated by types not by producing regions.
- In the long grain markets, Arkansas long is the leading reference price in the short term and rough rice futures price is the leading reference in the long term.
- In the medium grain markets, Arkansas is the leading reference prices in the short term and rough rice futures price is the limited impact on medium grain markets in the longer term.
- California medium grain market is weakly exogenous in the short run, but its price is affected by Arkansas-Missouri medium grain in the longer term.
- Rough rice futures prices are weakly exogenous in regards to milled rice prices.

The U.S. rice is competing in the overseas markets with other exporting countries, such as Thai, and thus an obvious extension of the study is to include an international rice price – such as Thai price. Unfortunately, adding one more price series reduces the degrees of freedom of data significantly, which lessens the level of confidence of estimated parameters and its inferred results.

It is important to note that despite our results not finding significant impact of California medium grain markets on the Southern U.S. medium grain markets, it is still well possible that this effect exists. This in light of southern medium grain production area increasing sharply during the recent California drought, and then sharply contracting once the California area returned to near-normal conditions. Thus it seems plausible that it may not necessarily be that California prices usually adjust to changes to southern medium grain prices, but the other way around, i.e. movements in California medium grain price (given its vast market size compared to that of the southern states) may affect southern medium-grain prices.

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