Dynamic Analysis and Forecasts of Rough Rice Price under Government Price Support Program: An Application of Bayesian VAR

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Abstract

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Introduction

In modern agricultural era, government support program has been constantly evolving and yet unsettling issue in political arena. The government intervention is, to equal extent, fascinating and practical topic in every standard economic text books. Surprisingly enough, economic literature, however, provides little theoretical guidance in the dynamic specification of agricultural price responses to government intervention (KwanSoo Kim, 2003 and Jean-Paul Chavas, 2004). It is critical to understand that full adjustments of agricultural prices responsive to changes in government support program are not likely to occur immediately. But how long a change from one equilibrium to the other equilibrium will take appears empirical issues, not suggested by the economic theory (Goodwin, 2005). Little publication has documented a dynamic analysis of the effects of a price support program on rough rice price dynamics.

Government and private institutions recurrently use and publish reports on the rice market. Forecasting market fundamental variables for the U.S. rice market is an important component of the U.S. Department of Agriculture's short-term and long-term baseline forecasting activities. A preliminary evaluation of forecasting performance, however, revealed that considerable discrepancy between actual outcomes and forecasting values. One hypothesis driving this paper is that forecasting accuracy can be improved by developing models that incorporate dynamic impacts of important government program variable and that are compatible with the time series properties of fundamental economic variables in rice market. Thus, the objectives of this study are to provide a dynamic analysis of the effects of a price support program on rough rice prices, and to provide forecasts of rough rice prices using a time-series model based on a structural economic model.

Data

Data are annual from 1941 to 2004, consisting of farm prices ($/cwt), ending stocks, and loan rates ($/cwt). The data were obtained from various issues of "*Rice: Situation and Outlook Yearbook*" (ERS/USDA). The midpoints of the USDA's farm price forecast are used for predictive ability comparisons.

Methodology

Government programs have played an important role in U.S. rice market for over 60 years (Knutson, Penn, and Flinchbaugh, 2003). While a variety of policy instruments, such as target price-deficiency scheme, acreage set-aside programs, have been used, this paper focuses on government support loan program because of its consistent presence in the government program over the period.

Let P_{t*} be the market price for a commodity at time t. Denote $S(P_{t*}\ ss_t)$ as the supply function, $D(P_{t*}, ds_t)$ the demand function, and $Q(P_{t*}, qs_t)$ for a function of ending stocks at time t, where ss_t are supply shifters, ds_t are demand shifters, and qs_t are ending stock shifters. Market equilibrium requires:

(1) $$S(P_{t*}, ss_t) - D(P_{t*}, ds_t) - Q(P_{t*}, qs_t) = 0.$$

This allows for a price-dependent reduced form expression: $P_{t*} = F(Q_t, ss_t, ds_t)$. As noted by Zellner and Palm (1974), there exist alternative dynamic reduced form equations that are consistent with the structural specification for market equilibrium above. More specifically, dynamic reduced form equations representing market equilibrium are assumed to take the form:

(2) $$Y_t = F(Y_{t-m}, X_t),$$

where $Y_t = (P_{t*}, Q_t, P_{ts})'$ is an (3x1) vector of endogenous variables, P_{ts} is government loan rates. Related previous research considered the government program variable exogenous. However, to the extent that the loan rates are set based on historical farm prices, government loan rates ($/cwt) are endogenous in the system. Y_{t-m} is a vector of m lagged dependent variables, and X_t is exogenous variables.

In familiar standard VAR model (Hamilton, 1994), Equation (2) can be rewritten as follows:

(3) $$[\, I_n - \Phi_1 L - \Phi_2 L^2 - \ldots - \Phi_p L^p] \; Y_t \; + X_t \; = u_t,$$

where I_n denotes an n x n identity matrix, $\Phi(L)$ indicates an n x n matrix polynomial in the lag operator, n is the number of dependent variables, Y_t denotes an n by 1 vector of dependent variables, X_t is an n by 1 vector of constants and u_t is an n by 1 vector of error terms. P is lag length and sufficiently large to make each of error terms white noise.

A major problem in the estimation of the dynamic reduced form in Equation (3) when p is large is over-parameterization, where too many coefficients must be estimated relative to sample size. Estimation of the system will typically yield numerous insignificant coefficients that can be properly excluded from the model. An alternative approach has been offered by the Bayesian vector autoregressive (BVAR) methodology of Sims and Zha (1998).

A BVAR model avoids the rigid inclusion/exclusion restrictions of VAR models by allowing the modeler to include many coefficients while simultaneously controlling the extent to which they can be influenced by the data. This reduces the extent to which spurious correlations are captured by the model. Hence, this study constructs a BVAR model to provide dynamic impact analysis as well as forecasts for US rough rice.

Afterwards, to evaluate a forecasting performance of BVAR model for rice, this paper adopts various parametric and nonparametric validation techniques that Sanders and Manfredo (2003) utilized in their recent publication. The parametric validation methods are based on certain assumptions regarding the probability distribution of estimators. Traditional parametric measures of forecast errors includes root mean square error: $\sum u_t^2 /T$, mean absolute percentage error: $\sum (u_t / A_t) * 100 / T$, and Theil inequality coefficient: square root of $\sum u_t^2 /T$ divided by the sum of square root of $\sum P_t^2 / T$ and square root of $\sum A_t^2 / T$, where u_t is forecast error and equals actual prices (A_t) minus predicted values (P_t) in corresponding forecasting models. T is number of forecasts considered.

The RMSE provides a measure of the average error measured in the same units as the actual observations, whereas the MAPE is a unit invariant measure. The smaller the measures are, the better the forecasting ability of the model is. Theil inequality coefficient is an extended version of RMSE. The TIC normalizes RMSE by dividing by the volatility of the forecast and actual prices, and lies between zero and one, where zero indicates a perfect fit. Similar to the MAPE, the TIC is a unit free measurement.

Recent parametric evaluation methods are popularized by Diebold and Lopez (1998) who defined optimal forecast as unbiased and efficient one. The test for forecast bias relies on an OLS regression of forecast errors, u_t on an intercept term α in the equation:

(5) $$u_t = \alpha + \varepsilon_t,$$

where the null hypothesis of unbiasedness would imply that $\alpha = 0$.

Sanders and Manfredo (2003) suggested tests for forecasting efficiency using following models:

(6) $$u_t = \beta_1 + \delta P_t + \varepsilon \text{ and}$$

(7) $$u_t = \beta_2 + \gamma u_{t-1} + \varepsilon_t,$$

where the null hypothesis of efficiency is that $\delta = 0$ in Equation (6) (hereafter, delta efficiency test) and $\gamma = 0$ in Equation (7) (hereafter, gamma efficiency test).

Third type of parametric forecasting testing procedure considered in this paper is a forecast encompassing test. A preferred forecast encompasses an alternative forecast if there is no linear combination between the preferred and alternative forecasts which could produce a mean squared error smaller than that produced by the preferred forecast (Sanders and Manfredo, 2003).

In practice, the one-step-ahead preferred forecasts are regressed on the difference between the one-step-ahead preferred and alternative forecasts as follows:

$$(8) \qquad u_{1t} = \beta_1 + \mu(u_{1t} - u_{2t}) + \varepsilon_t,$$

where u_{1t} is the preferred forecast error, u_{2t} is the alternative forecast error. The estimated μ is the weigh placed on the alternative forecast, whereas 1- μ is the weight placed on the preferred forecast to construct the optimal composite predictor. Harvey, Leybourne, and Newbold (1997) constructed a test statistic by taking the ratio of the sample mean of the composite errorr: (u_{1t} - u_{2t}) divided by its sample standard deviation times $n^{-1/2}[n+1-2h+n^{-1}h(h-1)]^{1/2}$, where n is the number of observations and h is number of steps ahead for forecasts (Sanders and Manfredo, 2003). A one tailed t-test with $n-1$ degrees of freedom on the test statistic is used for the forecast encompassing test. The null hypothesis of the test statistic equal zero is that the preferred forecast encompasses the alternative forecast.

Nonparametric validation techniques are distribution-free tests and refer to measures to obtain information on the qualitative performance of a forecasting model. One of the methods is a turning point analysis. Conventional turning point analysis uses a comparison of the signs of the forecast changes and actual changes to evaluate the model's ability to correctly predict turning points. There are four basic possibilities which usually are arranged into a 2x2 contingency table as in Table 1.

The first possibility is missing turns described by a pattern of + - + for actual prices, whereas the pattern in forecasts is + + + (F_{21}). The second possibility is false signals exemplified by a pattern of + + + for actual prices, as opposed to a predicted pattern of + - + (F_{12}). In addition, there are two types of correct forecasts. In one a turning point is predicted and it actually occurred (F_{22}). In the other no turning point was predicted and none occurred (F_{11}). The resulting patterns are arranged in a 2x2 contingency table as in Table 1. This 2x2 contingency table can give a detailed account of predicted and actual direction of price movements (Zarnowitz, 1967).

Table 1. 2x2 Contingency Table for Non-parametric Forecasting Evaluation

	Forecast Values	
Actual Values	No Turning Point	Turning Point
No Turning Point	F_{11}	F_{12}
Turning Point	F_{21}	F_{22}

Empirical Results

In a VAR, long lag lengths quickly consume degrees of freedom, let alone over-parameterization (Bauwns, Lubrano, and Richard, 1999). Therefore, to determine the optimal lag length, AIC and SBC selection criteria was applied to VAR. Lags 3 is considered optimal. Thus, the third order BVAR model is used to generate one-step-ahead forecast for rough rice prices over the thirteen year period from 1992 to 2004.

Over the out-of-sample period, actual rough rice prices ranged from a low of \$4.25/cwt to a high of \$9.96/cwt. The peak occurred in 1996. The mean and standard deviation for the period were \$7.08 and 1.93, respectively. For predictability comparison, one-year-ahead forecasts are generated from an AR(1) model. Obtaining forecasts by such a univariate time-series model has increasingly become popular because of inexpensive computation costs. Resulting summary statistics are reported in Table 1.

By inspection, one can see that the USDA, on average, considerably underestimates actual rice prices; whereas the average of BVAR forecasts are very close to the sample of actual rough rice prices. Surprisingly enough, the AR(1) model nearly replicates the volatility of actual rice prices during the ex-post sample period.

Table 2. Summary Statistics for the Ex-post Sample Period: 1992 – 2004.

Series	Min	Max	Mean	Standard Errors
Actual Rice Prices	4.25	9.96	7.08	1.93
USDA forecasts	4.25	10.25	6.84	1.82
BVAR forecasts	5.21	8.94	7.06	1.29
AR(1) forecasts	4.13	9.84	6.96	1.93

The results of accuracy measures are summarized in Table 3. First, comparison of the RMSEs across forecasting models does not reveal distinguishable pattern. However, the MAPEs indicate that the USDA model provides forecasts that are the most accurate. The AR(1) forecasts are far less accurate than the USDA forecasts. The Theil inequality coefficients for all three models lie close to zero, indicating that the forecasts reasonably well fit.

Table 2. Forecast Accuracy Measures for the Ex-post Sample Period: 1992-2004.

Series	RMSE	MAPE	Theil Inequality Coefficient
USDA Forecasts	1.11	16.43	0.0789
BVAR Forecasts	1.47	32.31	0.0568
AR(1) Forecasts	1.77	45.53	0.0563

The test results of the null hypothesis of unbiasedness are reported in Table 3. Based on a two-tailed *t*-test, the USDA model has much lower *p*-value than the BVAR model. This is consistent with the summary statistics in Table 1 that the USDA model, on average, underestimates the actual prices. In contrast, the *p*-values of BVAR and AR(1) are close to one, indicating that all time-series forecasts are unbiased.

Table 3. Forecast Bias Test for the Ex-post Sample Period: 1992-2004.

Models	Estimates	*t*-statistic	*p*-value
USDA	0.2400	0.8058	0.4361
BVAR	0.4214	0.0329	0.9243
AR(1)	0.1208	0.2375	0.8163

The test results of the null hypothesis of delta are reported in Table 4. Estimates and test results of gamma efficiency are presented in Table 5. The null hypothesis of weak efficiency for the AR(1) model is marginally failed to reject at the 10% significance level. Inspection of Tables 4 and 5 shows that BVAR and USDA models consistently generate efficient forecasts.

Table 4. Delta Efficiency Test for the Ex-post Sample Period: 1992-2004.

Models	Estimates	*t*-statistic	*p*-value
USDA	-0.1111	-0.6364	0.4343
BVAR	-0.0741	-0.2098	0.8377
AR(1)	-0.4499	-1.7811	0.1025

Table 5. Gamma Efficiency Test for the Ex-post Sample Period: 1992-2004.

Models	Estimates	*t*-statistic	*p*-value
USDA	0.3778	1.1060	0.2946
BVAR	-0.0733	-0.2182	0.8317
AR(1)	-0.1635	-0.4550	0.6588

As for encompassing tests, the paper hypothesized that the USDA model is the preferred forecast presumably because the USDA might have qualitative information on determination of rice prices. The null hypothesis of the test statistic equal zero is that the USDA model forecast encompasses the alternative forecast. The results of one tailed *t*-test on MDM statistic are presented in Table 6. *p*-values on MDM statistic reveal that the preferred USDA forecasts do not encompass either of the two.

Table 6. Forecasting Encompassing Test for the Ex-post Sample Period: 1992-2004.

	USDA Encompassing Selected VAR models	
	BVAR	AR(1)
Estimated Lamda	0.1088	-0.0517
MDM Statistic	0.9716	0.9525
p-value	0.0284	0.0475

To further explore forecasting performances, the turning point analysis is applied to the USDA model. The paper finds that F_{11} equals 4; F_{12} equals 1; F_{21} equals 4; and F_{22} is 4 in Table 7. Therefore, the USDA model generates false signals (FS) 7.69 percent of the time. In other words, 7.69 percent of the time when the USDA model predicted a change in direction, it was incorrect. Conversely, the USDA model correctly predicted a change in direction of rough rice prices 61.54% of the time. As for AR(1) model, combination of missing turns (*MT*) and false signals (*FS*) suggested that the univariate time-series model incorrectly predicted a change in direction of rough rice prices most of the time. On the other hand, BVAR forecasts are generated in the same direction that the actual rough rice prices move almost half of the time.

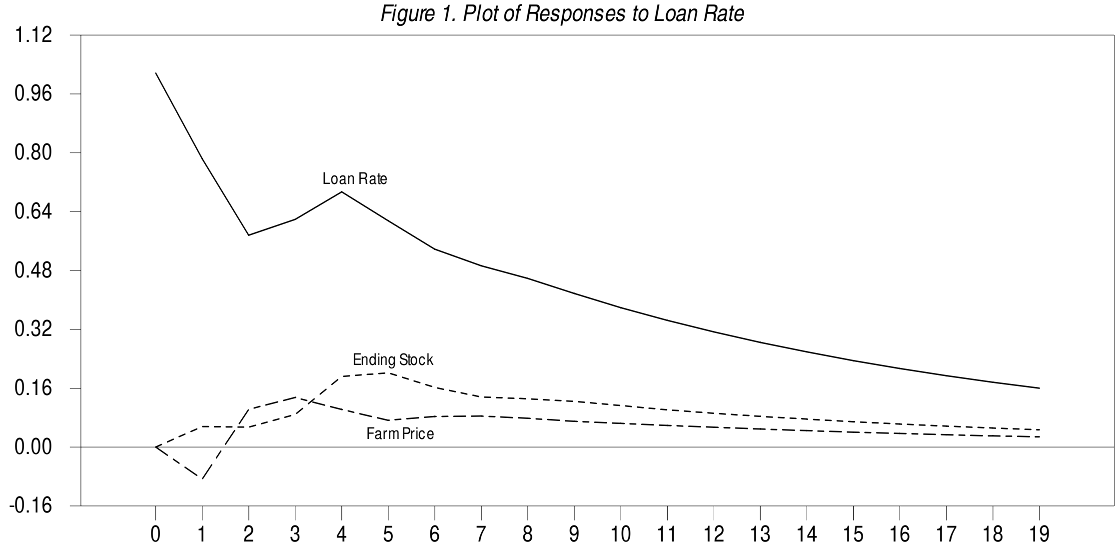
Table 7. 2 x 2 Contingency Table for Turning Point Analysis: 1992-2004

Models	Turning Point Elements						
	F_{11}	F_{12}	F_{21}	F_{22}	*MT*(%)	*FS*(%)	*CF*(%)
USDA	4	1	4	4	30.77	7.69	61.54
SVAR	4	1	6	2	46.15	7.69	46.15
AR(1)	3	2	7	1	53.85	53.85	30.74

In the past two decades there has been substantial progress in performing dynamic simulations using multivariate time-series model. Very few have documented full adjustments of rice prices responsive to changes in government support program. In this section, the paper, first, reports how unexpected shock in the government program, mainly loan rates affects ending stocks and farm prices based on impulse response functions within the context of a trivariate BVAR model.

Corresponding IRFs are presented in Figures 1, 2, and 3. A few points are, in summary fashion, worth noting. First, an initial one-standard-deviation government program shock induces a minimal positive response in ending stock. The effects are increasingly big and the maximal effect occurs at the fifth period after the initial shock. Similar yet smaller impacts of government program shock on farm prices are observed. The maximal effect on farm prices occurs at the third year. Not surprisingly, the positive unexpected loan rate shocks are persistent and nontrivial in loan rate itself.

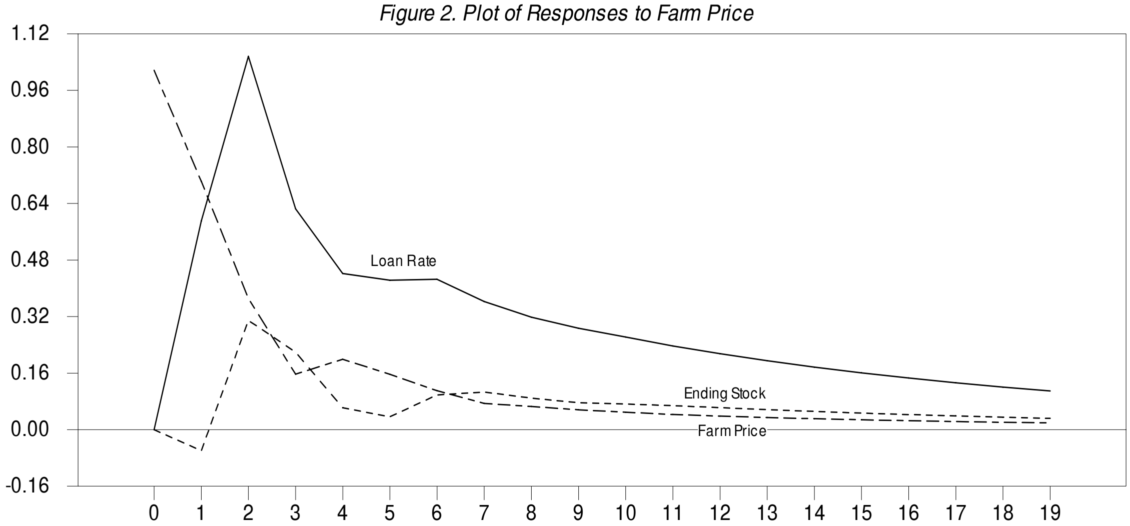
Figure 1. Plot of Responses to Loan Rate



Secondly, the initial effects of a one-standard-deviation shock in farm price are sharp and significant increases in ending stocks. The full positive effects come after two years. This is consistent with economic logic that following an increase in farm price, farmers are willing to increase in production and, in turn, the market would face greater ending stocks. Afterwards, the ending stocks follow adjustment path to the initial market equilibrium level, indicating the long-run effect of the ending stocks is minimal.

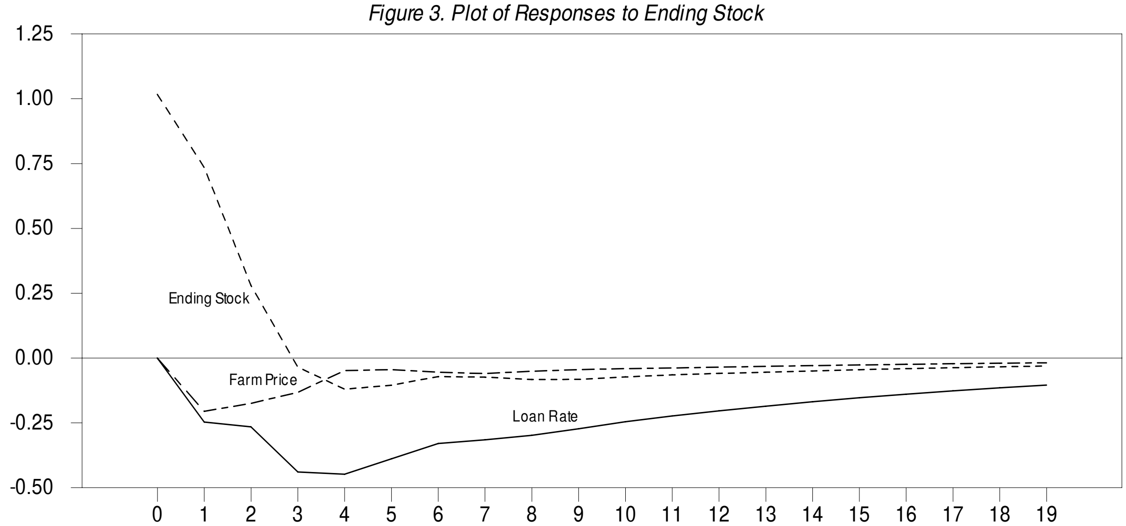
The responses of the loan rate to a positive price shock reveal a very interesting observation. The maximal effect occurs only three year period after the initial shock is over. But it appears that the turning point of the price shock occurs at the sixth period that is exact the same as the farm bill cycle.

Figure 2. Plot of Responses to Farm Price



Lastly, an unexpected positive ending stock in Figure 3 clearly suppress farm price almost four years after the initial shock is over. Similarly, the depressing effects of an unexpectedly positive ending shocks fall on loan rates. The maximal effect occurs at the fourth year and dies down afterwards. But much greater depressing effects and lasting effects have been observed in loan rates.

Figure 3. Plot of Responses to Ending Stock



Summary and Conclusions

Given some uncertainty surrounding USDA rice price forecasts, this study constructs a Bayesian VAR model of US rice prices, in conjunction with supply and demand functions for the U.S rice. Various validation tests are conducted to examine whether or not the proposed Bayesian VAR model satisfies its dual functionality: Generating reasonable short-term forecasts of rice prices and at the same time providing a dynamic analysis of the effects of a price support program on rough rice prices.

Conventional parametric evaluation measures, such as RMSE, MAPE, and Theil inequality coefficient reveal that the BVAR model provides comparable forecasts to USDA forecasts during out-of-sample period. Optimality tests also indicate that the BVAR and USDA models consistently are efficient and unbiased. However, unbiasedness tests suggested that the USDA model tends to underestimate actual prices. In contrast, non parametric evaluation measures showed that the USDA model outperforms the BVAR models. These findings suggest that market participants, in general and rice producers, in particular who seek a prediction of general rice price movements and at the same time accurate forecasts would be better off when they supplement the USDA rice price forecasts with BVAR forecasts.

Collectively, nine impulse response functions provide consistent dynamic adjustment paths of fundamental rice market variables only suggested by economic theory. Several observations have emerged from dynamic analysis. First, the positive unexpected loan rate shocks have persistent and nontrivial impact on both farm price and ending stocks. Second, it appears that positive farm price effects on loan rate are persistent for six years that is exactly the same as the farm bill cycle. Lastly, an unexpected positive ending stock clearly suppress farm price almost four years.

In sum, the evidence shows that the relatively simple structure of the BVAR model, with minimal data requirements, has appeal for short and medium term price forecasting, simultaneously providing dynamic simulation and policy analysis.

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