

## **Rice World Market Prices**

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## **Rice World Market Prices**

**Abstract:** The marketing loan program associated with rice features benefits calculated using a USDA-announced World Market Price (WMP) rather than the posted county prices that are used for most other commodities. This results in reduced risk protection for producers relative to other crops, and greater difficulty in making optimal use of program benefits. This research investigates the rice WMP, identifying the relative importance of various foreign prices and other potential influencing factors. The results of this research have important implications for financial planning and optimal risk management strategies for rice producers.

### *Introduction*

Producers of many crops in the United States are extended nonrecourse marketing loans by the Commodity Credit Corporation (CCC). Such loans feature an associated local "loan rate" specified by the government - a dollar amount of credit that is extended per unit of a producer's crop, which serves as the loan's collateral. The producer can later repay the loan at the lower of either the loan rate or a posted county price. Repayment at the posted county price entails either actual cash payment, or surrender to the CCC of the crop that serves as the loan collateral. Producers who forgo such loans are still eligible for equal benefits in the form of "loan deficiency payments" (LDPs).

Under the provisions of the marketing loan program for rice since 1985, however, producers can repay loans at the lower of either the loan rate or World

Market Price (WMP) for rice that is calculated by USDA using an essentially undisclosed formula. The motivation behind using a WMP rather than a local price in calculating marketing loan gains (MLGs) is to make these commodities available for export at more competitive prices when the CCC is releasing stocks. For producers, however, the use of world prices rather than local prices for the calculation of MLGs results in a reduced extent of price risk protection. In some marketing years producers experience low local prices, even as the WMP is relatively high and marketing loan gains are small or nonexistent. In other marketing years, the converse is true.

The objective of this research is to identify specific, easily obtained data that reliably co-vary with the rice WMP, and to identify other important modeling considerations. This information will provide important insights regarding effective modeling and forecasting strategies for the WMP, which might be used to improve producer financial planning and risk management.

Inference regarding WMP covariates will be initially conducted using the Bayesian Averaging of Classical Estimates (BACE) Approach advanced by Sala-I-Martin, et al. (2004). BACE provides a methodical approach to the task of model specification when the modeler faces significant uncertainty regarding appropriate explanatory variables. Inference regarding covariates will then be further refined by fitting an appropriate vector error-correction model (VECM). This will facilitate hypothesis testing over the long-run relationships that exist between the WMP and its covariates, while accounting for the possibility that some variables in the system are non-stationary.

We proceed by providing some background information regarding the WMP and the data series employed in the analyses. After presenting the BACE and cointegration analyses, we discuss the implications of our findings for WMP modeling and optimal producer decision making.

### *Background*

The world market for rice is currently described by USDA (2005) as “thin, volatile and risky.” They attribute this condition to the fact that only a small proportion of global production enters international trade, making world prices highly susceptible to production shortfalls. Most rice traded internationally is long grain indica rice (*cf.* japonica rice). Exporters other than the U.S. typically export only milled rice, in an effort to support local milling operations. Thailand, Vietnam, Pakistan, India, China, and the United States are the largest exporters, with India’s quantity of exports varying significantly from year to year. Indonesia, the Philippines, and Nigeria are among the largest importers in most years. Brazil also occasionally imports large quantities of rice, particularly from the U.S.

The marketing loan program for rice, and the associated WMP have received little attention in the academic literature. A single study by Taylor, et al. (1996) provides a multivariate cointegration analysis of the WMP, Thai and Texas cash rice prices, and the price of the nearby rough rice futures contract traded at the Chicago Rice and Cotton Exchange. They found no long-run equilibrium relationship between the WMP and the other prices. This is a surprising result – one would expect a stable long-relationship between the

Thai price and the WMP, given the Thai dominance of the world market and the expectation that the WMP should reflect world prices.

A description of the calculation of the WMP of rice appears in the U.S. Code of Federal Regulations (CFR), Title 7, Chapter XIV, Section 1421.10. This can be best characterized as a very rough guideline, providing no detail regarding the exact prices that are used as the starting point for the calculation, and providing only vague details regarding the adjustments that are made to those prices to arrive at the WMP. The calculation is described as starting with prevailing world prices of from “USDA field reports, international organizations, public or private research entities, international rice brokers, and other source of reliable information.” Adjustments are then made to those prices to arrive at the WMP for rough rice. These adjustments “to U.S. quality and location” are described as including the cost of bagging rice, the cost of transfer of rice to F.O.B. vessel at a port of export, adjustments for the proportion of broken kernels in US and foreign rice (a function of prevailing world prices for broken kernels), the market value of bran in rough rice, transportation from farms to mills, milling cost, and milling yields.

The marketing loan program for upland cotton might offer some insight to the possible details of the prices that the rice WMP calculation is based on. Similar to the rice program, the cotton program is based on a USDA-announced Adjusted World Price (AWP). The calculation of the cotton AWP price is described in extensive detail in CFR Title 7, Chapter, Section 1427.25. The weekly press releases announcing the cotton AWP also present the calculation fairly transparently, relative to the rice WMP. Essentially, the cotton

AWP calculation begins with an average competitive CIF price for a standard grade of cotton in Northern Europe (the Cotlook “A-Index”). A rice analog to this would be competitive milled rice prices at a trading hub that consistently imports large quantities of rice, most likely in Asia.

The weekly USDA WMP announcement contains world prices for milled, whole kernels of long, medium, and short grain rice, as well as prices for milled broken kernels. Simultaneously-announced typical U.S. milling yields are then used in conjunction with the milled prices to calculate the official WMPs for long, medium, and short grain rough rice. In this study, we examine the factors influencing the WMP for rough, long-grain rice. The majority of U.S. exports are long grain rice, and the rough price is used in the calculation of MLGs and LDPs. Additionally, modeling the rough WMP directly avoids the necessity of separately modeling both whole and broken kernel milled rice WMPs, and little international price data for milled broken kernels is available.

### *Data*

We use monthly observations from October 1997 through November 2004 of various easily obtained data that we believe may directly or indirectly impact the level of the WMP. Data series and sources are presented in Table 1. In addition to our dependent variable (*WMP*), we employ four rice price series. Unfortunately, rice price data at major Asian import centers (analogous to the data used in the cotton AWP calculation) are not commonly available. Our proxy price data include one European milled rice import price series (*ARAGP*), and three milled rice price series from exporters (*THAIP*, *VIETP*, *PAKIP*). The

15% broken export price series are selected to best balance the relative influences of the world values of whole and broken kernels on the U.S. rough rice WMP, given typical U.S. milling yields. Available Indian export price series contain extensive missing observations, and are not used. All prices are measured in U.S. dollars per metric ton. To attempt to capture the varying influence that these export prices would likely have on prices at import centers, we include a series that represents the approximate proportion of major exporters' shipments originating from the India and Pakistan (*IPEXP*), and the product of that series and our price series from that region (*IPEXPINT*).<sup>1</sup> This latter interaction term will allow us to, in a very crude way, nest models featuring foreign rice prices with fixed and variable weights (where variable weights are a function of export levels) in simple linear regressions.

In addition to the export price series, we include factors that may impact their translation into import prices. Interest rate series for major exporters (*PAKIR*, *THAIR*, *USR*) can be expected to impact the prices realized by importers, to the extent that they must borrow the exporter's currency while grain is in transit. Such relationships would likely be non-linear, so we include interaction terms with export prices as well (*PAKIPR*, *THAIPR*). All price series are measured in U.S. dollars per metric ton, and thus already reflect the relative values of the U.S. dollar and competing exporters' currencies. We do however include three variables that might capture the influence of the value of the U.S. dollar relative to importers' currencies (*INDOUSD*, *BRAZUSD*, *USDX*).

While the potential explanatory variables presented thus far attempt to proxy prices realized by rice importers, the other variables that we include in

the analyses attempt to capture the adjustments of those prices to “U.S. quality and location.” We include an ocean freight price index (*BDI*), and a dummy variable (*DAUGJAN*) that indicates the first half of the U.S. rice marketing year (the conversion from milled WMPs to the rough WMPs seems to undergo adjustment six months into each marketing year, possibly reflecting the evolution of the quality of U.S. rice available in that marketing year). Finally, we include a trend (*TREND*) variable to capture structural change and other factors for which we otherwise fail to account.

### *BACE Analysis*

The innovative econometric modeling approach recently advanced by Sala-I-Martin, Doppelhofer, and Miller (2004) can be distinguished from conventional practice in applied econometric analysis two primary respects. First is the treatment of model uncertainty. Inference under classical methods is conducted using a single empirical model. This model is typically arrived at via a recursive process, by which a tentative model is subjected to batteries of misspecification tests, re-specified, and retested, until a model that is believed free of serious defects is discovered. After the final model specification is fixed, inference is conducted with no further acknowledgement of model uncertainty – it is assumed that the researcher has, with certainty, uncovered the “true model” or actual underlying data generating process. By not accounting for this uncertainty, the modeler’s inferences will be, to some unknown extent, overly-confident.



By contrast, the BACE approach does not employ a single anointed model, but instead involves estimating numerous possible models. Insight regarding quantities of interest (elasticities, for example) is then gained through consideration of all estimates, with the importance of each individual estimate being determined by the perceived merit of the model from which it emanated. More concretely, weighted average results across all models are developed, using weights that are a function of the extent to which each individual model appears to explain the data. This model averaging, well-known to Bayesian practitioners (see, for example, Zellner), provides a framework for modeling and inference that explicitly acknowledges and incorporates uncertainty regarding model specification.

The second respect in which the BACE approach differs from the classical approach is in the nature and interpretation of the resultant information regarding quantities of interest. Under the classical approach, point estimates of quantities of interest are made, and sampling variation is assumed to be responsible for deviations of such estimates from the true but unknown values. This facilitates binary “yes/no” hypothesis testing regarding the true values. By contrast, the BACE approach follows the Bayesian mold of expressing initial beliefs regarding possible values of quantities of interest and then revising these beliefs upon revelation of additional information (i.e., the data). The resultant uncertainty over parameter values is multi-fold – including model specification uncertainty as one component. The BACE analysis does not generate sampling distributions that are used for binary hypothesis tests, but rather degrees of belief regarding various possible parameter values.

We now provide a brief overview of the approach, summarized from Sala-I-Martin, Doppelhofer, and Miller (2004). A prior density  $g(\cdot)$  that summarizes prior beliefs about a parameter vector  $\beta$ , a prior density  $f(y)$  that summarizes prior beliefs about observed data  $y$ , a likelihood function  $f(y|\beta)$  that summarizes the information regarding  $\beta$  that is contained in the data, and a posterior density  $g(\beta|y)$  that summarizes beliefs about  $\beta$  conditional on the data, are related via Bayes' rule in densities:

$$(1) \quad g(\beta|y) = \frac{f(y|\beta)g(\beta)}{f(y)}.$$

For two possible models  $M_0$  and  $M_1$  with prior probabilities  $P(M_0)$  and  $P(M_1)$ , we can write

$$(2) \quad g(\beta|y) = P(M_0) \frac{f(y|\beta)g(\beta|M_0)}{f(y)} + P(M_1) \frac{f(y|\beta)g(\beta|M_1)}{f(y)}.$$

Applying an analog to (1) which incorporates densities over  $y$  and a probability mass function over  $M_i$ , (2) can be rewritten as

$$(3) \quad g(\beta|y) = P(M_0|y) \frac{f(y|\beta)g(\beta|M_0)}{f(y|M_0)} + P(M_1|y) \frac{f(y|\beta)g(\beta|M_1)}{f(y|M_1)}.$$

where  $P(M_i|y)$  is the posterior probability of model  $i$  given the data. Thus the posterior distribution of parameters is the weighted average of the individual posterior densities conditioned on each model, where the weights are informed by the data.

For two multiple linear regression models with normal errors, differing sets of explanatory variables, and assuming g-priors over the parameters, the limit of the ratio of the two posterior probabilities as the data become very informative relative to the priors is

$$(4) \quad \frac{P(M_0 | y)}{P(M_1 | y)} = \frac{P(M_0) e^{SBC_0}}{P(M_1) e^{SBC_1}}$$

where  $SBC_i$  is Schwarz (1978) Bayesian information criterion for model  $i$ .

Equation (4) is a familiar Bayesian form in which the posterior odds ratio of two models is equal to the prior odds ratio multiplied by Bayes' factor, where here the latter quantity is replaced by an approximation applicable to a wide range of reasonably diffuse prior distributions. If a total of  $K$  possible explanatory variables are under consideration, then using the posterior odds ratio given in (4), and normalizing over all  $2^K$  possible models, individual posterior model weights can be recovered as

$$(5) \quad P(M_j | y) = \frac{P(M_j) e^{SBC_j}}{\sum_{i=1}^{2^K} P(M_i) e^{SBC_i}} .$$

A difficulty associated with standard model averaging over a large number of possible models is the need to specify prior probabilities  $P(M_i)$  for each. The simple approach of assigning equal prior probability to each model is associated with an implicit prior belief that the expected number of included explanatory variables,  $\bar{k}$ , should be half of the number considered. This presents a problem if  $K$  is large, but the modeler's expected model size is small, as is typically the case. The BACE methodology overcomes this difficulty by directly specifying the prior mean model size  $\bar{k}$ , and calculating individual model weights using the assumption that each explanatory variable has a prior inclusion probability of  $\bar{k}/K$ , independent of the inclusion of the other possible

regressors. An arbitrary model  $i$  that includes  $k_i$  explanatory variables is thus assigned a prior probability  $P(M_i) = (\bar{k} / K)^{k_i} (1 - \bar{k} / K)^{K - k_i}$ .

Once the model weights have been calculated, the means and variances of the posterior distributions of model parameters can be calculated by taking expectations over the  $2^K$  model analog to (3). The posterior mean is given by

$$(6) \quad E(\beta | y) = \sum_{j=1}^{2^K} P(M_j | y) \hat{\beta}_j$$

where  $\hat{\beta}_j$  is the parameter estimate emanating from model  $j$ . The posterior variance is given by

$$(7) \quad \text{var}(\beta | y) = \sum_{j=1}^{2^K} P(M_j | y) \left\{ \text{var}(\beta | y, M_j) + [\hat{\beta}_j - E(\beta | y)]^2 \right\}.$$

For the present analysis, the most interesting quantity generated by BACE methodology is the posterior probability that a particular variable should have a non-zero coefficient, which Sala-I-Martin, Doppelhofer, and Miller (2004) term the *posterior inclusion probability* (PIP). This is calculated by summing the posterior probabilities of all models in which a particular explanatory variable is included. The magnitudes of the PIPs reveal which among the set of possible explanatory variables we most strongly believe to be relevant after seeing the data, and in consideration of the relative explanatory ability of the other possible regressors. Here, we specifically use the PIPs to reduce the full set of possible WMP covariates to a subset that we believe may have superior explanatory power, which we will analyze further in the following section.

For our analysis, we set the prior over model size,  $\bar{k}$ , to 8.5. This implies that each of our 17 possible explanatory variables has a PIP of 0.5. All of the  $2^{17}$  possible models (i.e., combinations of possible explanatory variables) were estimated. The resulting PIPs, posterior mean coefficient estimates and their standard errors are presented in Table 2. Two groups of variables are clearly differentiated – one group of five variables with PIPs exceeding 0.9, and a second group with PIPs that are lower than the prior inclusion probability of 0.5. The data strongly decrease the strength of our belief that the adjustment-related variables (*BDI* and *DAUGJAN*), the interest rate variables, and exchange rate variables have explanatory power.

With the exception of *TREND*, conditioning on the data increases our belief that some of the price-related variables explain the variability in *WMP*. The data do not support the inclusion of the Vietnamese price series, suggesting that the strong price leadership of neighboring Thailand results in *THAIP* embodying relevant price information for that region. The trade-weighted version of Pakistani prices *IPEXPINT* is preferred to the basic price series *PAKIP*, suggesting that the *WMP* calculation is not based on a simple fixed-weight average of foreign export prices. The means of the posterior distributions of the price variables suggest that the *WMP* for rough rice might be well-represented by a weighted average of the data-supported milled rice price series. We also find that *IPEXP* is strongly supported by the data, and has a negative posterior mean coefficient. This would result in a sort of renormalization as the weight on *PAKIP* fluctuates.

The posterior means for *ARAGP* and *THAIP* sum to 0.57. The sample mean of *IPEXP* is 0.32, which, multiplied by the posterior mean of *IPEXPINT* of 1.52, results in an average weight for *PAKIP* of 0.47. The weight for *THAIP* and the average weight for *PAKIP* sum to 1.04. This is a curious result, as the dependent variable is price per metric ton of rough rice, while the independent variables are prices per metric ton of milled rice. Based on average milling yields, we might expect the weights on the miller price series to sum to around 0.7. However, this may simply be an artifact of our crude export-weighted average price nesting scheme. Also, simple linear regressions underlie the BACE methodology. As our analysis employs time series data, the possibility of spurious correlation is a concern. We therefore must consider these initial results preliminary; the primary value of the BACE analysis is that we have eliminated numerous possible *WMP* covariates and can conduct a focused time series analysis on the remaining variables.

### *Multivariate Cointegration Analysis*

Despite the results of our BACE analysis, the following time series analysis uses the simple *PAKIP* series rather than the export-weighted version (*IPEXPINT*) and associated normalizing variable (*IPEXP*). This results in a meaningful constant being recoverable from the long-run relationship between *WMP* and the other variables in the system, and makes possible a more meaningful interpretation of the weights on the foreign milled price series.<sup>2</sup>

Augmented Dickey-Fuller (ADF) tests for the *WMP* and cash rice price series are presented in Table 3. We cannot reject the null hypothesis of non-

stationarity for any of the spot price series, and the results for *WMP* are ambiguous – we can reject non-stationarity only if a trend is omitted from the ADF model. It is therefore possible that the potential *WMP* covariates identified in BACE analysis could be due to spurious correlation. The multivariate cointegration technique of Johansen (1988, 1991) and Johansen and Juselius (1990) provides a theoretically-consistent framework for conducting hypothesis testing over the possible long-run relationships identified in the previous section in the presence of non-stationarity.

We employ a vector error correction model (VECM) of the form

$$(8) \quad \Delta z_t = \Gamma_1 \Delta z_{t-1} + \dots + \Gamma_k \Delta z_{t-k+1} + \Pi \tilde{z}_{t-1} + \mu + \Psi D_t + \varepsilon_t$$

where  $z'_t = (WMP_t, PAKIP_t, THAIP_t, ARAGP_t)$ ,  $\tilde{z}'_{t-1} = (z'_t, TREND_t)$ ,  $D_t$  is a vector of deterministic variables (discussed below), and  $\varepsilon_t$  is a  $4 \times 1$  vector of normal *i.i.d.* innovations. All remaining terms are appropriately dimensioned parameter matrices or vectors. The existence of  $r$  stationary linear combinations of the variable in  $\tilde{z}_{t-1}$  implies that  $\Pi$  has rank  $r$ , and can be decomposed as  $\Pi = \alpha\beta'$ , where  $\alpha$  and  $\beta$  are  $5 \times r$  matrices of full rank. The  $\beta$  parameter matrix embodies the long-run equilibrium relations among the levels of the endogenous series, while the parameters of  $\alpha$  are estimated rates at which each of the series adjusts to deviations from those equilibria.

Preliminary modeling revealed the presence of two outlying observations of  $\Delta z_t$  that resulted in a non-normal  $\varepsilon_t$ , invalidating standard inference procedures. Investigation revealed that one of these observations, for May of 1998, was an unusually large price decline associated with the lifting of a

temporary Vietnamese export ban. We thus specified an exogenous policy shift dummy variable  $DVIET$  equal to one for this observation and zero for all others. The second troublesome observation concerned only the  $WMP$  component of  $\Delta z_t$ , for August of 1999. The cause of this large change is documented in USDA (1999): "...on August 3 USDA made its quarterly adjustment to its world price equation. This resulted in a [*sic*] about \$2-per-cwt (whole kernel basis) drop in the announced world price..." We discuss this interesting observation in the following section. For now, we simply note that we have defined another dummy variable  $DADJ$  to account for this unusually large move in  $WMP$ . We thus define the  $D_t$  in equation (8) as  $(DVIET, DADJ)'$ . The inclusion of these terms, and a single lag in the VECM (i.e.,  $k$  in equation (8) is one), result in well-behaved innovations according to standard diagnostic tests.

Given the relatively small number of observations available to us, and the well-documented problems of the traditional likelihood ratio tests for cointegrating rank (see, for example, Cheung and Lai, 1993; Toda, 1995; and Huag, 1996) in small samples, we adopt the more progressive approach of employing an information criterion for this task (see, for example, Phillips, 1996; and Aznar and Salvador, 2002). Specifically, we select the value for  $r$  which minimizes the Schwarz (1978) information criterion.

For our model, we find a cointegrating rank  $r$  of two, implying that at least some subset of the variables that we identify in the BACE analysis can indeed be reliably inferred to be  $WMP$  covariates. Moreover, we find a set of restrictions on  $\alpha$  and  $\beta$  which are not rejected by a likelihood ratio test at



conventional significance levels ( $\chi^2(3) = 4.12$ ,  $p\text{-value} = 0.25$ ), such that we identify unique cointegrating vectors. This restricted error correction term

$\alpha\beta'\tilde{z}_{t-1}$  is

$$(9) \quad \begin{bmatrix} 0.126 & -0.476 \\ 0.286 & 3.278 \\ 0.593 & -0.586 \\ 0.000 & 0.000 \end{bmatrix} \begin{bmatrix} 1.000 & -0.255 & -0.751 & 0.000 & 0.386 \\ 0.000 & -0.079 & 0.052 & 0.009 & 0.000 \end{bmatrix} \begin{bmatrix} WMP \\ PAKIP \\ THAIP \\ ARAGP \\ TREND \end{bmatrix}_{t-1} .$$

We first note that *ARAGP* is weakly exogenous to the system, as our restrictions include coefficients in associated with *ARAGP* of zero. This implies that *ARAGP* does not respond to deviations from either of the two long-run equilibria, perhaps due to the operation of the U.S. rice marketing loan program. During periods when world prices are low, U.S. production can move into the loan program, rather than being forced to compete on the world market. That is to say, U.S. rice gets discounted indirectly through the CCC, with the government making up the shortfall for producers, rather than producers having to directly discount their rice.

Our primary interest, however, is the pair of unique cointegrating vectors. The variables *WMP* and *TREND* do not enter the second cointegrating relation, which we interpret as representing an equilibrium between rice prices among the three competing major exporting regions (India-Pakistan, Thailand-Vietnam, and the U.S.). The magnitudes of the associated speed-of-adjustment parameters (the second column of ) indicate that *PAKIP* adjusts much more rapidly to deviations from this equilibrium than *THAIP* (3.278 vs. -0.586), confirming Thailand's dominant role in the world market.

We interpret the first cointegrating vector as representing the simple *WMP* approximation formula that we seek, and have thus chosen to normalize this vector on *WMP*. The *ARAGP* does not enter this relation, indicating that the high PIP found in the BACE analysis is due to its indirect influence via the second cointegrating relation or due to spurious correlation. We recover the series of deviations from the first long-run equilibrium,  $\{\beta'_1 z_t\}_{t=1}^{86}$  where  $\beta'_1$  is the first row of  $\beta'$ . The sample mean of this series is -98.238, and we can thus rewrite our simple approximation formula in an easily-interpretable form:

$$(10) \quad WMP = 0.255PAKIP + 0.751THAIP - 0.386TREND - 98.238 .$$

The negative coefficient on the *TREND* variable indicates that, on average, the *WMP* is being fixed at a steeper discount to foreign prices as time advances.<sup>3</sup>

We note that the *PAKIP* and *THAIP* coefficients in this vector are within six one-thousandths of unity.

### *Discussion*

Our evidence suggests that the rice *WMP* calculation is similar to that for the cotton *AWP*. In our BACE analysis, we find that among the possible price inputs to *WMP* that are easily available, the data support an export-weighted average of foreign export prices to a fixed-weight average. This suggest one of two possibilities – USDA actually uses an export-weighted average export price in the calculation of the *WMP*, or that such weighted averages are serving as a proxy for prices at one or more major import centers. As the levels of exports

vary, the relative influence of the various export prices on prices realized at an import center vary.

Additional evidence supporting a rice calculation that mirrors the cotton calculation is the dramatic change in the rice *WMP* at the beginning of the 1999/2000 marketing year, due to USDA altering the formula at that time. For the cotton *AWP*, the calculation of which is fairly well-documented each week, an adjustment factor that calibrates northern European prices with the quality of cotton available in the U.S. can be observed evolving as the marketing year progresses. As a new marketing year begins, this quality adjustment factor will be “reset” to reflect expectations and conditions regarding the new crop. Based on the comment in USDA (1999) quoted above, a similar quality factor reset appears likely to be responsible for the unusually large change in the *WMP* between the July 27, 1999 and August 3, 1999 announcements.

One aspect of the estimated relationships is very strange, however. In our cointegration analysis, we find that the *WMP* of *rough* rice can be estimated using estimated fixed weights on foreign export *milled* rice prices that sum to almost exactly to unity. Indeed, the coefficient on *PAKIP* is very close to India and Pakistan’s average collective share of exports among the four major Asian exporting countries (India, Pakistan, Thailand and Vietnam) of 0.31 over the sample period (and the weight on *THAIP* is thus close to the collective export share of Thailand and Vietnam). Again, we would expect weights on milled rice prices that sum to approximately 0.7, based on typical milling yields. We do not believe that quality adjustments that are proportional to rice prices could be the cause of this phenomenon, as this would imply that on average U.S. rice

commands a 42% premium in the world market. It stretches credibility to believe that interaction of all of the unaccounted for factors in the conversion from rough to milled rice (transportation from farms to mills, milling cost, value of bran and hulls) and unaccounted for *WMP* calculation factors (quality adjustments, ocean freight to foreign market(s)) coincidentally interact to produce weights that sum to almost precisely unity. Nonetheless, the parsimonious model embodied in equation (10) seems to be a very good fit, producing a mean absolute prediction error of slightly less than 6.9%, and an  $R^2$  of 0.95.

Our results imply that, on balance, it is apparently possible to generate reasonably accurate estimates of the announced *WMP* in the context of a structural econometric rice model by using a simple linear combination of Thai and Pakistani export prices for milled rice. We speculate that a structural modeler may possibly improve the predictions further by either 1) using prices for milled rice at a major import center in the Far East, if such data were available, or 2) using some variable weighting scheme for the export prices. Also, predictions might be somewhat improved by incorporating a some proxy for the quality of the US rice stocks within each marketing year.

Our findings point to important considerations for more specialized time series modeling of the *WMP*, as might be conducted for optimizing producers' marketing loan benefit elections and other risk management applications. Given that neither of the stable long-run equilibria that we identify relate the price of U.S. milled rice for export to Europe (*ARAGP*) to the *WMP*, it is very likely that a U.S. producer's local rough rice price and the *WMP*

will not be cointegrated. Incorporation of foreign price series is thus likely to be of limited benefit – likely providing small marginal improvements in  $n$ -step-ahead forecasts of *WMP*. On the other hand, a simple bivariate system that incorporated only a producer's local cash price for rough rice and the *WMP* for rough rice would facilitate estimation and forecasting with a weekly data frequency. This would simultaneously reduce the number of parameters to estimate and greatly increase the number of available observations. Also, our investigation has revealed that a careful conditional second moment specification that accounts for the seasonal evolution and annual reset of *WMP* quality adjustments would be warranted.

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**Table 1: Data Series**

Series	Description	Source
<i>WMP</i>	World market price of rough, long grain rice	USDA
<i>ARAGP</i>	Amsterdam- Rotterdam area price of U.S. no. 2 rice	USDA
<i>PAKIP</i>	Pakistani 15% broken milled rice price	USDA
<i>THAIP</i>	Thai 15% broken milled rice price	USDA
<i>VIETP</i>	Vietnamese 15% broken milled rice price	USDA
<i>IPEXP</i>	Approx. Indian and Pakistani proportion of exports	USDA
<i>IPEXPIN</i> <i>T</i>	$IPEXP \times PAKIP$	-
<i>PAKIR</i>	Pakistani 15-day repo rate	Datastream
<i>THAIR</i>	One month Euro-baht deposit rate	Datastream
<i>USR</i>	One month Eurodollar deposit rate	Datastream
<i>PAKIPR</i>	$PAKIP \times PAKIR$	-
<i>THAIPR</i>	$THAIP \times THAIR$	-
<i>INDOUS</i> <i>D</i>	Indonesian Rupiah per U.S. dollar	Datastream
<i>BRAZUS</i> <i>D</i>	Brazilian Real per U.S. dollar	Datastream
<i>USDX</i>	New York Board of Trade U.S. Dollar Index, spot	Datastream
<i>BDI</i>	Baltic Dry Ocean Fright Index	Datastream
<i>DAUGJA</i> <i>N</i>	Dummy variable equal to one Aug. through Jan.	-
<i>TREND</i>	Centered trend variable	-



**Table 2: BACE results**

Variable	Posterior Inclusion Probability	Posterior Coefficient Distributions	
		Mean	Standard Deviation
<i>ARAGP</i>	0.999	0.131	0.026
<i>PAKIP</i>	0.418	-0.107	0.162
<i>THAIP</i>	1.000	0.439	0.062
<i>VIETP</i>	0.104	-0.003	0.029
<i>IPEXP</i>	0.969	-199.230	98.981
<i>IPEXPIN</i>			
<i>T</i>	0.997	1.518	0.577
<i>PAKIR</i>	0.217	-0.272	0.982
<i>THAIR</i>	0.170	0.050	0.681
<i>USR</i>	0.135	-0.007	0.565
<i>PAKIPR</i>	0.188	0.001	0.005
<i>THAIPR</i>	0.266	-0.001	0.003
<i>INDOUS</i>			
<i>D</i>	0.174	0.000	0.000
<i>BRAZUS</i>			
<i>D</i>	0.125	-0.230	1.412
<i>USDX</i>	0.130	0.024	0.154
<i>BDI</i>	0.158	0.000	0.001
<i>DAUGJA</i>			
<i>N</i>	0.106	-0.051	0.544
<i>TREND</i>	0.944	-0.305	0.109

**Table 3: Augmented Dickey-Fuller Tests<sup>a</sup>**

Variable	ADF Test Statistics	
	Trend <sup>b</sup>	No Trend <sup>c</sup>
<i>WMP</i>	-1.181	-3.233*
<i>PAKIP</i>	-1.482	-1.863
<i>THAIP</i>	-0.253	-1.221
<i>ARAGP</i>	-1.489	-1.857

<sup>a</sup> Test statistics marked with an asterisk indicate that we reject the null hypothesis of non-stationarity.

<sup>b</sup> Test statistics are the t-test statistics on the coefficient  $\alpha_1$  from the following model:

$\Delta X_t = \theta_0 + \theta_1 X_{t-1} + \theta_2 T + \sum_{k=1}^K \beta_k \Delta X_{t-k}$ . The 5% critical value is -3.467 (MacKinnon, 1991). The optimal lag length ( $K$ ) was chosen using the Schwarz (1978) information criterion.

<sup>c</sup> Test statistics are the t-test statistics on the coefficient  $\alpha_1$  from the following model:

$\Delta X_t = \theta_0 + \theta_1 X_{t-1} + \sum_{k=1}^K \beta_k \Delta X_{t-k}$ . The 5% critical value is -2.899 (MacKinnon, 1991). The optimal lag length ( $K$ ) was chosen using the Schwarz (1978) information criterion.

*Notes*

<sup>1</sup> The *IPEXP* series was constructed as follows. Series of annual observations of the levels of exports from the U.S., Pakistan, India, Thailand, and Vietnam were collected. For each of these five series, the total exports for each year were distributed to the months within that year, under the assumption of an AR1 data-generating process. The five resulting monthly series were then used to calculate the approximate proportion of exports in each month emanating from India and Pakistan.

<sup>2</sup> An analogous cointegration analysis was conducted using the exact variables identified in the BACE analysis (i.e., including *IPEXP* and *IPEXPINT*, but excluding *PAKIP*), with identical qualitative results regarding the variables found to enter into the long-run relationship with *WMP*.

<sup>3</sup> This is consistent with the AWP for cotton, which has, on average, been trading at increasing discounts to the A-Index in recent years.