The Impact of Futures Market on U.S. Soybean Processors

by

Sergio Lence, Dermot Hayes, and William Meyers

THE IMPACT OF FUTURES MARKETS ON U.S. SOYBEAN PROCESSORS

Sergio H. Lence, Dermot J. Hayes, and William H. Meyers*

I. Introduction

The central paradigm in both theoretical and empirical research about the behavior of marketing firms is the *contemporaneous marketing margin* (CMM), by which we mean the relationship between the cash price of the final good and the (weighted) cash price of material input measured at the same point in time.[1] For example, if one unit of output is obtained from θ units of material input, the CMM expressed in ratio form is $[(p_t/\theta)/s_t]$, where p_t is the cash price of final good at period t, and s_t is the cash price of material input at t.

A shortcoming of the CMM is that it is a static concept, and is based upon the assumption that inventories do not change: at each period the amounts of final good sold and produced are hypothesized to be identical and equal to the weighted quantity of material input bought. Therefore, the CMM is of little use in analyzing the behavior of marketing firms over periods in which sales, production and purchases are substantially different from each other. For example, it is perfectly plausible for firms to have substantial profits even if the CMM ratio equals one. They can achieve this by stockpiling when prices are low and depleting stocks at high prices.

Another problem with the CMM is that futures markets play no role. In many marketing industries futures trading is an important component of the firms' overall financial strategy. This motivates the incorporation of futures markets explicitly into a model of marketing/processing firms.

There is a large body of literature on the theory of the firm in the presence of forward and futures markets (Holthausen 1979, Feder et al. 1980, Batlin 1983, Ho 1984, Lapan et al. 1991), but little work has been done to apply its results to empirical supply and demand analysis. The majority of the theoretical studies are static, but Lence (1991) recently introduced a theoretical model that allows for output and material input storage as well as forward trading. This model is based upon a nonstochastic Leontief production function, which makes it particularly suited to analyze marketing firms. He derived a set of results regarding the response of purchases, production and sales to changes in cash prices, forward prices, interest rate and beginning stocks.

The object of this study is to test empirically Lence's model. We use monthly data because of the noticeable disregard for the very short run in empirical supply and demand analysis, and the importance of having a model that allows us to discriminate and understand the different patterns of sales, production and purchases.

Among many other uses, this model could be employed to assess the conduct and performance of an industry, to improve the estimates of the short-run elasticities of demand and supply, and to better understand the price-transmission mechanisms.

The paper proceeds as follows: first, we outline the theoretical model and present the theoretical results relevant to our purposes. Then, we describe the data and the market used for the empirical estimation. Next, we report and discuss the empirical results. In the final section we draw the conclusions of our findings.

---

*Sergio H. Lence, Dermot J. Hayes, and William H. Meyers are, respectively, Research Assistant, Associate Professor, and Professor, Department of Economics, Iowa State University, Ames.

II. A Sketch of The Theoretical Model

To save space, we will only outline the model developed by Lence. This consists of a competitive firm characterized by an intertemporal constant absolute risk averse utility function, whose objective is to maximize the expected utility of its discounted profits:

$$U_t = -exp[-\lambda\,(\pi_t + d\,\pi_{t+1} + d^2\,\pi_{t+2} + \ldots + d^{e-t}\,\pi_e)] \tag{1}$$

where: $U_t(\cdot)$ = multiperiod utility function corresponding to period t
λ = coefficient of absolute risk aversion, $\lambda > 0$
π_t = cash flow at period t
d = discount factor, $0 \le d \le 1$

The stream of cash flows ends at period e, at which the firm ceases to exist. It is assumed that the firm has a nonstochastic Leontief production function represented by

$$Q_t = min[Q_t^S/\theta,\ g(\cdot)] \tag{2}$$

where: Q_t = production of final good
Q_t^S = use of material input
θ = fixed input-output coefficient, $\theta > 0$
$g(\cdot)$ = strictly concave production function for nonmaterial inputs

and that the particular form of the cash flow at t is

$$\pi_t = p_t\,P_t - s_t\,S_t - q(Q_t) - i(I_t - P_t) - i^S(I_t^S + S_t - Q_t^S)$$

$$+ (f_{t-1,t} - p_t)\,F_{t-1,t} + (f_{t-1;t}^S - s_t)\,F_{t-1;t}^S \tag{3}$$

s.t. $I_t = I_{t-1} - P_{t-1} + Q_{t-1} \ge P_t$
$I_t^S + S_t \ge Q_t^S = \theta\,Q_t \ge 0$

where: p_t = cash price of final good
P_t = sales of final good
s_t = price of material input
S_t = purchases of material input
$q(\cdot)$ = strictly convex variable nonmaterial cost function
$i(\cdot)$, $i^S(\cdot)$ = strictly convex variable inventory cost functions of final good and material input, respectively
I_t = beginning inventory of final good, $I_t = I_{t-1} - P_{t-1} + Q_{t-1}$

I^s_t = beginning inventory of material input, $I^s_t = I^s_{t-1} + S_{t-1} - Q^s_{t-1}$

$f_{t-1,t}$ = forward price of final good at t-1 for delivery at t

$F_{t-1,t}$ = net short position for delivery of final good at t open at t-1

$f^s_{t-1;t}$ = forward price of material input at t-1 for delivery at t

$F^s_{t-1;t}$ = net short position for delivery of material input at t open at t-1

At any period t the firm chooses purchases and use of material input (S_t and Q^s_t), production ($Q_t = \theta\ Q^s_t$), sales of final good (P_t), and the hedge levels for delivery at t+1 ($F_{t,t+1}$ and $F^s_{t;t+1}$) so as to maximize expected utility. In the solution to this problem there is a separation between "physical" decisions (i.e., purchases, production and sales) and hedging.[2] In addition, it can be shown that the comparative static results summarized in Table 1 hold. Although Table 1 is self-explanatory, a comment is due regarding the effect of beginning stocks on production. The impact of stocks on output is null if production and storage are separated, but nonzero otherwise. The theoretical results reported in Table 1 provide the basis for the empirical analysis pursued in the following sections.

Table 1. Effect of Exogenous and Predetermined Variables on Production, Purchases and Sales

EXPLANATORY VARIABLES	ENDOGENOUS VARIABLES		
	Production (Input Use)	Input Purchases	Output Sales
Cash prices: input	–	–	
output			+
Forward prices: input		+	
output	+	+	–
Discount factor	+	+	–
Beginning stocks: input	0/+	–	
output	0/–		+

III. Testable Hypotheses, Data and Methodology

The main limitation to testing the preceding theoretical results is the lack of reliable data on any commodity forward market. Since the best approximation to forward prices are futures, we used these as surrogates of forward prices in the empirical analysis.

We chose the U.S. soybean-processing industry for our study, because there are highly liquid futures markets for both material input (soybeans) and products (soyoil and soymeal) in the Chicago Board of Trade. A major drawback of using this industry for our purposes is its relative concentration, which may violate the assumption of perfect competition. Before 1984 the four biggest crushers processed about half of the total (Marion 1986), but beginning in 1984 concentration increased sharply leading to the two largest firms having 51 percent of the total capacity in 1985 (Consultants International Group et al. 1986). Since there are doubts as to the competitive performance of this industry in the most recent years, the period used for the study ends in 1986. Although the concentration in previous years was by no means negligible, it can be argued that compared to other food-processing industries it was not particularly high. Further, during the period under analysis the soybean exports ranged from a low of 30 percent of total soybean use in 1967/68 to a peak of 45 percent in 1981/82, providing keen competition for the supply of the material input. The ample availability of domestic and imported substitutes for domestically produced soybean oil and meal also lends support for a fairly competitive behavior during the period analyzed. On the other hand, the futures markets for soybean products are widely used by operators from all over the world. These are highly liquid markets, and the rules imposed to trade in them make these the closest real-world counterparts to the theoretical model of perfect competition.

We employed an observation horizon of one month, even though the decision horizon for soybean processing firms may be roughly estimated as one week (Tzang and Leuthold 1990).[3] We did so because data on receipts, crushings and shipments are not available covering periods shorter than one month. On the other hand, we did not use quarterly data because the dynamics of the firm's decisions becomes more difficult to analyze as the observation horizon lengthens. As we move from monthly to quarterly data the averages of cash and futures prices tend to converge to each other, and the same is true of (weighted) purchases, crushings and sales. This convergence hides much useful information on firm behavior.

The fact that the observation horizon is longer than the decision one poses a problem even with monthly data. For example, whenever the observation horizon exceeds the decision horizon we must include the use of material input (Q_t^s) and production (Q_t) as explanatory variables in the regressions for material input purchases (S_t) and output sales (P_t), respectively.[4] Since Q_t^s and Q_t are endogenous themselves, utilizing ordinary least squares yields inconsistent parameter estimates. Instead, we must do the estimation by means of a simultaneous equations model.

The use of monthly instead of quarterly or annual data has some drawbacks. It is reasonable to think that the decision horizon for many nonmaterial cost components is longer than one month: we certainly should not expect large changes in purchases, production or sales in response to changes in wages or other input prices within a one-month period. One consequence of this is that the number of exogenous variables other than beginning inventories and prices of output and material input that can be used successfully in the system of regressions is sharply reduced. Another consequence is that lagged observations of the endogenous variables must be used as explanatory variables in the econometric model.

In the analysis presented below we used the ratio specifications of the *futures marketing margin* (FMM), which for the particular case of production is defined as

$$d_t \, [(f_{t,t+1}/\theta)/s_t] \tag{4}$$

Conceptually, the FMM is similar to the CMM (recall that this is $[(p_t/\theta)/s_t]$), but the FMM uses the futures price of the final good instead of the cash price, and in addition it involves the discount factor. We employed the ratio specification of the FMM for four main reasons. First, it is consistent with the theoretical model. Second, it is easy to interpret: expression (4) tells us that the ratio is an of end-of-period return per unit of material input above the market end-of-period return ($1/d_t$). In general, the ratio will be around unity, with values higher (lower) than unity suggesting profits (losses). Third, with the ratio specification we do not need to choose a price index to express the price series in real terms. Fourth, the problem of not having delivery positions for all months in the futures market is easier to overcome, as discussed below.

In the Chicago Board of Trade the delivery months for soybean oil and meal are January, March, May, July, August, September, October, and December. Hence, in many months we must use $f_{t,t+2}$ instead of $f_{t,t+1}$, because $f_{t,t+1}$ does not exist.[5] But the ratio $[(f_{t,t+2}/\theta)/s_t]$ involves a two-month return and is certainly different from the ratio $[(f_{t,t+1}/\theta)/s_t]$, which involves a one-month return only. This suggests converting them to a same base. We chose an annual base for convenience of interpretation of the results. Then, the annualized end-of-period rates of return are $[(f_{t,t+2}/\theta)/s_t]^{12/2}$ and $[(f_{t,t+1}/\theta)/s_t]^{12/1}$, respectively. Consequently, we used the FMM ratios

$$d_t \; [(f_{t,t+k}/\theta)/s_t]^{12/k}, \; k \geq 1 \tag{5}$$

where d_t is the annual market discount rate, and k is the number of months between the placement of the hedge and the delivery month.

The procedure outlined in the preceding paragraph is important because in practice the positions most used for hedging are not always the "nearest" ones. For example, in February most hedges are placed against the May position instead of the March position, therefore the relevant futures price for our purposes is not $f_{Feb,Mar}$ but $f_{Feb,May}$. More specifically, in the analysis we employed $f_{Jan,Mar}$, $f_{Feb,May}$, $f_{Mar,May}$, $f_{Apr,Jul}$, $f_{May,Jul}$, $f_{Jun,Aug}$, $f_{Jul,Dec}$, $f_{Aug,Dec}$, $f_{Sep,Dec}$, $f_{Oct,Dec}$, $f_{Nov,Jan}$, and $f_{Dec,Mar}$. As inferred from the information on the volume of open contracts, on average these are the most used combinations of hedge-placement/delivery months.

Soybean processing involves one material input and not one but two outputs in fixed proportions: oil and meal. Hence, we had to redefine slightly the FMM for production (i.e., expression (5)) to make it suitable to analyze the soybean complex:

$$d_t \; [(f^{o}_{t;t+k}/\theta^{o} + f^{m}_{t;t+k}/\theta^{m})/s_t]^{12/k}, \; k \geq 1 \tag{6}$$

where the superscripts "o" and "m" stand for oil and meal, respectively. Expression (6) should be interpreted in the same way as for the single-output case, with the difference that the numerator in (6) consists of a composite index of two "prices" of final goods, each one weighted by its corresponding production share.

Due also to the existence of two products we had to estimate four behavioral equations, instead of three as it had been the case with only one output. The basic specification of the regressions for the soybean complex is:

Soybean Crushings: $$Q^{s}_{t} = Q^{s}_{t}(FMM^{s}_{t}, I^{o}_{t}, I^{m}_{t}, Q^{s}_{t-1}, CAP_t) \tag{7}$$

Soybean Purchases: $$S_t = S_t(FMM^{s}_{t}, I^{s}_{t}, Q^{s}_{t}, S_{t-1}) \tag{8}$$

Oil Sales: $$P_t^o = P_t^o(FMM_t^o, I_t^o, Q_t^o, P_{t-1}^o) \tag{9}$$

Meal Sales: $$P_t^m = P_t^m(FMM_t^m, I_t^m, Q_t^m, P_{t-1}^m) \tag{10}$$

which are estimated subject to the following identities:

Soybean Stocks: $$I_t^s = I_{t-1}^s + S_{t-1} - Q_{t-1}^s \tag{11}$$

Oil Stocks: $$I_t^o = I_{t-1}^o - P_{t-1}^o + Q_{t-1}^o \tag{12}$$

Meal Stocks: $$I_t^m = I_{t-1}^m - P_{t-1}^m + Q_{t-1}^m \tag{13}$$

Oil Production: $$Q_t^o = Q_t^s/\theta^o \tag{14}$$

Meal Production: $$Q_t^m = Q_t^s/\theta^m \tag{15}$$

The variables FMM_t^s, FMM_t^m and FMM_t^o are the corresponding FMMs, and CAP_t is the crushing capacity.[6] In particular, the coefficients for the FMMs are expected to be significantly different from zero and positively related to soybean crushings and purchases, but negatively related to oil and meal sales. According to our previous discussion, the expected signs of the coefficients for the remaining explanatory variables in regressions (7) through (10) are:

Soybean Crushings:[7] $$\frac{\partial Q_t^s}{\partial I_t^o} \le 0,\ \frac{\partial Q_t^s}{\partial I_t^m} \le 0,\ \frac{\partial Q_t^s}{\partial Q_{t-1}^s} > 0,\ \frac{\partial Q_t^s}{\partial CAP_t} > 0 \tag{16}$$

Soybean Purchases: $$\frac{\partial S_t}{\partial I_t^s} < 0,\ \frac{\partial S_t}{\partial Q_t^s} > 0,\ \frac{\partial S_t}{\partial S_{t-1}} > 0 \tag{17}$$

Oil Sales: $$\frac{\partial P_t^o}{\partial I_t^o} > 0,\ \frac{\partial P_t^o}{\partial Q_t^o} > 0,\ \frac{\partial P_t^o}{\partial P_{t-1}^o} > 0 \tag{18}$$

Meal Sales: $$\frac{\partial P_t^m}{\partial I_t^m} > 0, \quad \frac{\partial P_t^m}{\partial Q_t^m} > 0, \quad \frac{\partial P_t^m}{\partial P_{t-1}^m} > 0 \tag{19}$$

The data covers the period September, 1965 through December, 1986. Cash prices are the quotations FOB Decatur published by the USDA, and the data on crushings, receipts and shipments are those reported by the U.S. Bureau of the Census. Note that the available data corresponds to receipts and shipments instead of actual purchases and sales, so that we assumed that receipts and shipments are identical to purchases and sales, respectively. This is not a very stringent requirement when working with monthly data; it had certainly been much less tenable if the observation horizon had been only one- or two-week long. Data sources for the crushing capacity are USDA's Fats and Oils--Outlook and Situation, Consultants International Group (1986), and the Statistical Annual of the Chicago Board of Trade for the most recent years. Since these sources only report the crushing capacity at the beginning of October, the capacity for the remaining months was approximated by linear interpolation. All prices and quantities for the soybean complex are expressed in \$/short ton and millions of short tons, respectively. The discount factor was calculated by means of the prime rate reported by the USDC's Survey of Current Business. Finally, the futures prices employed in the regressions are the average of the highest and lowest futures prices in each month for the selected delivery positions from the Statistical Annual of the Chicago Board of Trade.

IV. Results and Discussion

The fixed input-output coefficients estimated from the monthly data are $\theta^o =$ 5.537 and $\theta^m = 1.263$. The coefficients of variation for θ^o and θ^m are only 2.35 percent and 0.85 percent, respectively, lending strong support to the assumption that soybean processing is characterized by a Leontief production function. Using these empirical input-output coefficients, we estimated the system of equations (7)-(10) s.t. (11)-(15) by means of full information maximum likelihood (FIML).

The results are reported in Table 2. The signs of the coefficients corresponding to the basic explanatory variables are as expected. We included monthly dummy variables in the regression for soybean crushings because crushings were extremely seasonal, and employing only their lagged values yielded very unstable parameter estimates for them. In the equation for soybean purchases we modeled the seasonality by means of the endogenous variable lagged twelve months plus a dummy variable accounting for October. October marks the beginning of the crushing year, and purchases are abnormally high compared to other months: in the period 1965/66-1985/86 at least 15 percent of the annual purchases were performed in October, with the only exception of the year 1984/85 in which that percentage was just 11.8. In the equations for oil and meal sales the seasonal patterns were captured by the autocorrelation coefficients at lag 12 (for oil), and lags 3 and 12 (for meal). Only the equation for meal sales exhibited significant first-order autocorrelation.

Crushing capacity was a highly significant explanatory variable of the amount of soybeans processed. The corresponding coefficient of 0.210 seems low, but

Table 2: Estimated System of Equations for the Futures Marketing Margin Hypothesis, U.S. Soybean Processors, 1965:9-1986:12.

EXPLANATORY VARIABLES	ENDOGENOUS VARIABLES			
	Crushings	Soybean Purchases	Oil Sales	Meal Sales
FMM: soybeans	0.110 (2.38)*[a]	0.74 (6.96)**		
oil			-0.0474 (-5.00)**	
meal				-0.043 (-3.86)**
BEG. STOCKS: soybeans		-0.153 (-5.12)**		
oil	-0.270 (-3.68)**		0.078 (4.91)**	
meal	-0.309 (-4.06)**			0.139 (4.33)**
CRUSHINGS		0.573 (8.25)**		
PRODUCTION: oil			0.572 (11.97)**	
meal				0.938 (45.10)**
CRUSHING CAPACITY	0.210 (6.21)**			
LAGGED ENDOG.: lag 1	0.896 (20.06)**	0.272 (8.32)**	0.159 (3.08)**	0.042 (1.83)
lag 2	-0.114 (-2.81)**		0.165 (3.93)**	
lag 12		0.193 (3.90)**		

[a] Numbers in parenthesis are t-ratios.

* (**) means statistically significant at the 5 (1) percent level.

Table 2: Cont.

EXPLANATORY VARIABLES		ENDOGENOUS VARIABLES			
		Crushings	Soybean Purchases	Oil Sales	Meal Sales
INTERCEPT		−0.136	−0.68	0.064	0.040
		(−1.82)[a]	(−3.88)**	(4.71)**	(1.84)
DUMMY:	February	−0.187			
		(−5.70)**			
	March	0.163			
		(4.73)**			
	April	−0.106			
		(−3.40)**			
	May	0.094			
		(2.60)**			
	June	−0.130			
		(−4.48)**			
	September	−0.116			
		(−3.70)**			
	October	0.392	1.74		
		(12.12)**	(10.32)**		
	December	0.133			
		(4.19)**			
AUTOCORRELATION COEFFICIENTS:	t-1				−0.353
					(−5.80)**
	t-3				0.296
					(4.25)**
	t-12			0.159	0.221
				(2.15)*	(3.24)**
STANDARD ERROR OF REGRESSION		0.112	0.322	0.0226	0.0415
DURBIN-WATSON		2.024	2.158	1.946	2.005

[a]Numbers in parenthesis are t-ratios.
* (**) means statistically significant at the 5 (1) percent level.

this was probably caused by the high correlation between capacity and the lagged endogenous variable.

As hypothesized, the beginning inventories of final goods had a significantly positive impact on their respective sales, while the beginning stocks of soybeans had a significantly negative effect on input purchases. In addition, the results indicate that the quantity crushed is negatively related to the beginning inventories of oil and meal, suggesting that production and storage are not separated functions.

Most important of all for our study, the FMM coefficients had the expected signs and were highly significant in all instances. Moreover, their magnitudes are consistent with each other when considering the variability of the respective endogenous variables. For example, the intra-year coefficient of variation (CV) of soybean purchases has been on average 5.9 times larger than the intra-year CV of soybean crushings, 8.0 times larger than the intra-year CV of oil sales, and 6.2 times larger than the intra-year CV of meal sales.

We also estimated analogous regressions employing *expected marketing margins* (EMMs) instead of FMMs, to address the possibility that similar or even better results could be obtained by using expected prices instead of futures. For example, the EMM equivalent to (6) is:

$$d_t\,[\mathbb{E}_t(p^o_{t+k}/\theta^o + p^m_{t+k}/\theta^m)/s_t]^{12/k},\ k \geq 1 \qquad (20)$$

We addressed two particular hypotheses of price expectations to build EMMs, namely naive expectations and perfect foresight.[8] To save space, and since the structural equations for the EMMs are basically the same as for the FMM model, we only report a comparative summary of the coefficients corresponding to the FMM and the two EMM variables (see Table 3). The statistical significance of the FMM coefficients is even more evident after observing Table 3: at the 1 percent level of confidence the coefficients corresponding to the EMMs are not significantly different from zero, and at the 5 percent level of confidence only the EMM coefficients for soybean purchases were significantly different from zero. The likelihood ratio test for the null hypothesis that the EMM coefficients of the equations for crushings and oil and meal sales are simultaneously equal to zero was 3.02 for naive expectations, and 2.50 for perfect foresight. These statistics are well below the critical χ^2 at the 5 percent level of significance, which is 7.82 for three degrees of freedom. Hence, the null hypothesis could not be rejected in either case. In addition, the EMM systems had more problems of autocorrelation in the residuals: it was necessary to incorporate a first order autocorrelation coefficient in the regression for soybean purchases in both EMM models. It is clear that the two EMM models fitted had poorer explanatory power than the FMM, so that we did not perform any model specification tests to decide the best among the three.[9] Other reasons for not performing such tests are their extremely low power, and the presence of autocorrelated disturbances.

It is interesting, however, to point out the difference in magnitude between the coefficients for FMM and EMMs in the purchase equation: the first is 0.74, the naive EMM is 0.0205, and the perfect-foresight EMM is 0.0049. Since all three marketing margins are measured in the same units and are significant (although the last one is so only at the 5 percent level of significance), the disparity in the coefficients seems to deserve further study.

In Table 4 we report the average short-run elasticities of purchases, crushings and sales with respect to each of the individual components of the FMM.[10] The most interesting feature of this table is that the elasticities are relatively high, given that we are dealing with monthly data.[11] This is particularly true for soybean purchases,

Table 3: Comparison of Coefficients Corresponding to Marketing Margins for FMM, Naive EMM, and Perfect-Foresight EMM Hypotheses

EXPLANATORY VARIABLES	ENDOGENOUS VARIABLES			
	Crushings	Soybean Purchases	Oil Sales	Meal Sales
FMM: soybeans	0.110 (2.38)*[a]	0.74 (6.96)**		
oil			−0.0474 (−5.00)**	
meal				−0.043 (−3.86)**
NAIVE EMM: soybeans	0.0010 (0.29)	0.0205 (2.15)*		
oil			−0.148 (−1.53)	
meal				−0.05 (−0.44)
P-F EMM: soybeans	0.0010 (0.74)	0.0049 (2.07)*		
oil			0.00012 (0.24)	
meal				−0.00007 (−0.19)

[a]Numbers in parenthesis are t-ratios.
* (**) means statistically significant at the 5 (1) percent level.

Table 4: Average Short-Run Elasticities of Crushings, Purchases and Sales with Respect to Prices, Estimated by Means of the FMM Model

EXPLANATORY VARIABLES	ENDOGENOUS VARIABLES			
	Crushings	Soybean Purchases	Oil Sales	Meal Sales
CASH PRICES: soybeans	−0.31	−2.43	−0.18	−0.29
oil			0.51	
meal				0.13
FUTURES PRICES: oil	0.11	0.90	−0.44	0.11
meal	0.19	1.53	0.11	0.05
DISCOUNT FACTOR	0.06	0.52	−0.07	0.03

whose elasticities with respect to soybean prices and meal futures are greater than unity in absolute value.[12] A closer look at the data, however, reveals that the high responsiveness of monthly soybean purchases to prices is not implausible, because the intra-year fluctuations in purchases are much higher than the inter-year ones: the average intra-year CV of purchases for the period studied was 48 percent, while the inter-year CV was just 23 percent. In contrast, intra-year fluctuations in crushings and sales are smaller than inter-year ones. The average intra-year CVs were 9 percent for crushings and meal sales, and 7 percent for oil sales, while the inter-year CVs for all three quantities was 23 percent. Our results indicate that processors adjust to price changes mainly through purchases of soybeans, which implies that the short-run price formation process for soybeans is different from those for oil and meal.

It is also worth noting that an increase in the futures price of oil has a negative net impact on oil sales, but that an analogous increase in the futures price of meal affects meal sales positively. The explanation for this is that in the case of meal the direct negative effect on sales stemming from a rise in futures is outweighed by the indirect positive effect of such rise through the increase in production. An analogous interpretation applies to the fact that the elasticity of oil sales with respect to the discount factor is negative, while the equivalent elasticity for meal sales is positive.

V. Conclusions

The main conclusion from the empirical application of the theoretical model to the U.S. soybean-processing industry is that it fits the data well. In fact, it shows that in the very short run soybean crushers have responded significantly and as hypothesized to price incentives, and to changes in other exogenous variables. This highlights the relevance of the model, and it also stresses the weakness of empirical models that adopt longer observation horizons under the assumption that in the very short run firms cannot adapt to variations in prices and/or other variables.

A particularly important result from our study is that it strongly supports the hypothesis that futures prices have played a key allocative role in the processors' decisions concerning soybean purchases and crushings, and oil and meal sales. This finding stresses the importance of analyzing the informational efficiency of futures markets, as these appear to be used by marketing firms to allocate their resources. It also implies that the price risk faced by marketing firms is related to the basis risk rather than to risk on the level of cash prices.

As we mentioned in the introductory section, some of the possible important uses of the model are a) to assess the conduct and performance of marketing industries, b) to improve the estimates the short-run elasticities of demand for material inputs and supply of final goods, and c) to shed more light about the price transmission mechanisms.

Endnotes

1. A thorough exposition of the CMM is done in Tomek and Robinson (1990), where it is simply referred to as *marketing margin*.
2. Holthausen (1979) and Feder et al. (1980) also obtained separation, but their model is static and does not involve inventories.
3. According to Merton (1982), the observation horizon is "the length of time between successive observations of the data by the researcher", and the decision horizon is "the length of time between which the investor makes successive decisions, and it is the minimum time between which he would take any action."
4. A fuller rationale for this is given in Lence (1991).
5. Examples of nonexistent $f_{t,t+1}$ are $f_{Jan,Feb}$, $f_{Mar,Apr}$, $f_{May,Jun}$, and $f_{Oct,Nov}$.
6. The complete expressions for the FMMs is given in the Appendix.
7. We did not address the impact of CAP_t on crushings, but the expected sign of its coefficient is obvious.
8. The complete expressions for the EMMs is given in the Appendix.
9. These tests for multivariate models include the P_0 and P_1 tests, suggested by MacKinnon (1983), and the N test advanced by Pesaran and Deaton (1978).
10. For example, the elasticity of crushings at month t with respect the cash price of oil at t is 0.11.
11. For comparison, Paul and Wesson (1966) found that the elasticity of annual crushings with respect to the difference form of the CMM was between 0.1 and 0.2.
12. It is worth mentioning that the high elasticities of soybean purchases are not due to the peak in purchases that occurs in October, because we included a dummy variable in the model to take care of this problem (see Table 2).

References

Batlin, Carl A. "Production under Price Uncertainty and Imperfect Time Hedging Opportunities in Futures Markets." Southern Economic Journal 49 (1983): 682-692.

Chicago Board of Trade. Statistical Annual. Various issues.

Consultants International Group, Inc., and Abel, Daft & Earley, Inc. Estudio Sobre los Efectos de los Subsidios en el Complejo Oleaginoso en Países Relevantes. Buenos Aires: CIARA, 1986.

Feder, G.; Just, R. E.; and Schmitz, A. "Futures Markets and the Theory of the Firm under Price Uncertainty." The Quarterly Journal of Economics 94 (1980): 317-328.

Ho, Thomas S. Y. "Intertemporal Commodity Futures Hedging and the Production Decision." Journal of Finance 39 (1984): 351-376.

Holthausen, D. M. "Hedging and the Competitive Firm under Price Uncertainty." American Economic Review 69 (1979): 989-995.

Lapan, H.; Moschini, G.; and Hanson, S. "Production, Hedging, and Speculative Decisions with Options and Futures Markets." American Journal of Agricultural Economics 73 (1991): 66-74.

Lence, Sergio H. "Dynamic Firm Behavior under Uncertainty." Ph.D. diss., Iowa State University, 1991.

MacKinnon, James G. "Model Specification Tests against Non-Nested Alternatives." Econometric Reviews 2 (1983): 85-110.

Marion, B. W., and NC 117 Committee. The Organization and Performance of the U.S. Food System. Lexington: Lexington Books, 1986.

Merton, Robert C. "On the Microeconomic Theory of Investment under Uncertainty." In Kenneth J. Arrow and Michael D. Intriligator (eds.). Handbook of Mathematical Economics. Volume II. Amsterdam: North-Holland Publishing Co.,1982.

Paul, A. B., and Wesson, W. T. "Short-Run Supply of Services--The Case of Soybean Processing." Journal of Farm Economics 48 (1966): 935-951.

Pesaran, M. H., and Deaton, A. S. "Testing Non-Nested Nonlinear Regression Models." Econometrica 46 (1978): 677-694.

Tomek, William G., and Robinson, Kenneth L. Agricultural Product Prices. Ithaca, N. Y.: Cornell University Press, 1990.

Tzang, Dah-Nein and Leuthold, Raymond M. "Hedge Ratios under Inherent Risk Reduction in a Commodity Complex." Journal of Futures Markets 10 (1990): 497-504.

U.S. Department of Agriculture, Economic and Statistics Service. Fats and Oils--Outlook and Situation. Various issues.

U.S. Department of Commerce, Bureau of the Census. Current Industrial Reports--Fats and Oils--Oilseed Crushings. Various issues.

U.S. Department of Commerce, Bureau of Economic Analysis. Survey of Current Business. Various issues.

Appendix

The expressions for the FMMs are:

$$FMM_t^s = d_t\,[(f_{t;t+k}^o/\theta^o + f_{t;t+k}^m/\theta^m)/s_t]^{12/k} \tag{A.1}$$

$$FMM_t^o = d_t\,(f_{t;t+k}^o/p_t^o)^{12/k} \tag{A.2}$$

$$FMM_t^m = d_t\,(f_{t;t+k}^m/p_t^m)^{12/k} \tag{A.3}$$

The variable k is 2 for t = January, March, May, June, October and November; it is 3 for t = February, April, September and December; it is 4 for t = August; and it is 5 for t = July.

The EMMs for the naive-expectations hypothesis are:

Soybeans: $$d_t\,[(p_t^o/\theta^o + p_t^m/\theta^m)/s_t]^{12} \tag{A.4}$$

Oil: $$d_t\,(p_t^o/p_t^o)^{12} = d_t \tag{A.5}$$

Meal: $$d_t\,(p_t^m/p_t^m)^{12} = d_t \tag{A.6}$$

Finally, the EMMs for the case of perfect foresight are:

Soybeans: $$d_t\,[(p_{t+1}^o/\theta^o + p_{t+1}^m/\theta^m)/s_t]^{12} \tag{A.7}$$

Oil: $$d_t\,(p_{t+1}^o/p_t^o)^{12} \tag{A.8}$$

Meal: $$d_t\,(p_{t+1}^m/p_t^m)^{12} \tag{A.9}$$