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by

Matthew A. Diersen and Philip Garcia

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Output price risk has been found to affect firm behavior in the soybean complex. Here, we investigate the influence of price risk on the supply of soybean products, using futures prices and implied volatilities from options markets to generate the first and second moments of the crushers' returns distribution. Our findings suggest that implied volatilities can be a useful measure of price risk in a supply response context. This measure has the advantages of being forward-looking, market generated, and relatively easily implementable for those commodities with futures and options markets.

Introduction

Risk is prevalent in the soybean complex or crushing industry. Crushers face supply risk since they may have difficulty obtaining soybeans when margins warrant crushing. By holding inventories they face financial risks from changing interest rates. However, the largest risk is output price risk; unexpected changes in the prices of meal and oil can erase a profitable margin or present an opportunity cost if products are hedged. Developing a better understanding of the extent to which price risk affects output decisions in the soybean complex can further our understanding of this complex, and may permit more efficient forecasts and provide insights into the effectiveness of risk management strategies.

Risk has been found to be an important influence on firms' decisions. Conceptually, for example, Sandmo (1971) has shown that increases in output price risk result in lower production for a firm. Within the soybean complex, Boyd, Brorsen, and Grant (1987), and Lence, Hayes, and Meyers (1992) have found that price risk can influence margins and crush. While these theoretical and empirical results are widely accepted, the methods used to measure the relevant risk have varied substantially. The earliest measures were simple historical averages of past prices. Later, risk was measured as a deviation from an expectation based on past forecast errors. More recently, using GARCH procedures, anticipated deviations, rather than past deviations from expectations were incorporated into the risk measurement process. This procedure has been further extended to permit the expectations to be specified as a function of a structural model in a rational expectations context. Over time, the procedures to identify the effects of risk on markets have become more complicated and somewhat cumbersome to use. Here, we propose an alternative measure of price risk based on the implied volatilties from options markets. The measure is forward looking, market generated, and can be implemented in a relatively straightforward manner for those commodities with efficient futures and options markets.

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The objective of this paper is to measure the effect of risk on soybean crushing outputs using information from the futures and options markets. Futures and options markets for meal and oil are actively traded in a rather efficient environment. These markets provide readily available information on the first and second moments of the expected price distribution for these commodities. Futures markets provide an indication of expected prices, while options markets and their implied volatilities give the market's prediction of the risk associated with the rate of return on futures until maturity[1]. The use of these measures is consistent with the idea that risk measures should be forward looking and reflect changes in expected supply and demand conditions.

Literature

Sandmo (1971) and Ishii (1977) show that output is negatively related to uncertainty in the output price by firms with nonincreasing absolute risk aversion. Risk measures are assessed as to how well they would reflect that theoretical result. Although there is limited research on the soybean complex, several studies have focused on risk and risk management.

Risk Measures

Price risk has been measured in several ways. One risk measurement is past price variability. For example, Sengupta and Sfeir (1982) use a moving variance of past prices as a risk measure in an acreage response model. Brorsen, et al. (1985) use annual coefficients of variation in a wheat marketing margin model. Brorsen, Chavas, and Grant (1987) use a weighted deviation from past price levels in a rice model. Antonovitz and Green (1990) incorporate futures by using the variance of futures prices as a measure of risk. The ad-hoc nature of these specifications limits the information used and hence the results may be sensitive to weights and lag lengths. These studies, while showing the importance of variance of prices, fail to differentiate between variability and unexpected changes in prices.

A more appropriate measure treats risk as a deviation from expectations. Traill (1978) is an early study which distinguishes empirically between price variability and risk. Traill (1978) measures risk as a function of past absolute deviations from expected price formulated in a polynomial context, and compares it to a moving standard deviation. Hurt and Garcia (1982) consider risk as squared deviations from expectations from cash or futures prices in sow farrowing models. Tronstad and McNeill (1989) find that asymmetric deviations are better at explaining risk than symmetric deviations in a sow farrowing model. While based on unexpected price changes, these approaches still lack a forward-looking nature.

The advent of GARCH expanded the incorporation of risk into pricing models. Aradhyula and Holt (1988) explain the GARCH method and apply it to meat production. Holt and Aradhyula (1990), looking at broiler prices, compare GARCH effects to lagged deviations

[1] Sanders (1994) also suggested the use of implied volatility to measure risk.

from price expectations. GARCH models are another variation of the lagged variance used in Traill (1978). While a reaction to past error variance or its size is not disputed, typical GARCH models suffer the same shortcoming of the deviations from expectations models. They are not forward looking in the sense of incorporating expected changes in supply and demand, but simply forecast deviations from expectations based on historical patterns. In addition, early GARCH models were not simultaneously estimated, possibly biasing results. GARCH models are also notoriously poor as forecasting models, both from an accuracy standpoint, and because of their limited forecast horizons.

Aradhyula and Holt (1989) in a broiler price model and Holt and Moschini (1992) in a farrowing model both outline rational expectations approaches, but are only able to implement GARCH models. Holt (1993) models the risk response in the beef marketing channel generating expected beef prices and risk simultaneously in a rational expectations framework using a GARCH process. This procedure provides a theoretically appealing method of approaching the problem of risk measurement in a forward looking context, but its complexity and modeling demands which require complete specification of the entire structure may make its usefulness in multiple, highly complex, and interrelated markets problematic.

Soybean Complex

Boyd, Brorsen, and Grant (1987) is an early study of the effects of risk in the soybean complex. They measure risk as the coefficient of variation (calculated using the moments of monthly prices) in an annual margin model covering 1963-1983. In their sample, risk has a significant and positive effect on crushing margins. Lence, Hayes, and Meyers (1992) assume that processors make the selling decision before crushing and receive the futures price for outputs at that time. After crushing, the output is sold in the cash market and the futures are bought back. They define risk as the expected difference between cash and futures prices at this time and estimate the difference in a monthly ARIMA framework. The monthly forecasts are divided by soybean price, then used to compute an annual average risk variable weighted by stocks. This measure of risk is found to have a significant and positive (negative) effect on the margin (crush) in an annual model spanning 1967-1986.

In contrast to earlier models, Lence, Hayes, and Meyers (1995) invoke the separation theorem where risk is assumed to be hedged in futures markets and to have no effect on output decisions. Separate models are derived for soybean purchases, crush level, and output sales. Crush is specified as a function of the cash price of soybeans, the futures prices of meal and oil, the interest rate, and beginning stocks of meal and oil. In a monthly model from 1965-1986 they report that all variables have significant partial and total elasticities. They also report that processors adjust soybean stocks in response to price changes. The basic assumption used to avoid risk, the separation theorem, may be difficult to justify with basis risk, with possible losses when putting on the crush, and with data aggregated across an entire industry.[2]

Theoretical Model

An output supply model is needed to assess the Sandmo/Ishii contention. In this section a supply model is modified to incorporate expectations[3]. The ability of crushers to use futures and options markets, either directly or through provided information, gives flexibility to the modeling process. Risk is incorporated by including the first two moments of the margin. The model assumes a competitive framework. While perhaps this is somewhat questionable because of market concentration, the framework allows risk to be incorporated in a manner familiar to economists.[4]

Processors are assumed to make product supply decisions at the beginning of each month. The firms look at the current soybean price and the (weighted) futures prices of meal and oil. These are used to estimate an expected margin. This approach is consistent with cash purchases of soybeans occurring before crushing, and assumes no soybean input price risk. Thus soybeans exhibit no price risk. The meal and oil prices can fluctuate before the soybeans can be crushed and outputs sold. The variance of output prices is thus a measure of risk faced by crushers.

Supply Model

A processing firm is modeled following Brorsen, et al. (1985). The firm chooses the optimal level of supply to maximize the expected utility of initial wealth and profits. Supply for the firm is some volume of meal and oil, Q, obtained from the crushed soybeans. The production function [increasing and concave in inputs] can be written as

(1) $Q = \min [q_b/k, g(q_i)]$

where q_b is the quantity of soybeans crushed, k is a constant and $g(q_i)$ is a function of a vector of other input quantities. This seems reasonable for crushers and assumes a single output is produced, a basket of meal and oil products from a bushel of soybeans.

Let P be the random price for the meal and oil products derived from a bushel of soybeans (a weighted average of meal and oil prices). Let p_b be the price of soybeans, assumed

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[2] The extent to which crushers hedge continuously is uncertain. Johnson et al. (1991) have demonstrated the profitability of putting on the crush when margins are profitable and taking the opposite position when margins are unprofitable. While crushers may not participate in this particular type of marketing strategy, it seems reasonable to assume that at a minimum it would induce them to limit their hedging when margins are negative.

[3] The focus is on the marketing sector. The farm level is not incorporated since soybean production is determined on an annual basis and selling decisions are based on storage incentives. Modeling the protein and oil sectors is complicated by the absence of forward or futures prices for competing commodities.

[4] While concentration has increased dramatically since the mid 1980s, the availability of substitutes for domestically produced soybean oil and meal, and the highly liquid and efficient futures markets for soybeans and their products supports the notion of a degree of competition in these markets.

known. Let p_i be a vector of input prices, also assumed known. Let w_o represent initial wealth of the firm. The firm is assumed to choose input levels to maximize expected utility:

$$(2) \quad \underset{q_b, q_i}{\text{Max}}\, EU\left[w_o + PQ - p_b q_b - p_i' q_i \middle| Q = \min\left[q_b/k, g(q_i)\right]\right].$$

Expected utility is a function [increasing and concave with risk aversion] of initial wealth plus revenue from meal and oil less costs of production.

Brorsen, et al. (1985) use a two-stage optimization procedure to solve for optimal supply, Q^*. The second stage gives $Q^* = Q(w, p_i, P - kp_b)$, the "risk responsive supply function." Because P is the distribution of output price, using its first and second moments gives $Q^* = Q(w, p_i, E(P) - kp_b, \sigma)$ where E(P) is the expected price of outputs and σ is the variance of output prices. This can be reformulated in terms of an expected marketing margin $E(M) = E(P) - kp_b$, the difference between the price of output goods less the cost of soybeans, and the margin variance, V(M), which is equal to σ.

The first stage of the optimization in Brorsen, et al. (1985) assumes a simple indirect cost function which gives the optimal input demand as a function of output. At the optimal level of output $q_b^* = kQ^*$. The constant k (k = 60/59) reflects the loss of about a pound of by-product during crushing. This relation has implications for models with crush as the dependent variable. Unless accounted for, the constant, k, will scale the estimated coefficients. This would also occur when "supply" models are inverted to form margin models as a function of crush.

Empirical Model and Data

This section begins with an investigation into the consistency of the data and the decision process assumed for firms. Crush and beginning soybean stocks data are examined. The theoretical model has identified the important variables needed - namely input prices, expected margin and margin variance. These variables are defined and data described. The link between implied volatility and margin variance is formalized, incorporating the correlation between output returns. Data are monthly from January 1992 to August 1996 for a total of 56 observations. The section ends with an econometric specification of supply.

Crusher Behavior

Supply is the variable of interest, and is defined as the product of crush and (59/60). Monthly crushing volume is reported in USDA. After multiplying the crush by the appropriate scaling factor, these data are standardized to generate daily supply for each month, by dividing total monthly supply by the number of days in that month[5]. Daily supply varies across and

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[5] This standardization eliminates differences in soybean supply per month due to only differences in the number of operating days, e.g., a February effect where supply would be lower because of fewer days in the month.

within years as shown in Figure 1. The general pattern is somewhat cyclical but not smooth. The lows generally occur right before harvest and the highs shortly after harvest.

The potential supply of soybean products can be influenced by the timing of soybean purchases and the level of stocks available. There is a continuum along which soybean purchases and stock build up can occur. At one extreme, soybeans are purchased as they are crushed and stocks do not accumulate. At the other extreme, soybeans are purchased as soon as possible to use storage facilities.

The level of beginning soybean stocks provides an indication of soybean purchase patterns and stock use. Beginning soybean stocks reported by USDA are also standardized by dividing by the days in a month and are shown in Figure 1. There is clearly a build up of stocks at harvest time, perhaps in a rush to assure quality and/or to obtain quantity. Stocks decline as the processing year moves along, reaching a minimum right before harvest. Initially, the supply and stock behavior is consistent with a pattern where crushers purchase more soybeans than they crush. This continues for three or four months. Then they purchase less than they crush until the next harvest. This suggests that soybeans are generally purchased before the crush decision is made and that the supply of soybean products will be influenced directly by the level of soybean stocks available.

Expected Margin

Assume that crushers use futures prices to determine the value of meal and oil for (cash) sales to occur in one month. Expected output price is a weighted average of futures prices for meal and oil. Hence, futures prices for meal and oil are converted into their portions of the value of a crushed bushel of soybeans. Monthly crushing yields for meal and oil, $Y_{m,t}$ and $Y_{o,t}$, are assumed constant at 48 and 11 pounds per bushel, respectively[6]. Futures prices of meal and oil, $FP_{m,t}$ and $FP_{o,t}$, are available daily from CBOT. Monthly prices were computed by taking the average of daily closing prices of the nearby contracts. No adjustment was made when there were two months until an expiring contract. Meal futures price is in \$/short ton. This is divided by 2000 to get \$/lb. Oil futures price is in \$/cwt. This is divided by 100 to get \$/lb. This allows specification of the expected margin as:

(3) $E(M_t) = Y_{m,t}(FP_{m,t}/2000) + Y_{o,t}(FP_{o,t}/100) - P_{b,t}$.

$E(M_t)$ is in \$/bu and is the expected value of meal and oil from a given bushel of soybeans less the current price of soybeans, $P_{b,t}$. Expected margin is plotted in Figure 2. The pattern shows small spikes reflecting low current soybean prices, high futures prices for meal or oil, or both.

Implied Volatility and Margin Variance

Processors use the expected margin distribution to determine optimal output supply. Here, we use the implied volatility of the options on futures prices to measure the corresponding

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[6] The approach used here is consistent with the assumption that $Q^* = (59/60)\, q_b^*$, since Q^* would be a weighted average (by yields) of meal and oil.

price risk. Implied volatility has several advantages over other common risk measures. It does not capture seasonal variability, such as past variance approaches. It only captures the variability of the rate of return expected to exist. Further, it is market generated, and in most instances should provide a fair representation of price risk in adequately traded options markets.

Daily implied volatilities on nearby contracts are from Cosgrove (1996). The volatilities are reported as percentages and are annualized. The volatilities were measured using Whaley's pricing formula and are an average of at-the-money, one tick out-of-the-money, and one tick in-the-money strike prices. A monthly volatility was computed for each meal and oil, $IV_{m,t}$ and $IV_{o,t}$ by taking an average of daily nearby volatilities. To account for contract rollovers, all observations past the 20th of the month are excluded. This should be safely before the current nearby option stops trading.

Starting with the implied volatilites, the variance of the rate of returns on futures' prices can be computed for the time period relevant to the selling decision. In other words, by assuming that the variance is constant, the variance can be computed from the time soybeans are purchased until meal and oil are sold.

Because volatilities are reported as percentages and are annualized, they must be converted to the relevant time frame of decision makers. Monthly price variance is defined as

(4) $V(FP_{m,t}) = (IV_{m,t})^2/12$

for meal and similarly for oil. Variances are of the rate of return of the underlying futures. As such it matches the time, one month, until the meal and oil are sold.

Looking at the formula for $E(M_t)$ it is straight-forward to define the variance of the margin, $V(M_t)$. Because soybean price is known, variance is just a weighting of the variances of output prices. The formula is

(5) $V(M_t) = a^2\, V(FP_{m,t}) + b^2\, V(FP_{o,t}) + 2ab\,Cov(FP_{m,t}, FP_{o,t})$

where $a = Y_{m,t}FP_{m,t}/2000$, $b = Y_{o,t}FP_{o,t}/100$ and $Cov(FP_{m,t}, FP_{o,t}) = \rho_{m,o}\sqrt{V(FP_{m,t})V(FP_{o,t})}$.

$\rho_{m,o}$ should reflect the correlation between the instantaneous returns on meal and oil futures. The average of the monthly correlations of the natural log of daily futures price changes for meal and oil is about 0.5 over the sample period and this is used for the empirical models. Margin variance, shown in Figure 2, has periodical peaks whenever the implied volatilities are high for meal, oil, or both.

Other Variables

While initial wealth is specified in the theoretical model, it is assumed constant for the time frame considered in the empirical analysis. Since less than four years of data are used, it is doubtful that the wealth of crushers changed greatly. Also, it seems reasonable to assume that their risk aversion did not change over the time period. Cost is somewhat ambiguous as crushing is a private industry. Initially, capacity was to be included as a proxy for fixed costs, however, recent data are unavailable. It is assumed that crushers did not add significant capacity in the time frame considered.

The theoretical model calls for prices of inputs. USDL monthly price indices of labor and fuel are included in the analysis to reflect the prices of labor and fuel[7]. The fuel index (table 1) is the producer price index, by stage processing, grouping: processed fuels and lubricants. The labor index is average hourly earnings of production or nonsupervisory workers on private nonfarm payrolls by industry: industry, food and kindred products. The price of soybeans (#1 at the processing facility) is available monthly from USDA. Preliminary examination of these data suggests they possess adequate variability, except the labor index which primarily approximates a linear trend over the sample period.

Supply Model with Expected Margin

The optimal supply was specified as a function of input prices, expected margin and margin variance. The econometric specification for supply is

(6) $Q_t = \alpha_0 + \alpha_1 E(M_t) + \alpha_2 V(M_t) + \alpha_3 P_{f,t} + \alpha_4 P_{l,t} + \alpha_5 S_t + \varepsilon_t$

where Q_t is the standardized quantity of output from crushing activity, $E(M_t)$ is expected margin, $V(M_t)$ is margin variance, $P_{f,t}$ is an index of fuel prices, $P_{l,t}$ is an index of labor prices, S_t is beginning standardized stocks of soybeans, and ε_t is an i.i.d. error term. The expected sign of $E(M_t)$ is positive. The input prices, $P_{f,t}$ and $P_{l,t}$, have negative expected signs. $V(P_t)$ has a negative expected sign. Sample statistics are show in table 1.

Q_t is measured in bushel units and is the standardized daily supply in each month (Figure 1). Expected margin is in dollars per bushel. Risk is measured by the margin variance, reflecting the variability of the returns associated with the value of output. Stocks are included in the estimated relationship to incorporate the effect of the regular stocking and purchasing patterns on the supply of soybean products. A positive relationship is expected between the supply of soybean products and the level of beginning stocks as larger (smaller) stocks provide potential for larger (smaller) supply of soybean products.

Results

The empirical findings of the estimated relationships are presented in Table 1. Three models are presented: the complete specification of (6) estimated using ordinary least squares (OLS); a reduced model which excludes the labor and fuel price variables estimated using OLS; and the reduced model estimated by maximum likelihood correcting for first-order autocorrelation.

In general, most of the coefficients of the variables are significant with expected signs.

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[7] This source is consistent with Boyd, Brorsen, and Grant (1987).

However, in the complete model, the two input prices, fuel and labor, have coefficients with positive signs in disagreement with economic theory. The coefficient of fuel variable is not significant, but the labor coefficient is statistically significant at standard levels of significance. The significance of the labor coefficient may be reflecting the small common increasing trends of the labor variable and soybean product supply over the sample period. Fuel and labor prices were dropped from the model, and the model was re-estimated using OLS. There appears to be little difference in the degree of explanatory power in the estimated relationships, and little change in the magnitude of the coefficients. To correct for the presence of first-order autocorrelation, the reduced model was estimated again using an MLE procedure. Here, the coefficients are smaller in magnitude but are all significant at standard statistical levels.

The t-tests, regular from OLS and asymptotic from MLE, both show that $V(P_t)$, risk, has a significant and negative effect on supply. Thus, with higher margin variance the supply is lower. A significant and positive coefficient on $E(M_t)$ indicates that higher expected margins increase supply. Beginning stocks has a significant and positive effect, which is consistent with idea that larger (smaller) stocks provide the potential for a larger (smaller) supply of soybean products.

To assess the stability of the findings, two ancillary analyses were performed. In the first, the correlation coefficient ($\rho_{m,o}$) between the instantaneous returns on meal and oil futures used to calculate the margin variance in (5) was varied systematically between -1 and 1, and the models were re-estimated. In moving from -1 to 1, the magnitude of the risk coefficient declines but remains significant at roughly the same level of significance.

The second ancillary analysis attempted to assess the importance of the spacing of the contracts and the length of expectations. Meal and oil have eight contract months per year: January, March, May, July, August, September, October, and December. Futures prices for the months immediately preceding contract months reflect a one-month expectations horizon. However, for the other months prices reflect a two-month expectations horizon. The months January, March, May, and October were dropped from the sample to test for effects of differences in expectations horizons. The OLS findings revealed little difference between the full and reduced samples estimates. Results for the reduced model without fuel and labor similarly revealed no large differences from the full sample. The findings of these ancillary analyses suggest that there is little difference in the expectations between one and two months, and provide some confidence of the robustness of the estimated relationships.

Conclusions

The results indicate that the first and second moments of the returns distribution influence supply. These empirical findings are consistent with Sandmo and Ishii, and other previous studies that have documented the effects of risk on agricultural supply. Within the soybean complex, the results agree with Lence, Hayes, and Meyers (1992), and Boyd, Brorsen, and Grant (1987) that soybean processors appear to be somewhat risk averse and that their behavior is affected by price risk.

Our findings also suggest that implied volatility can be used to measure price risk in a supply response context. This measure of price risk is forward-looking, market generated, and can be implemented for those commodities with well-defined and functioning futures and options markets. It provides an accessible risk measure that can be incorporated into price analysis. As with all risk measures, it may be limited in use in the presence of costless and perfectly hedged market opportunities.

While our results are encouraging with regards to the use of implied volatilities to measure price risk, our findings also suggest that more detailed analysis may be necessary to completely understand the role of risk in the soybean complex. The presence of significant first-order autocorrelation in the estimated results may be a function of simply the dynamic properties of short-term (monthly) data used in the analysis, or it may be an indication that the structural model is somewhat misspecified. In either case, future research on risk response in the soybean complex may need to more carefully detail the relationship between stock accumulation and the supply of soybean products to the market.

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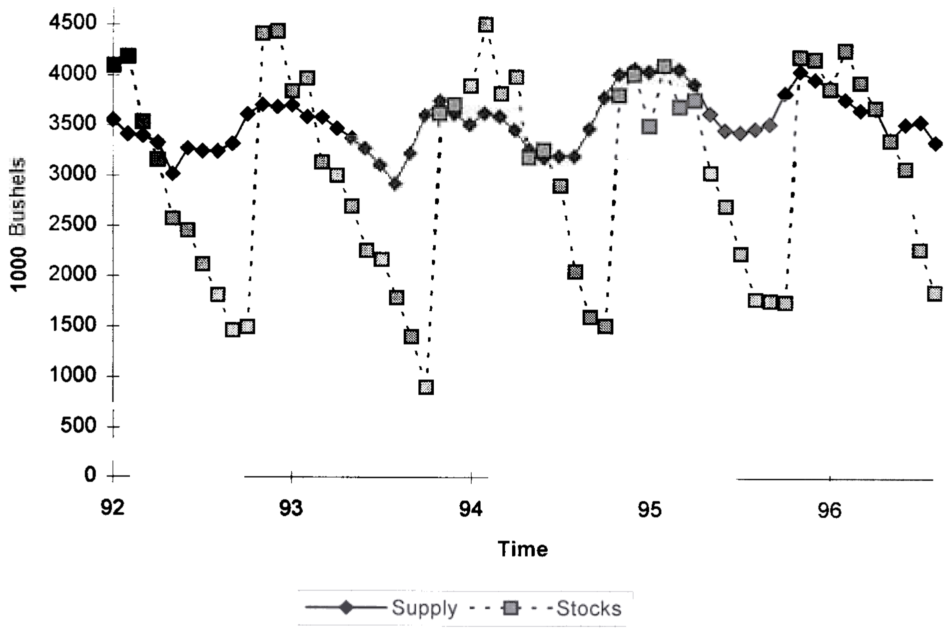

Figure 1. Daily supply of meal and oil and daily beginning soybean stocks by month

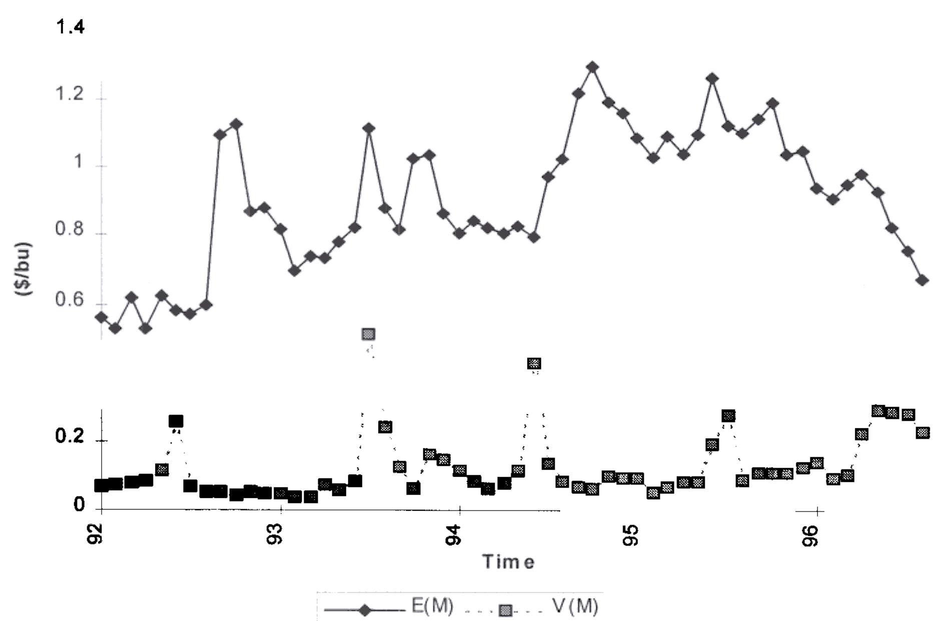

Figure 2. Expected margin and margin variance between meal and oil and soybeans

Table 1. Sample Statistics of Monthly Data from 1992-1996

Variable	Mean	Standard Deviation
	:8.30	281.43
	0.94	0.22
	0.13	0.10
	ı0.15	993.87
	.1.26	0.47
	'8.39	1.99

Table 2. Model Estimates Determining Daily Output Supply

Variable	Full Set - OLS	Reduced - OLS	Reduced - MLE
	326.69	2582.80*	2598.09*
	(929.56)	(144.43)	(167.82)
	546.55*	662.10*	691.46*
	(120.90)	(112.09)	(136.48)
$V(M_t)$	-1152.43*	-836.29*	-717.09*
	(261.73)	(254.17)	(233.07)
Stocks	0.15*	0.15*	0.13*
	(0.02)	(0.03)	(0.02)
Labor	151.63*		
	(72.12)		
	8.94		
	14.61)		
AR(1)			0.46*
			(0.13)
n	56	56	
R^2	0.67	0.60	
Adjusted R^2	0.64	0.58	
F-Statistic	20.17	26.37	
D-W Statistic	1.23	0.85	

Notes: Standard errors are in parentheses. Asterisks denote significance at the 0.05 level.