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AE Staff paper no. 89-14

CORNELL
AGRICULTURAL ECONOMICS
STAFF PAPER

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by

Deborah H. Streeter
William G. Tomek

May 1989

89-14

Department of Agricultural Economics
Cornell University Agricultural Experiment Station
New York State College of Agriculture and Life Sciences
A Statutory College of the State University
Cornell University, Ithaca, New York, 14853

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Deborah H. Streeter and William G. Tomek*

Price variability is a major source of uncertainty in agriculture, but typical models of price behavior attempt to explain changes in the mean of prices, while assuming that the variance of prices around the mean is constant. Only recently have analysts come to understand that measures of volatility, such as the variance of price changes, shift over time in systematic ways. This paper is about the specification and evaluation of models designed to explain price volatility.

Predicting changes in price volatilities is important both for private and public decision-making. For example, changes in the volatility of prices of a futures contract influence the premium (price) paid for an option on that contract. Variability is also an important factor influencing policy-makers who set margins and daily price limits for futures contracts or who are concerned about the possible effects of increased market concentration on price behavior. Accordingly, if important decisions are to be based on statistical estimates of the behavior of price volatilities, it is essential to appraise the associated models on both theoretical and empirical grounds.

In terms of a theoretical framework for exploring futures price volatility, past research has focused either on "state variable" or "market structure" effects. The first type of study has emphasized that the variance of futures prices depends on the seasonal or time-to-maturity components of information flows about supply and demand (e.g., Anderson and Danthine, 1983). In contrast, the second area of research is related to the possible effects of increased concentration or decreased liquidity on price behavior (e.g., Peck, 1981). To date, a unifying framework is lacking, in part because the common assumption that futures markets are competitive and liquid rules out the role of market structure effects.

In addition to examining theoretical frameworks for explaining price volatility, attention also should be given to empirical concerns. During the last ten years, serious questions have been raised about the validity of standard econometric methodology. For example, the empirical results of models often appear to be good in a superficial sense: coefficients have logical signs and large t-ratios; R^2 is large; and the Durbin-Watson statistic is near two. However, upon closer examination, the results may be fragile. For example, coefficients may be unstable, or the models may not perform well when subjected to an extensive battery of diagnostic tests, thereby showing that the assumptions underlying the statistical model have not been met. Thus, where researchers have stopped short of carrying out specification tests, the resulting published econometric results in many areas of economic investigation (including price volatility) may be flawed.

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*Deborah H. Streeter is an assistant professor and William G. Tomek is a professor in the Department of Agricultural Economics, Cornell University. This research was funded in part by USDA Cooperative Agreement 58-3AEK-8-00102. Presented at the NCR-134 Conference, Chicago, April 20-21, 1989.

Accordingly, this paper has two broad objectives: (1) to specify and estimate econometric models of short-run volatility of futures prices and (2) to use recent developments in econometrics to evaluate the proposed models. In the process, a unifying framework is proposed for modeling the variability of commodity futures prices and the results are used to evaluate the roles of information flows and market structure variables in determining price variability. To accomplish these objectives, a comprehensive model is specified and estimated for prices of the November soybean contract during the years 1976-1986 inclusive.

Previous Work and the Model

Early work on price volatility focused on the validity of the so-called Samuelson effect, in which the variance of futures prices is a decreasing function of time to maturity (Rutledge, 1976; Miller, 1979). More recently, time-to-maturity effects have been seen as a special case of the state variable hypothesis posed by Anderson and Danthine (1983), which argues that the ex ante variance of futures prices depends on the expected pattern of demand and supply uncertainties, which are resolved with the passage of time (Kenyon, et al., 1987). In addition, Kenyon et al. make a distinction between economic variables, such as current production levels and government price support levels, and the state variables. In general, they found that both types of variables influenced price volatilities.

Implicit in the foregoing research is the assumption that markets are competitive. Other researchers, however, have focused on market structure issues. Peck (1981) explored the impact of changes in the level of speculation on wheat, corn, and soybean prices. She found for the 1964-78 period that speculation and price variability are inversely related. Thus, Peck concluded that the growth in the hedging use of commodity markets had strained the liquidity of these markets and hence that inadequate speculation had been manifested in increased price variability. In another study of structural variables, Brorsen and Irwin (1987) sought to measure the impact of futures funds, which often rely on technical trading systems, on the volatility of futures prices. A popular hypothesis is that the growth in such trading has increased the variability of prices, but their findings did not support the hypothesis.

The results of these alternative approaches to studying price variability suggest the need for a unifying framework. Thus, the general model of price volatility to be discussed in this paper includes explanatory variables from three general categories: the flow and certainty of information, market structure, and current economic information. In addition, interaction variables are included to take account of the interplay between variables in the information flow category and the economic information category. It is likely that the effect of information flows, as reflected in seasonality effects, depends in part on existing information on supply and demand. For example, information such as spring plantings intentions, which effect expectations of future production, is likely to have a larger price effect when stocks are small than when stocks are large.

Turning to specific details, the prices used in constructing the dependent variables are for the November soybean contract.[1] Observations on daily prices are used to compute monthly observations. Likewise, other variables are provided on a monthly basis for the period 1976 to 1986 inclusive. The remainder of this section discusses the variables, while the next section deals with the specifics of estimation.

Various measures of price volatility have been used in previous research, but two general concepts emerge: measures which focus on the variance in daily price changes and those which are based on the daily range of prices.[2] Variances typically are computed from daily price changes (or the changes in the logarithms of prices). In contrast, trading range measures, such as the monthly average of the daily price ranges (Peck, 1981) or the ratio of quarterly average daily price range to quarterly average prices (Brorsen and Irwin, 1987), reflect intraday variability.

Although the two measures of volatility are linked, the variance of price changes can be interpreted as a reflection of adjustments to information flows, while the range measures liquidity effects which occur on an intraday basis (i.e., the price response to large transactions). Thus, two models are estimated. In the first, the dependent variable is the monthly variance of the daily change in the logarithm of closing prices.[3] In the second model, volatility is measured as the monthly average of the daily price range, which is the difference between the daily high and the daily low.

There are several components to the flow and certainty of information effects in the soybean market. If the Samuelson effect holds, then *ceteris paribus*, volatility should increase as the time-to-maturity decreases; time-to-maturity is measured as the number of months left to contract expiration. The hypothesis is that as contract maturity approaches, more and more information becomes available about the factors determining the expiration price. In an abstract sense this must be true. For example, when maturity is five years distant, little or no new information would be available from one

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[1] November is the most actively traded soybean contract. However, we do plan to model the price variability of other actively traded soybean contracts, using a seemingly unrelated regression framework.

[2] To create the time series used in this research, futures contracts must be linked from year to year. Twelve months of observations are used for each contract, running from the prior November through the October just prior to maturity. Thus, the maturity month observations are ignored as are observations prior to 12 months before maturity. This is justified (a) by the relative thinness of trading in the distant months and (b) by possible aberrant observations that sometime occur at expiration. In constructing price differences, the difference between one year and the next is dropped.

[3] Initially, a model was also considered that used differences of the observed closing prices (not the logarithms), but the results closely parallel those for the differences of logarithms. Hence, only the results for the variance of the logarithmic price differences is reported. The implicit assumption of the log transformation is that the price changes have the log normal distribution. Since this is a common assumption in the futures literature, it is used here.

day to the next that would affect the price for that contract, while if maturity is five months distant, much new information would be flowing into the market each day which would affect price. However, in practice, commodity futures contracts start trading only about 15 month prior to maturity, and it is likely that contracts only start trading when the trading is economically important (significant price risk exists). Thus, the time-to-maturity effect may be difficult to measure in the futures market.

Clearly the uncertainty about soybean supply has a seasonal component, which in the models used here, is defined by harmonic (trigonometric) variables. In this case, the hypothesis is that price variability is largest during the growing season and declines as crop prospects become more certain. Harmonic variables are used because they provide a smooth seasonal with perhaps less than 11 variables. The choice of sine and cosine variables is made on an empirical basis.[4] The seasonal and time-to-maturity effects are represented by proxy variables, and the quality of the estimates depends on minimizing the measurement error of the proxies.

Various facets of market structure are captured in the models with three different variables: a speculative index, a measure of scalping, and a measure of concentration. The speculative index, originally developed by Working (see Peck, 1981), is an attempt to measure the adequacy of speculation as an offset to hedging. The precise variable is defined in a footnote to Table 1. The components of the index are taken from monthly Commitment of Traders data published by the Commodity Futures Trading Commission.[5] The

[4] A full specification of the seasonal effect would make the dependent variable a function of the sum of six sine and six cosine variables (Doran and Quilky, 1972). However, one of the variables must be dropped in a linear model to avoid perfect collinearity. Thus, potentially, 11 harmonic terms could be included in the regression, but as the text indicates, seasonality usually can be adequately represented with fewer than 11 variables.

[5] Three problems arise in using the Commitment of Traders data: (1) how to allocate small traders, who are not required to report whether their positions are hedging or speculative, (2) how to deal with missing observations for the period December 1980 through November 1982, and (3) how to account for a new CFTC reporting procedure which started in December 1982. With respect to the first issue, all small traders are treated as speculators. Other analysts (Larson, 1960; Rutledge, 1978; Peck, 1981 and 1982) have used periodic surveys of all traders as a basis for estimating the allocation among hedging and speculation. No such surveys are available for our sample period. The assumption that all small traders are speculators is conservative in the sense that it errors in the direction of overestimating the amount of speculation. In fact, the large majority of small traders are speculators. The missing data are forecast via a time-series method, using the earlier sample. This was done in the context of evaluating several ways of estimating the missing observations. By using the forecasts, we are assuming that the missing commitments data are generated in the same way as in the earlier part of the sample. Then, the change over to the new reporting procedure was accounted for by including a dummy variable which takes the value zero for the earlier period and one for the later period. However, its coefficient was not statistically significant. Thus, the effect of the new procedure, if any, is not detectable in our analysis. We did examine the coefficients of the model

speculative index is expected to be inversely related to price volatility, since a large index implies that speculation is large relative to hedging use, hence hedgers have a large quantity of speculation available on the opposite side of their trades. Some observers, however, think that speculation can be too large relative to hedging use. Thus, a negative sign could be justified, or the relation could be nonlinear or U-shaped.

A distinction can be made between position trading of speculators, which is reflected in the speculative index variable, and scalping activity. Unfortunately, data are not available on the level of scalping in a market, and in the absence of a better variable, the ratio of daily volume to open interest in the contract is computed and then averaged for the month.[6] Students of futures markets typically expect increased liquidity (scalping) to be associated with smaller price variability, but Peck obtained a positive relation. Again, a linear relation may not be appropriate, and as mentioned, it is likely that the variable is an imperfect proxy for scalping.

While the speculative index and scalping variables focus specifically on effects of speculation, market concentration variables are intended to reflect the presence of large positions relative to total open interest, whether they are hedging or speculative positions. As Paul (1976) has pointed out, large hedgers may have more opportunities than large speculators to influence price behavior. Although it is not completely clear whether market concentration influences the variance of prices, a common presumption is that larger concentration increases price variability. As data limitations prevented the direct measurement of the effects of large market pools in this study, the concentration variable is included to reflect the notion of large trader effects. The concentration measures are defined as the percent of total open interest in soybeans held by the four largest traders in long and short positions respectively, as reported by the Commodity Futures Trading Commission.

Three quantity variables are intended to measure the current economic context: annual total supply (production plus carryin), monthly disappearance, and mill stocks at the beginning of the month. Thus, use is measured relative to stocks currently in the hands of soybean crushers and relative to the initial total supply for the crop year. A price level variable, computed as the average of daily closing prices for each month, also is included. It might be viewed as redundant in light of the quantity variables, but it is clearly important empirically. Since current price is influenced by changes in expected economic conditions, it also can be justified as a proxy for information flow effects.

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to determine whether any changes could be attributed to the generation of the commitments of traders data during the 1980-1982 period; in general no such changes were detected. Thus, the "pooling" of the earlier sample, the forecasts, and the later sample seems appropriate.

[6] Peck (1981) constructed this variable as the average daily volume during a month divided by the open interest at the end of the month. In light of the puzzling results in her paper and in ours, we plan to revisit the definition of this variable.

As explained above, interaction effects are thought to be important in the model. Information released throughout the seasonal cycle influences expected supply and demand, and the extent of its impact on prices is conditioned by the size of current supplies. This type of nonlinearity can be accommodated by interaction variables. The interaction variables are defined as the products of various supply-type variables with seasonality and time-to-maturity variables. Specific definitions are given in Table 2.

Finally, the procedure used in building these models is based on a philosophy of model building which starts with a large model with the hope of simplifying it. The larger model must contain sufficient lags in the variables to capture adequately the dynamic behavior of the relationships. The specification strategy and the simplification process, are described in the next section.

Estimation Procedures and Preliminary Results

The focus of this section is the model specification approach used in this paper, which makes use of some of the recent developments in the econometrics literature. The intent is not only to demonstrate the challenges facing those undertaking empirical econometrics research but also to obtain a relevant model. The procedures follow the suggestions of Hendry and his colleagues (e.g., see Hendry and Richard, 1982, or McAleer, et al., 1985). The methodology has three general steps: (1) selection of a general model, (2) consideration of whether the general model can be simplified, and (3) use of a battery of diagnostic tests as a quality control device (McAleer, et al., 1985, p. 299).

Most of step one has been outlined in the previous section, which contains a discussion of relevant concepts to be considered in modeling the volatility of commodity prices. In addition to including the relevant concepts, the general model selected in the first step must also contain a specification with sufficient lags to ensure that the full dynamic relationships among variables are captured. In other words, the model must be "sufficiently general" both in terms of its conceptual components and its dynamic specification. Thus, in contrast to a philosophy of starting with a parsimonious model and making it larger if necessary, the Hendry approach prescribes the specification of a large model (which might be criticized as overparameterized), which is then subjected to a logical simplification procedure.

In the case of the two models estimated in this paper, four lags were used for every variable except the time-to-maturity, seasonal, and interaction variables. The use of four lags is based on a judgment that adjustment processes in futures prices take place rapidly and hence should take place within four months or less. From a practical point of view, it is also true that longer lags would have resulted in relatively few degrees of freedom. In any case, the full model was subjected to a sequence of nested tests in order to identify possible common factors in the lag structure and thereby simplify the lag structure of the regressors (McAleer, et al., 1985).[7] The resulting

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[7] Clearly the autoregressive (AR) structure of the resulting models is partly dictated by the starting point--the number of lags--in the initial model. That is, if one starts with only two lags in the regressors and simplified to

models have a one period lag in the regressors and third-order autocorrelation in the residuals; that is, three common factors were identified.

Two reactions are possible to this result. One is that the identified lag structure is correct; namely random changes in volatilities persist over a period of months. The second is that the current versions of the models suffer from undetected specification errors which result in autocorrelated residuals. The discussion that follows assumes the lag structure is correct; however a discussion of possible specification errors follows in a later section.

Once the initial simplification of the lag structure has been carried out, low t-ratios may still be observed for the parameters of some variables, including the autocorrelation (common factors) in the residuals. Typically, these variables are dropped from the model, and, if the autocorrelations are statistically unimportant a simpler autocorrelation structure can be used. For example, in this study, the model for the price range appears to have a simpler than third degree autocorrelation structure, indicating that in future work, the autocorrelation terms might be dropped.

The results for the two models, both assuming third degree autocorrelation, are presented in Tables 3 and 4. In general, both models seem to perform well, with reasonable R^2's and with "significant" variables in each of the major conceptual areas. In a many cases, the signs of coefficients are consistent with intuition. The larger the total supply at the beginning of the crop year, the smaller the volatility of prices, other factors held constant. The larger the four firm concentration ratios, the larger the price variability, while the smaller the speculative index, the larger is price variability.

Nonetheless, there are some troubling signs on coefficients. For example, the inverse of current mill stocks has a negative sign, implying that larger inventories are associated with larger variability. The use or disappearance variable also has a negative sign, though with t ratios just slightly larger than one. However, the overall results seem sufficiently good that in a typical analysis, they would be presented for publication with an accompanying discussion of the implications of the results. In fact, discussions of research with a similar quality of results often includes ex post rationalizations of any illogical results.

However, the specification philosophy which guides this study views a standard discussion of the model results at this point as premature. Instead, the tentative model was subjected to a battery of diagnostic tests or "indexes of adequacy" (McAleer, et al., 1985, p. 304). Test results for four possible problems are presented: linearity (specification error) in the

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one, then only an AR(1) model can result. With four lags in the regressors, it is possible to simplify to an AR(3) model as occurred. In this research, the regression coefficients are little different for the AR(1) and AR(3) models. Also, as noted in the text, the model for the price range does not have significant autocorrelations even though the nested tests imply three common factors. Thus, in fact, the model could be treated as having no autocorrelation and estimated by OLS rather than GLS.

relationships,autocorrelation, heteroscedasticity and normality of the residuals (Table 5). In interpreting the test results, the rejection of any one of the respective null hypothesis (as indicated by large test statistics) will suggest that the assumptions of linear regression model are not met. Unfortunately, rejection does not provide the analyst with specific clues about what alternative hypothesis is correct.

In addition to the tests, the stability of the coefficients was examined over the sample period by estimating the equations recursively, starting with a model with one degree of freedom and adding one row of data at a time.[8] Selected plots of the recursive coefficients are provided in Figure 1. Formal confidence intervals can be placed on these coefficients, but this is not essential for our purposes.

The two models fare somewhat differently under the battery of tests. The variance model passes only the autocorrelation test and the trend version of the specification error test, failing all others. Also, the coefficients change drastically in the 1978-83 period, before stabilizing at the values reported in this paper. In a number of instances, the coefficients change from negative to positive or positive to negative over the sample period. Examples of these patterns are shown in Figure 1. Thus, given the model, the signs of coefficients could have been varied just by the selection of the sample period.

While any model might be expected to fail at least one of the misspecification tests, the persistent problems uncovered in the variance model suggest that specification error or errors in variables exist. The model clearly fails the tests of adequacy.

Performance of the daily range model is less uniformly poor, as it passes both the autocorrelation test, one of the heteroscedasticity tests and the trend version of the specification test. However, the coefficient plots (see Figure 1) still have much variability over the sample period. Persistent upward or downward trends appear to exist in some of the coefficient values as data points are added. The scalping effect is persistently positive but trending downward. The speculative index coefficient has a general upward trend, but with a large dip during the 1982 period. Thus, the results for the range model, although better than the variance model, are hardly satisfactory.

Conclusions and Future Directions

One of the objectives of this research is to build a comprehensive model to explain changes in price volatilities in futures. Some progress has been made. The results suggest that variables in each of the conceptual categories are important explainers of price volatility. In particular, it does not appear appropriate to ignore market structure variables even if the emphasis is on so-called state variables. We expect to show in future work how comprehensive models, in Hendry's terms, encompass models which omit relevant

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8 With modern computer software, it is relatively easy to estimate the coefficients recursively. The update procedure outlined in Harvey (1981, pp. 54-56) is used. The initial sample is defined to provide one degree of freedom; subsequent estimates are obtained by adding one row of data at a time.

concepts.

However, building a model which adequately explains the changes in price volatilities is a daunting task, and it is probably correct to say that most empirical studies have greatly underestimated the difficulty of obtaining a correct model. Thus, our second objective is to demonstrate one procedure for a more comprehensive appraisal of econometric results. While it would have been ideal to have the initial results pass the battery of adequacy tests, it is not surprising that they did not. We conjecture that many of the econometric results presented in journals and at conferences would also fail such tests.

The tests imply that nonlinear relationships may exist among some of the variables or perhaps that relevant variables are omitted. Thus, one step is to review the model specification. An improved model specification could also reduce the seeming heteroscedasticity and non-normality of the residuals. It is also true, however, that the regressors involve a number of proxies for underlying, but unmeasurable, concepts. Measurement errors may be serious. This could be an insurmountable problem; naturally, we hope that it is not.

In addition, we expect to model the price volatilities for other contract maturities for soybeans. Thus, a complete model would involve one equation for each contract in a seemingly unrelated regression framework.

To summarize, we have demonstrated the potential fragility of econometric results even when a careful modeling approach has been taken. We suspect that other carefully done studies have equally fragile results. Obviously we are unwilling to draw strong economic conclusions from these initial results. They do suggest, however, that market structure, flow of information, and economic status variables are important. Moreover, there appear to be interaction effects. Thus, at a minimum, our results throw into question the results from earlier studies of price volatilities in futures markets.

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Table 1. Definition of Variables

Variable Name	Description	Mean[a]	Standard Deviation
AVMO	Monthly Average of Daily Close(November contract)	6.57	.97
DARANG	Monthly Average of Daily Price Range(November contract)	.100	.047
MILL	USDA Estimate of Mill Stocks (million bushels)[b]	88.92	39725.
LOGDIF	Monthly Variance of Daily Differences in Log Prices(November contract)	.0002	.0001
LONG4	Monthly % Long Open Interest Held by 4 Largest Traders	9.46	3.99
SCALP	Monthly Average of Daily Ratio of Volume to Open Interest	.374	.2045
SHORT4	Monthly % Short Open Interest Held by 4 Largest Traders	13.11	4.86
SPINDEX	Speculative Index[c]	1.54	.142
SUPTOT	Annual Total Supply Estimate of USDA (million bushels) (includes carryover stocks and production)	2149.	269.5
TOTDIS	Monthly USDA Estimates of Soybean Disappearance (million bushels)	148.33	232702.

a. The sample period is 1975.12-1986.12.
b. Inverse of this variable used in model.
c. The speculative index is:

$$1 + \frac{SS}{HS + HL} \quad \text{when } HS > HL, \text{ and } 1 + \frac{SL}{HL + HS} \quad \text{when } HL > HS$$

where SS = speculation short positions
SL = speculation long positions
HL = hedging long positions
HS = hedging short positions

and unbalanced matching trades are allocated to short or long.

Table 1. **Definition of Variables (continued)**

Variable Name	Description	Mean	Standard Deviation
Seasonal Variables			
COS1	Cosine of first harmonic wave [$\cos(\lambda_k t)$, where $\lambda_k = 2\pi k/12$, and t=2]	.0075	.7097
COS2	Cosine of second harmonic wave	.0075	.7097
COS4	Cosine of fourth harmonic wave	.0075	.7097
SIN2	Sine of second harmonic wave	0	.7044
SIN3	Sine of third harmonic wave	0	.7044
SIN4	Sine of fourth harmonic wave	0	.7044

Table 2. Definition of Interaction Variables

Symbol	Variable Definition		
A1	COS1	X	AVM0
A3	COS4	X	AVM0
*A4	SIN2	X	AVMO
*A7	TIME	X	AVMO
B1	COS1	X	SUPTOT
*B2	COS2	X	SUPTOT
*B5	SIN3	X	SUPTOT
B6	SIN4	X	SUPTOT
*B7	TIME	X	SUPTOT
*D2	COS2	X	INVMILL
D6	SIN4	X	INVMILL
*E6	SIN4	X	LOGDIF (-1)
G4	SIN2	X	DARANG (-1)
G6	SIN4	X	DARANG (-1)

*Terms included in Model 1 (variance model). Model 2 (daily range model) included A4 and all terms without asterisk.

Table 3. Model for Variance of Price Changes

Dependent Variable: LOGDIF

Flow of Information Variables:	Coefficient	t-stat
LOGDIF (-1)[a]	0.562	5.98
TIME	-4.29 E-05[b]	-2.05
COS1	-4.67 E-05	-1.99
COS2	0.0003	4.02
SIN2	-1.26 E-05	-0.23
SIN3	-0.0002	-3.26
SIN4	3.14 E-05	1.56
Interaction Terms:		
A4	6.20 E-06	0.75
A7	-1.70 E-06	-0.92
B2	-7.23 E-08	-2.42
B5	1.06 E-07	3.05
B7	2.51 E-08	3.51
D2	-.007	-2.92
E6	.100	1.3
Market Structure Variables:		
SPINDEX	-7.15 E-05	-1.38
SCALP	.00027	3.96
SCALP (-1)	-0.0001	-1.58
LONG4	3.50 E-06	1.89
SHORT4	3.28 E-06	2.27

[a] (-1) indicates a one period lag.
[b] Denotes scientific notation.

Table 3. Model for Variance of Price Changes (continued)

Dependent Variable: LOGDIF

Economic Variables:	Coefficient	t-stat
SUPTOT	-6.69 E-08	-0.55
SUPTOT (-1)	-9.62 E-08	-0.8
AVMO	9.56 E-05	3.96
AVMO (-1)	-7.18 E-05	-3.38
INVMILL	-.0109	-4.62
INVMILL (-1)	.0033	1.87
TOTDIS	-1.79 E-07	-0.32
TOTDIS (-1)	-1.18 E-06	-1.97
Other:		
CONSTANT	0.0005	2.79
AR (1)	-0.404	-2.91
AR (2)	-0.065	-0.45
AR (3)	0.145	1.21

Adj. R^2= 0.75
DW Stat= 1.98
N= 133 (1975.12-1986.12)

Table 4. Model for Range of Daily Prices.

Dependent Variable: DARANG

Flow of Information Variables:	Coefficient	t-stat
DARANG (-1)[a]	0.57	4.79
TIME	0.0006	0.37
COS1	-0.026	-1.21
COS4	-0.044	-2.19
SIN2	-0.018	-1.07
SIN4	0.018	0.76
Interaction Terms:		
A1	-0.004	-1.91
A3	0.008	2.49
A4	0.005	1.54
B1	2.28 E-05[b]	3.03
D6	-0.403	-1.00
G4	-0.096	-1.55
G6	0.065	1.25
Market Structure Variables:		
SPINDEX	-0.033	-2.16
SCALP	0.085	5.44
SCALP (-1)	-0.016	-0.80
LONG4	0.0005	1.07
SHORT4	0.0006	1.52
Economic Variables:		
SUPTOT	1.63 E-05	.60
SUPTOT (-1)	-1.78 E-05	-0.66
AVMO	0.039	7.67
AVMO (-1)	-0.028	-4.94
INVMILL	-1.034	-1.82
INVMILL (-1)	0.384	1.00
TOTDIS	-.0002	-1.36
TOTDIS (-1)	-8.94 E-05	-0.65
Other:		
CONSTANT	0.039	1.32
AR (1)	-0.19	-1.15
AR (2)	-0.065	-0.43
AR (3)	0.08	0.63

Adj. R^2= 0.89
DW Stat = 1.98
N= 133 (1975.12-1986.12)

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[a] (-1) indicates a one period lag.
[b] Denotes scientific notation.

Table 5. Summary of Diagnostic Test Results[a]

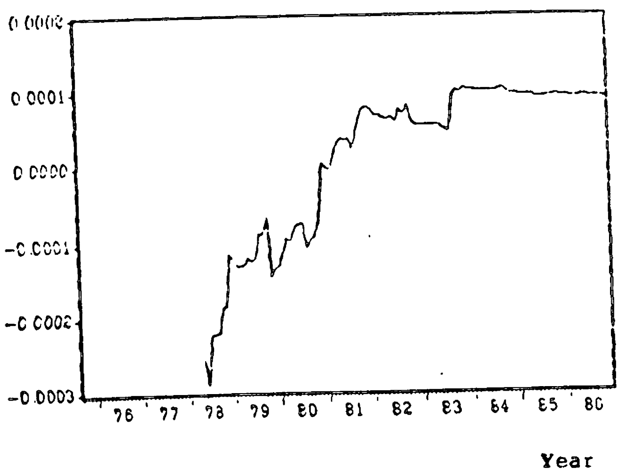
Test for:	Statistic Values LOGDIF	DARANG	Critical Values (.05 significance)
Specification error (RESET test)			
-Linearity	72	100	$F(2,100) = 3.09$
-Trend	1.18	2.13	$F(2,100) = 3.09$
Normality of residuals (Bera-Jarque test)	35	8.49	$\chi^2_{(2)} = 5.99$
Heteroscedasticity			
-(Breusch-Pagan test)	53.3	49.4	$\chi^2_{(13)} = 22.4$
-(ARCH-Type test)	11.61	2.58	$\chi^2_{(4)} = 9.49$
Autocorrelation			
	ρ_1 .04	-.03	$t(120) = 1.98$
	ρ_2 .02	-.16	$t(120) = 1.98$

[a] All but one of the tests used in the study are described in Spanos (1986). The linearity version of the specification error test (p. 460) used the squared and cubed residuals in the auxiliary regression of a Lagrange multiplier-type test. Thus, the test can be interpreted as a test for linearity in the relation between the regressors and the dependent variable (or more generally as a test for omitted variables). In addition, another version of the auxiliary regression was run using a trend variable and its squared and cubed terms. The test for normality is described on p. 453, the Breusch-Pagan test for heteroscedasticity on p. 469, and the test for autocorrelation on p. 542. The ARCH-type test for heteroscedasticity is described in Engle (1982, p. 1000), and used four lags of the squared residuals.

Figure 1. Recursive Coefficient Estimates for Selected Variables (1978-1986)

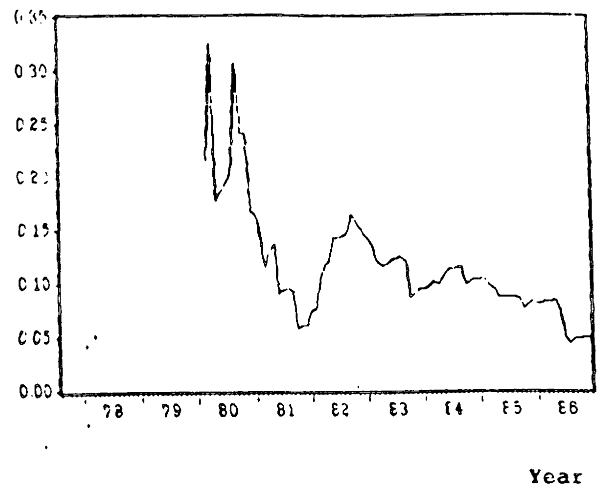
Variance Model

Coefficient for
AVMO Variable

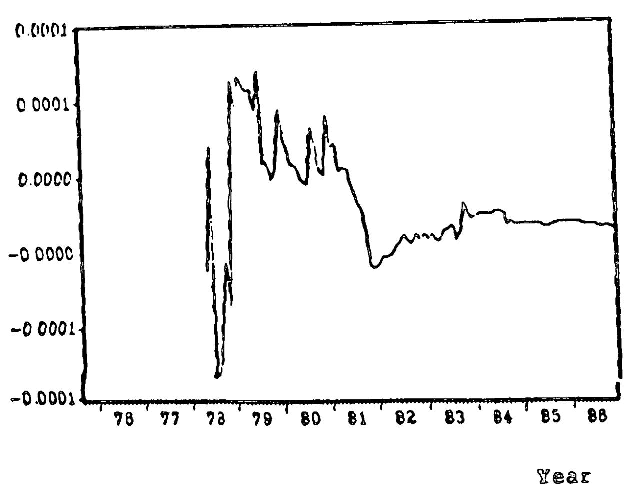


Daily Range Model

Coefficient for
SCALP Variable



Coefficient for
TIME Variable



Coefficient for
SPINDEX Variable