SIMULATING COMMODITY MARKET TRADING POLICIES

by

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SUMMARY

This paper describes a simulation model that was developed to help a company analyze and improve its rules for purchasing one of its key raw materials. The material is traded on a commodity market and the company had successfully developed a system for forecasting price changes in the commodity market. The corporate executives were interested in evaluating the sales and returns that could be expected when various constraints were placed on commodity trading. The simulation was initially developed to address these questiond on trading limits and subsequently expanded to provide a basis for analyzing the trading system itself.

BACKGROUND

The largest single category of expense for most companies is the purchase of rqw materials. Because of this, when the prices of these materials change very much the company's profits are usually greatly affected. Since companies normally prefer to grow at a steady rate, price fluctuations of raw materials usually necessitate counter-balancing changes in other operating policies within the organization. To the extent that raw material price changes can be forecasted in advance of their occurence, the counter-balancing actions, such as price changes, can be planned and implemented smoothly.

In some situations companies are forced to depend entirely on raw materials whose prices not only fluctuate greatly but also whose changes cannot be predicted very long before they occur. Most often, companies in this position are users of highly perishable agricultural commodities whose price is determined by supply/demand relationships and for which the supply is usually smaller than the potential demand. Thus, commodity supply is largely a function of changes in environmental conditions, such as weather, and this in turn has a large effect on the price of the commodity at any time.

In order that companies who depend on such commodities as their primary raw material can develop stable marketing and pricing policies without having violent swings in their profits, commodity trading markets have been established. These markets permit manufacturers to buy their future supply of the raw material at a guaranteed price. The risks of price fluctuations above or below the guaranteed price. The risks of price fluctuations above or below the guaranteed price are thus transferred to third party speculators who believe that the actual price at the time of delivery will be lower than the guaranteed price they offer to the manufacturer. If enough speculators believe the commodity price will be lower, then the guaranteed price quoted on the commodity market will fall. Similarly, if most speculators believe the commodity price will rise by the delivery date, then the guaranteed price will rise accordingly. Thus the prices on the commodity market remain in supply/demand equilibrium according to the combined beliefs of the market speculators.

Although the commodity markets permit manufacturers to know what price they must pay for the materials, the inherent risk of fluctuations remain with the manufacturers. This is because some manufacturers may buy their supply of the commodity at significantly lower prices than others and then use the price differential to achieve competitive marketing advantages over the less fortunate companies.

Because prudent buying on commodity markets can significantly affect the profit position of manufacturers who rely on such commodities as raw materials, many such companies have developed sophisticated decision-making systems for their commodity purchases. These systems determine when and how much of the material to buy at any time by forecasting likely changes in commodity market prices, and combining this with information about the company's own future requirements for the commodity. The key to the success of any of these systems rests on the accuracy of the forecasts of prices on the commodity market. If prices are expected to rise, the company should buy more than it plans to use right away (i.e., it should "inventory" future contracts). If prices are expected to fall, the company should defer purchases until lower prices occur. If a company has an accurate forecast of the commodity prices, the average price it pays for raw materials will be below the normal market price.

Without a good price forecasting system, it is clearly impossible to use the commodity market for anything besides a hedge against violent changes in prices. Once a system is available to a company, however, major issues must be faced on how it is to be used. These issues arise because the commodity trading system must compromise two mutually incompatible objectives:

1. the company's desire to increase its profits by successfully speculating on market price changes.
2. the company's desire to avoid unexpected cash requirements that could jeopardize plans for expansion and growth.

A manufacturer who acts as a speculator must be willing to take extreme positions in the market based on the price forecasts he has developed. If these forecasts prove accurate, the company can buy the commodity at a low price on the futures market, sell it when the price rises, and rebuy it when the price falls again. Profit levels will increase as the company takes larger and larger positions. However, as the size of the position increases, so does the risk of loss due to an incorrect judgement as to the direction of the price move. Thus, action as a speculator is likely to increase the average return from commodity trading, but at the cost of potentially large short term losses. To operate in such a fashion, a company must keep a relatively large portion of its assets in a liguid form as protection. This would reduce the amount of funds available for expansion of physical plant and equipment or working capital-- a condition that would be unacceptable to most companies who see their primary mission as the manufacture and marketing of physical products.

On the other hand, the only way to avoid large cash risks in the commodity market is to maintain a relatively constant inventory of commodity contracts in the futures market. This is equivalent to buying the commodity on a hand-to-mouth basis and is obviously unsatisfactory in the extreme because it eliminates all the potential benefits from the price forecasting system.

SIMULATION RESEARCH PROBLEM

The company for whom the research was carried out has been actively trading in the commodity market for more than a decade. Over that period, a very sophisticated trading system has been developed that provided a great deal of information about the likelihood of market price changes. Partly as a result of the success of this trading system, the company began to take larger positions in the market in the hope of increasing the already substantial profits being generated by it. This continued until the market failed to behave as expected one year and the company found itself in a severe cash squeeze. This was the first time the company had experienced any significant losses from its commodity trading and the experience triggered a major corporate review of the commodity trading activity.

The corporate officers were concerned about two issues:

1. could automatic "stop-loss" rules be instituted that would limit the company's exposure in the event of unexpected price changes.
2. how much inherent risk of cash loss existed in the current trading system and what would the profit/risk tradeoff be for different coverage constraints.

The questions are both related to the corporate executives' concern that the commodity trading operate as effectively as possible without jeopardizing the company's basic mission as a manufacturer/marketer.

Since the company's commodity trading system had been in operation for many years, the researchers had no difficulty finding enough historical data to describe the system's performance. Some thought was given to trying to address the questions posed by developing a closed form mathematical model of the trading system. But this was rejected in favor of a simulation model because the trading decisions were affected by several factors that jointly could not be easily represented mathematically. Furthermore, the output of a simulation model could be represented in a form similar to what the managers had been using to analyze trading decisions. This made it easier to explain to the managers what kinds of analyses were being done to provide answers to their questions.

One additional reason for using a simulation model was that it provided a flexible structure that could be revised and refined as necessary to answer future research questions. It was hoped at the start of the research project that the simulation analysis would spark interest in research on improving the trading system itself and that the simulation model might provide a structural format for specifying the areas of research that should be initiated. Before these broader issues could be addressed, however, the merits of simulation models had to be proved to management by successfully applying them to issues regarding limits of commodity coverage. Thus the model was first designed to handle only the specific areas that were of immediate concern. Its structure is described next.

STRUCTURE OF SIMULATION MODEL

We begin with some basic definitions that were used in constructing our simulation model:

n = year count	
t = month count	$t = 1,2,\dots,12$
k = futures months	$k = 1,3,6,9,11$

At any point of time seven contracts are traded on the commodity market.

$X^{(n_t)}_{(n_k)}$ = Market price of the k-th futures of year n during month t of year n

$F^{(n_t)}_{(n_k)}$ = Forecast price of the k-th futures of year n during month t of year n

The operating company had its price forecasting system built around the 6th month's futures. Hence our simulation model was also based on the 6th month's futures; the farthest of these was chosen to minimize the effects due to extreme volalitity of the market.

Thus, our prices are of the form $X^{(n_t)}_{(n+1)_6}$ or $F^{(n_t)}_{(n+1)_6}$, which will be referred to as $X^{(n_t)}$ or $F^{(n_t)}$ henceforth.

Market Price Subroutine

For each month, the monthly average of the 6th month's closing prices was calculated from 16 years of historic price data.

$$\bar{X}^{(n_t)} = \frac{1}{s}\sum_{i=1}^{s} X^{(n_t)}(i)$$ where index i refers to the i-th trading day of the month

$t = 1,2,\dots,12$

$n = 1,2,\dots,16$ $\quad$ s = number of trading days in the month n_t.

These averages were used as the data points on market behavior. We then found coefficients of a polynomial equation that provided the best fit to yearly price curves. The equation we used was:

$$\hat{X}^{(n_t)} = a_0(n) + a_1(n)*t + a_2(n)*t^2 + a_3(n)*t^3;\ \forall t,\ n \text{ where}$$

$\hat{X}^{(n_t)}$ = predicted price for month t of year n; $a_i(n)$ –coefficients for the n-th year; $i = 0,1,2,3$.

The coefficient of correlation R for the polynomial fit for each of the 16 years are given below:

n:	1	2	3	4	5	6	7	8
R:	0.95	-0.91	-0.90	-0.29	0.96	0.80	0.93	-0.85
n:	9	10	11	12	13	14	15	16
R:	-0.48	-0.84	-0.80	-0.94	0.94	0.06	-0.12	0.56

It is seen that the fit is very good for most years, and not good at all for a few years like 4, 14 and 15. A cursory look at the historic price curve revealed that during these years the prices had hit both a peak and a trough (different from the end points) during the twelve month period. This could be attributed to the particular crop arrival characteristics and market expectations. In later research the model was refined to take this into account more easily.

Since there is a serial correlation between the monthly prices on the market, the coefficients a_0, a_1, a_2, a_3 for a given year should be correlated. This correlation was exploited in the reconstruction of the market.

The correlation table for the 16 sets of data points a_0, a_1, a_2, a_3 is:

	a_0	a_1	a_2	a_3
a_0	1.00	-0.76	0.85	-0.51
a_1		1.00	-0.73	0.88
a_2			1.00	-0.59
a_3				1.00

and the following regression equations enable variables to be predicted based on the values of the others:

$a_1 = 7.00413 - 0.23392 \times a_0 + \varepsilon_1;\ \varepsilon_1 \sim N(0, 2.45)$

$a_2 = -0.00825 - 0.14457 \times a_1 + \varepsilon_2;\ \varepsilon_2 \sim N(0, 0.075)$

$a_3 = 0.00001 - 0.04434 \times a_2 + \varepsilon_3;\ \varepsilon_3 \sim N(0, 0.004)$

The detailed procedure for predicting market prices in the simulation is shown in the flow chart (Figure 1). The salient features of this procedure are:

a) the starting price of the simulated market was chosen from a distribution of average market monthly prices;

b) the first month's price for year n+1 was predicted by extrapolating the equation for year n one additional month;

c) prices were constrained within historically observed limits to prevent the simulator from "going wild," or sticking at the top or bottom price levels.

We tested our simulated price generator in two ways:

1. comparison of aggregate statistics like mean, S.D. and quartiles. The simulated market was slightly upward biased but not significantly so.
2. correlogram analysis to test the inter-year and intra-year price relationships. We did this by simulating the market for 35 years; thus we had 35 x 12 = 420 values of $\bar{x}^{(n_t)}$; $n = 1,2,\ldots,35$; $t = 1,2,\ldots,12$. From this, two series were formed.

(i) $\bar{y}_0(i) = \bar{x}^{(n_t)}$ where $i = 12 \times n + t$, n,t

(ii) $y_\ell(j) = \bar{x}^{(n_t)}$ where $\ell = 0,1,2,\ldots,60$; $j = 12 \times n + t + \ell$

for $\forall \ell$; for largest $j = J$, $\bar{x}^{(n_t)}$ is defined

$$R_\ell = \frac{1}{J} \sum_{r=1}^{J} \frac{(\bar{y}_0(r) - \bar{\bar{y}}_0)(\bar{y}_\ell(r) - \bar{\bar{y}}_\ell)}{\sqrt{\check{\bar{y}}_0} \times \sqrt{\check{\bar{y}}_\ell}}, \forall \ell.$$

The plot of R_ℓ vs ℓ was compared for the historic price data and simulated price data. The correlograms, though not exactly the same, seem to exhibit fairly similar characteristics. Especially, they agree on the point of no correlation, which relates to the cyclical characteristics-- and general volatility of the market. (See Figure 2.)

Generation of Forecasts

Actual historical price forecasting errors were used as the basis for generating forecasts in the simulator. From the historic data, the distribution of errors were obtained. The mean squared error of forecast was computed historically using the formula:

$$E(t) = \sum_{n=1}^{M} [F^{(n_t)} - X^{(n+1)6}]^2$$

where M = number of years which forecast history was available. From this relationship, the table of mean squared price forecasting errors was generated. This is shown in Figure 3. By analyzing this data we were able to establish that:

(i) the forecasting errors for different months are serially related. This is evident in the linear relationship between the price forecast error and the length of time by which forecast proceeded the contract month.

(ii) a given forecast has least error during certain month of the year than during the other month. This was incorporated in a refined version of the model which is a part of continuing research.

From the linear relationship of (i), regression equation was formed relating month t's forecasts to month (t+1)'s forecast. The initial month's forecast was drawn from a normal distribution where the mean and variance were estimated from historic price forecast data.

Representing Current Coverage Decisions

In practice, the additional coverage to be bought or sold during any year was arrived at through a process of discussion and consensus. Two important factors that entered into this deliberation were the coverage already held and the difference between the forecast and the actual market prices at that time. Since the buy or sell strategies were not framed very frequently (only several such major decisions were made each year) the time of the year was also critical. For the purposes of simulation we needed a programmable decision rule. Analysis of the historic coverage decisions revealed a rule of the form:

$$\Delta C(I) = [NC(I) - 1)] * \alpha + [F^{(n_t)} - X^{(n_t)}] * \beta + \gamma$$

where $I = n \times 12 + t$; for $\forall n,t$

$\Delta C(I)$ = additional coverage during month I

$\Delta C(I) > 0$ Buy decision

$\Delta C(I) < 0$ Sell decision

NC(I) = Net coverage at the end of month I

$\alpha < 0 < (\beta, \gamma)$.

The unit of coverage is the number of months, which denotes the amount of commodity position held equivalent to that many months' average usage.

DEVELOPING MEASURES OF PERFORMANCE

The Corporation considered its primary role as a manufacturer and not a speculator. It looked askance at cornering the market with a view to pushing up the prices or going short with the intention of cashing-in on a crashing market. A logical outcome of this policy was that the company imposed lower and upper limits on the coverage held at any point of time. This had the effect of restricting the opportunities for making profits and limiting the risk due to over exposure. Thus measures of performance had to be developed that reflected these conditions and management attitudes.

In the commodity market, every operator has to pay an initial cash deposit depending on the size of the position and continue to pay or receive money according to the movement of the prices in the market. This additional payment or receipt is called the margin call. Margin call is defined as:

$$MC(I) = NC(I)\,[X^{(n_t)} - X^{(n_{t-1})}] * W;\ W = \text{constant}$$

when $t=1$, $n=1$, $X^{(n_t)} \sim N(\bar{\bar{x}}, \check{\hat{x}})$

$t=1$, $n>1$, $X^{(n_{t-1})} = X^{(n-1)_{12}}$

$I = 12 * n + t$

NC(I) < 0 short position; that is, the company has sold more commodity contracts than it has bought.

NC(I) > 0 long position; that is, the company has purchased more contracts than it has sold and has an inventory of the commodity (actual or fictitious).

Cumulative margin call at the end of month I',

$$CMC(I') = \sum_{I=1}^{I'} MC(I').$$

Two measures of performance were used to evaluate the simulated commodity trading activities:

(i) Measures of exposure:

The measure used was the distribution of margin calls on a monthly, quarterly, semi-annual, and an annual basis. One important statistic was the maximum single outflow during each of the above periods. The general formula is

$$\text{Min}\,[\sum_{I=(\gamma-1)*m+1}^{\gamma * m} MC(I)]\quad \gamma = 1,2,\ldots, \text{till } MC(420)$$

where m = 1 for monthly
3 for quarterly
6 for semi-annual
12 for annual.

Histogram for simulated monthly calls is shown in Figure 4 to give an idea of the distribution.

(ii) Measure of return:

In arriving at a measure of return, the following two concepts were defined:

a) Average price of commodity position, $\bar{P}(I)$ and
b) the profit, $\pi(I)$.

There are six possible trading positions that must be evaluated with different formulas. The positions are:

1. Transition from a short to a long position:

$\bar{P}(I) = X^{(n_t)}$

$\pi(I) = NC(I-1)\,[X^{(n_t)} - \bar{P}(I-1)]$

2. Long and buying on the margin:

$\bar{P}(I) = [NC(I-1) + \bar{P}(I-1) + \Delta C(I) \times X^{(n_t)}] / NC(I)$

$\pi(I) = 0$

3. Long and Selling on the margin:

$$\bar{P}(I) = [NC(I-1) * \bar{P}(I-1) + \Delta C(I) * \bar{P}(I-1)] / [NC(I)]$$

$$\pi(I) = |\Delta C(I)| * [X^{(n_t)} - \bar{P}(I-1)]$$

4. Short and Buying on the margin:

$$\bar{P}(I) = \bar{P}(I-1)$$

$$\pi(I) = \Delta C(I) * (\bar{P}(I-1) - X^{(n_t)})$$

5. Short and Selling on the margin:

$$\bar{P}(I) = [\,|NC(I-1)| * \bar{P}(I-1) + |\Delta C(I)| * X^{(n_t)}] / |NC(I)|$$

$$\pi(I) = 0$$

6. Transition from a long to a short position:

$$\bar{P}(I) = X^{(n_t)}$$

$$\pi(I) = NC(I-1)\,[X^{(n_t)} - \bar{P}(I-1)]$$

where $I = 12 * n + t$;

for $n = 1,\ t = 1,\ X^{(n_{t-1})} \sim N(\bar{\hat{x}}, \check{\hat{x}})$; $NC(I-1) =$ Starting Coverage

$n > 1,\ t = 1,\ X^{(n_{t-1})} = X^{(n-1)}{}_{12}$.

A run of the model consisted of a simulated 35 years of com modity trading under the specified constraints on coverage. For each run, the measures of performance were computed and frequency functions of the two types of performance were plot-ted.

Two types of coverage policy changes were evaluated using the model. The first was an evaluation of the effects on performance when the range of permissible coverage was narrowed or expanded over current levels. As expected, when the range was expanded, profits went up, but so did margin call levels. By running a large number of trading ranges on the simulator, however, we wer able to see what the upper and lower limits of trading ranges were by analyzing at what point performance flattened out. Graphs similar to those in Figure 5 were produced.

The second use of the model concerned the feasibility of instituting stop loss rules. The role of stop loss routine is to stop or suspend trading, or get out of the market until more favorable climate exists. The philosophy behind a stop-loss routine is that the errors in the forecasting system should not blind the company to the realities of the market place. It is reactive in nature. We imposed a flat stop-loss rule of the form, "if the market continues to rise by more than X cents when we are short, reduce position; or, if the market continues to fall by more than X cents when we are long, dispose off so many months' coverage."

When the stop-loss rule was tested, we found that it eliminated many of the erroneous decisions which would have been implemented had only the normal coverage rules existed. On occasions, the rules incorrectly removed coverage positions that would have been correct retrospectively, but these did not seriously reduce total profits from the trading system.

The most critical characteristics of a stop-loss system that had to be evaluated using the simulator were determining the right "trigger" for instituting the rule and establishing a neutral coverage position once a rule was to be applied. When these characteristics were defined, it was found that stop-loss rules could be effectively used in conjunction with the normal trading system.

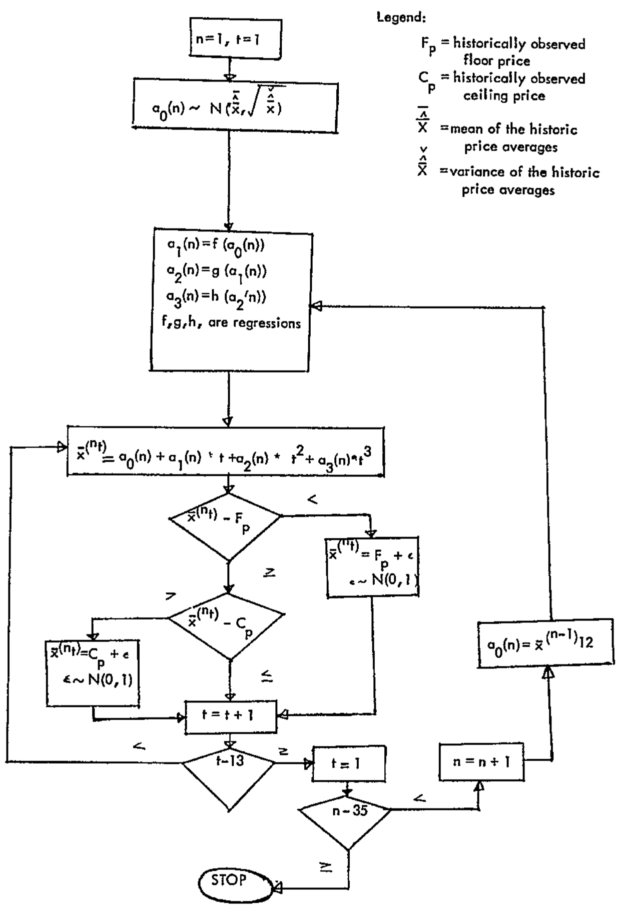
CONCLUSIONS

When the simulation results were analyzed and presented to corporate management, the questions of stop-loss rules were integrated with the analysis of coverage ranges. The simulator clearly showed that coverage ranges could be greatly expanded over current minimum and maximum positions with less risk than was currently being experienced as long as an effective stop-loss rule could be implemented. These recommendations were accepted by management.

Implementation of the model findings depended on translating stop-loss concepts to a daily trading system. Pricing and coverage decisions in the simulator assumed monthly decision points. Therefore, the research team agreed to restructure the model's input data to provide such analyses.

The commodity trading group also became interested in using the simulator to analyze the strengths and weaknesses of the trading system itself. This interest led to a restructure of the simulation research team so as to include more personnel who had detailed knowledge of the commodity environment. Each aspect of the original model which was presented by historical distribution data (e.g., market prices and forecasting errors) was replaced by a more detailed structure that included some of the causal factors in the overt behavior. This second version of the simulator is nearing completion. It will not only provide more specific and reliable recommendations for stop-loss, but is expected to provide a basis for on-going trading system diagnosis and research strategy design. Plans for a third generation simulation model, which is even more sophisticated, are now in preparation.

Figure 1. Price Forecasting Subroutine



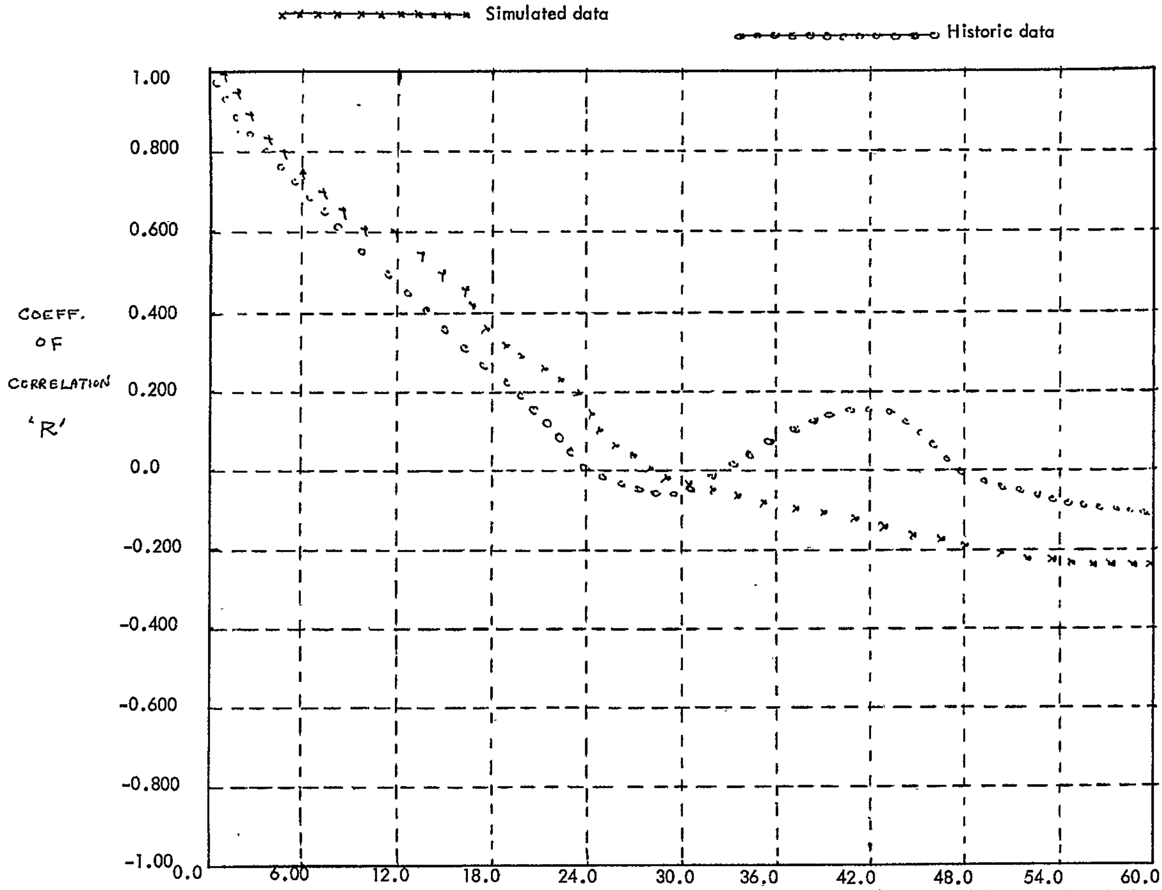
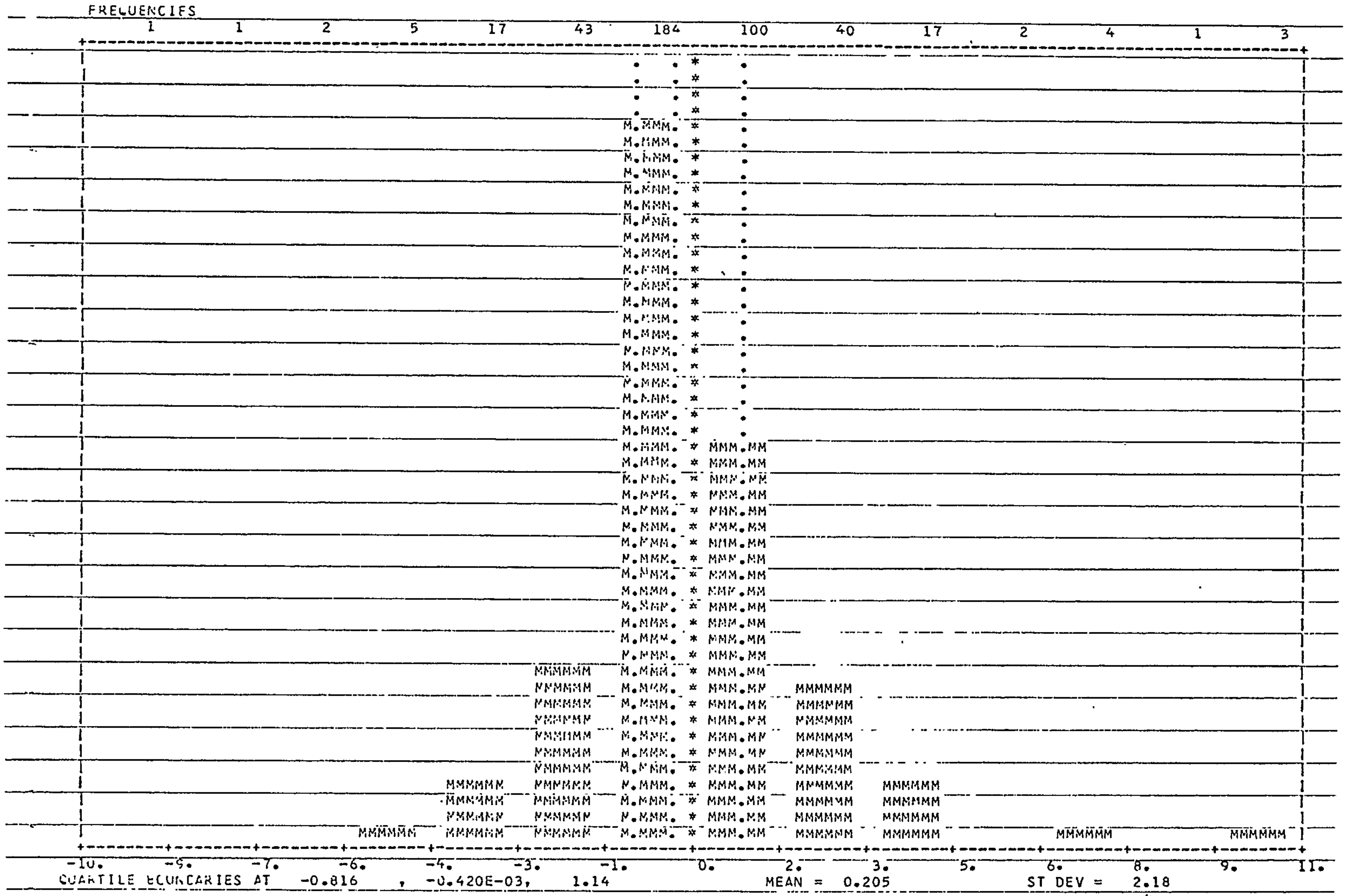


Figure 2 Correlograms of price data - historic and simulated markets

against current price in month \ Forecast made in Month	1	2	3	4	5	6	7	8	9	10	11
2	25.07										
3	15.36	18.62									
4	15.32	16.22	7.96								
5	17.87	15.06	8.58	7.65							
6	33.99	29.37	17.34	14.06	16.6						
7	27.38	39.53	22.62	17.86	14.86	16.6					
8	47.7	49.45	26.85	20.30	16.08	16.51	7.45				
9	49.30	50.72	27.17	21.35	16.37	16.39	7.70	5.12			
10	54.55	56.22	32.15	26.64	19.54	18.99	8.99	5.03	4.81		
11	67.39	70.31	41.67	35.00	27.87	26.61	14.98	8.80	8.02	7.84	

Figure 3 Mean Squared Error of Forecasts Made in Different Months



'–' ⇒ CASH OUTFLOW

'+' ⇒ CASH INFLOW.

Figure 4 MARGIN CALLS (MONTHLY)

MILLION $

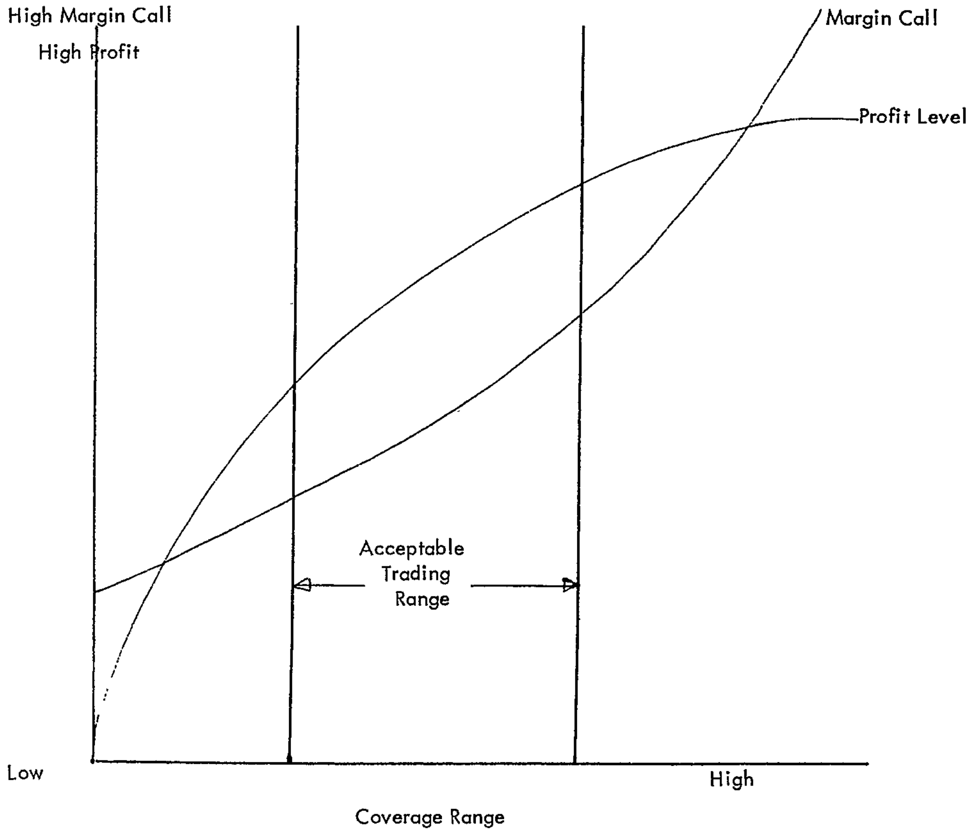


Figure 5 Relation Between Margin Call, Average Profit Level and Coverage Range