A SEMI-STRONG FORM EVALUATION OF THE EFFICIENCY OF THE WHEAT FUTURES MARKET

by

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ABSTRACT

Futures market efficiency is of concern to both market participants and non-participants. The practical problem is that inefficient futures markets can lead to resource allocation problems. The specific objective of this study is to perform a Fama (1970) semi-strong efficiency test on the Chicago Board of Trade's wheat futures market.

In this study, three wheat price prediction models are used as a standard with which to compare, on the basis of root mean squared error and bias, the futures market. One of the models, an autoregressive integrated moving average model, succeeded in obtaining a semi-strong efficiency rejection. Returns from speculating with the autoregressive integrated moving average model are then examined to see if the incremental returns are sufficiently large to cover all costs of speculating. A 19.5 percent after cost return was generated by simulating speculation with this model. Since a risk premium is expected when using unproven methods to forecast price, it was not determined whether this return is large enough to compensate for the risks involved.

The results of this study indicate that there exists a possibility that the Chicago Board of Trade's wheat futures market is not allocating resources efficiently, at least for the time frame examined and efficiency definition chosen. As to whether this detected inefficiency is just an anomaly caused by the time frame examined, efficiency definition chosen, or the examination method, little can be said. The results of this test are only strictly interpreted relative to the particular definition of efficiency and time period chosen, and are not used to infer that the futures market can be replaced by a "more efficient" marketing tool.

CHAPTER 1

INTRODUCTION

Introduction

This study offers a semi-strong test of the efficiency of the Chicago Board of Trade's wheat futures market. Specifically, the study compares the Chicago Board of Trade's wheat futures markets quarterly price predictions with predictions made by autoregressive integrated moving average (ARIMA), United Stated Department of Agriculture (USDA), and market trader's models. The basis for comparison is root mean squared error (RMSE) and bias. The approach follows the format set forth by Leuthold and Hartman's (1979) analysis of the Chicago Board of Trade's hog futures market with the exception that the structural models used to forward price predict in this study were chosen from the literature rather than explicitly created from economic analysis. Choosing models from the literature allows conclusions about the forward price predicting ability of commonly accepted models while avoiding questions of model specification validity.

Following Fama (1970, p. 1), the definition of efficiency explicitly tested in this study is, "A market in which prices fully reflect available information is called efficient." This definition was made testable by Fama (1970) and is the model of choice for studies such as these. Upon completion of this study some conclusions about wheat futures market efficiency and model choice are reached for the period 1966 to 1986.

Statement of the Problem

Grain production and export trade is of tremendous importance to the United States; the United States produces 14% of the world's grain and exports 50% of the world's grain trade (Cramer et al., 1983). The futures markets play an integral part in this grain trade with the number of contracts traded increasing fifteen fold from 1960 to 1985. Presently, there are approximately 9000 contracts traded per day (Peck, 1985). The Chicago Board of Trade's wheat futures market is generally considered the key grain futures market for two reasons: (1) the largest volume of grain futures trading, approximately 75% of the total grain futures trade, occurs on the Chicago Board of Trade; and (2) while the contracts tendered on the Chicago Board of Trade are for soft red winter wheat, other grain varieties such as soft white wheat, hard red winter wheat, and hard red spring wheat are accepted for delivery with the appropriate premiums and discounts.

The above statements demonstrate the prominent role that grain futures trading plays in the United States economy. A question of concern to participants in this market is whether or not this market is operating efficiently since an inefficient market could potentially lead to the misallocation of resources. This question is also important to individuals that may not directly participate in the wheat futures market, but still use the wheat futures market's forward pricing function to make decisions.

The procedure for testing a market for pricing efficiency must take into consideration the cost and availability of any models that are chosen for comparison. For this reason, readily available USDA and futures trader's models were selected and modeling procedures were deliberately kept simple. Upon selection of a "best" competing model, hypothetical trading with relevant commission charges will be executed over a prospective test period.

Objectives

The specific objectives of this research project are:

1. To test the hypothesis that the Chicago Board of Trade's wheat futures market is efficient.
2. To rank, on the basis of RMSE and bias, USDA, ARMA, and futures trader's models.
3. To test any model(s) that succeed(s) in rejecting the hypothesis in objective (1) for after commission above average returns where above average returns are defined to be returns in excess of the return rate of "safe" investments such as cash deposits (CDs) at a bank.

Organization of this thesis is as follows: the second chapter reviews previous research done on futures markets and efficiency, summarizes wheat models that are present in the literature, briefly develops the theory behind autoregressive integrated moving average modeling, and develops a testable implication from the chosen definition of efficiency. Chapter 3 presents the empirical results of the efficiency tests undertaken. Chapter 4 includes the summary, suggestions for further research, and other concluding remarks.

CHAPTER 2

REVIEW OF LITERATURE

This chapter consists of six sections. The first traces the development of the theory of efficient markets. The second section summarizes previous research done on the subject of efficient futures markets. The third section reviews recent literature on wheat price models; two of these models will be chosen to use in the efficiency tests. The fourth section briefly reviews the theory behind auto-regressive integrated moving average modeling. The fifth section develops the efficiency tests that are to be undertaken in this study. The sixth section considers data requirements and availability. The list of references cited in this review is not complete. However, it does contain those works considered by the author to be important to the development and motivation of this project.

The Theory of Efficient Markets

Working (1958) writes that the sources of market mistakes are information and judgment, and classed market inaccuracies as "necessary" and "objectionable." An efficient market contains only necessary inaccuracies; unexpected price changes are due only to new information. Any error beyond that is objectionable inaccuracy, often termed as speculative error, and likely results from the bad judgment of traders or from noncompetitive market situations. Working (1949) implies that, if future price changes are predictable, objectionable inaccuracies must exist. If the changes are unpredictable, objectionable error is absent. Samuelson (1965, p. 105) followed this line of reasoning when he noted that "expected profits in an efficient market can't be increased by charts or any other esoteric device of magic or mathematics."

Fama (1970) took general statements such as the ones above, and, in an article that has become a classic in the relevant literature, defined concise tests for market efficiency. First, Fama (1970) stated the following sufficient conditions for market efficiency: (1) there are no transaction costs involved in trading; (2) all available information is costlessly available to all market participants; and (3) all agree on the implications of current information for the current market price and distributions of future market prices. In such a market, the current market price would obviously "fully reflect" all available information. However, while the above conditions are sufficient for market efficiency, they are not necessary. The market may still be efficient if "sufficient numbers" of investors have access to available information, and there are no investors who can consistently make better evaluations of available information than are implicit in market prices (Fama 1970). Next, Fama (1970) concisely defined an efficient market as one in which prices "fully reflect" all available information. Then Fama (1970) defined exactly what he meant by the term "fully reflect". His theoretical development went as follows:

$$E(\tilde{p}_{j,t+1} | \Phi_t) = [1+E(\tilde{r}_{j,t+1} | \Phi_t)]p_{jt}, \tag{1}$$

where E is the expected value operator, p_{jt} is the price of security j at time t, $p_{j,t+1}$ is its price at t+1 (with reinvestment of any intermediate cash income from the security), $r_{j,t+1}$ is the one-period percentage return $(p_{j,t+1} - p_{jt})/p_{jt}$, Φ_t is a general symbol for whatever set of information is assumed to be "fully reflected" in the price at t, and the tildes indicate that $p_{t,j+1}$ and $r_{j,t+1}$ are random variables at t. The value of the equilibrium expected return $E(\tilde{r}_{j,t+1}|\Phi_t)$ projected on the information Φ_t would be determined from the particular expected return theory at hand. The conditional expectation notation of (1) is meant to imply, however, that whatever expected return model is assumed to apply, the information in Φ_t is fully utilized in determining equilibrium expected returns. This is the sense in which Φ_t is "fully reflected" in the information of the price p_{jt}.

Fama (1970) then took his equation (1) and developed some empirically testable implications. His development went as follows: The assumptions that the conditions of market equilibrium can be stated in terms of expected returns and that equilibrium expected returns are formed on the basis of (and thus "fully reflect") the information set Φ_t have a major empirical implication -- they rule out the possibility of trading systems based only on the information in Φ_t that have expected profits or returns in excess of equilibrium expected profits or returns. Thus let

$$x_{j,t+1} = p_{j,t+1} - E(p_{j,t+1}|\Phi_t) \tag{2}$$

Then

$$E(\tilde{x}_{j,t+1}|\Phi_t) = 0 \tag{3}$$

which, by definition, says that the sequence $\{x_{jt}\}$ is a "fair game" with respect to the information sequence $\{\Phi_t\}$. Or, equivalently, let

(4) $$z_{j,t+1} = r_{j,t+1} - E(\tilde{r}_{j,t+1} \mid \Phi_t)$$

Then

(5) $$E(\tilde{z}_{j,t+1} \mid \Phi_t) = 0,$$

so that the sequence $\{\tilde{z}_{jt}\}$ is also a fair game with respect to the information sequence $\{\Phi\}$.

In economic terms, $x_{j,\ t+1}$ is the excess market value of security j at time t+1; it is the difference between the observed price and the expected value of the price that was projected at t on the basis of the information Φ_t. Similarly, $z_{j,t+1}$ is the return at t+1 in excess of the equilibrium expected return projected at t. Let

(6) $$\alpha(\Phi_t) = [\alpha_1(\Phi_t), \alpha_2(\Phi_t), \ldots, \alpha_n(\Phi_t)]$$

be any trading system based on Φ_t which tells the investor the amounts $\alpha_j(\Phi_t)$ of funds available at t that are to be invested in each of the n available securities. The total excess market value at t+1 that will be generated by such a system is

(7) $$V_{t+1} = \sum_{j=1}^{n} a_j(\Phi_t)[r_{j,t+1} - E(\tilde{r}_{j,t+1} \mid \Phi_t)],$$

which, from the fair game property of (5) has expectation,

(8) $$E(\tilde{V}_{t+1} \mid \Phi_t) = \sum_{j=1}^{n} a_j(\Phi_t) E(\tilde{z}_{j,t+1} \mid \Phi_t) = 0.$$

The testable implications of Fama's (1970) work are quite straightforward. It is impossible to create a model that outpredicts an efficient market to the extent that expected profits or returns in excess of "normal" profits or returns are generated.

Fama (1970) broke the tests of efficient markets into three categories. These categories were named weak form test, semi-strong form test, and strong form test in order to reflect Fama's judgment of how powerful each efficiency test was.

The first category, the weak form test for efficiency, requires testing a market to see if price changes follow a random walk. A random walk implies that successive price changes (or successive one-period returns) are independent and identically distributed. Formally, this says

(9) $$f(r_{j,t+1} | \Phi_t) = f(r_{j,t+1}),$$

which is the usual statement that the conditional and marginal probability distributions of an independent random variable are identical. In addition, the density function f must be the same for all t. Expression (9), of course, says much more than the general expected return model summarized by (1). For example, if we restrict (1) by assuming that the expected return on securitiy j is constant over time, then we have

(10) $$E(\tilde{r}_{j,t+1} | \Phi_t) = E(\tilde{r}_{j,t+1}).$$

This says that the mean of the distribution of $r_{j,t+1}$ is independent of the information available at t, Φ_t, whereas the random walk model of (9) says in addition that the entire distribution is independent of Φ_t. This, however, does not preclude the possibility of a trend (random walk with a drift) since expected price changes can be non-zero; earlier work by Samuelson (1965) had previously shown that prices could follow deterministic trends while still fluctuating randomly. Fama (1970) was careful to note that, as shown above, the fair game assumption is not sufficient to lead to a random walk. The random walk implies much more, i.e. that the expected return (indeed the entire distribution of returns) be stationary (zero serial correlations) through time. However, while zero serial correlations are consistent with the "fair game" model, the "fair game" model does not specifically require zero serial correlations. In his 1970 article, Fama did show that many markets that tested "fair game" efficient were serially correlated. However, he felt that the small levels of serial correlation that seem to be often present in markets could not very likely be exploited for profitable returns. Fama (1970) went on to explain that it is probably best to regard the random walk model as a special case of the more general expected return model ("fair game" model) in the sense of making a more detailed specification of the economic environment. That is, the basic model of market equilibrium is the "fair game" expected return model, with a random walk arising when additional environmental conditions are such that one-period returns repeat themselves through time. From this viewpoint, violations of the pure independence assumption of the random walk model are to be expected. But, when judged relative to the benchmark provided by the random walk model, these violations can provide insights into the nature of the market environment. Fama (1970) concluded his section on weak form tests by noting that there isn't much evidence against the "fair game" model's more ambitious offspring, the random walk.

Fama's (1970) second category, the semi-strong form tests, contains tests of efficient market that are concerned with whether current prices "fully reflect" all obvious publicly available information. Each individual test is concerned with the adjustment of market prices to some kind of information generating event(s) (e.g., export reports, domestic usage, dollar values, substitute prices, etc.). Leuthold and Hartmann (1979) interpreted this test to include comparisons between econometric models and futures markets; if an econometric model better utilizes available information and thereby out-forecasts the futures market in question, then this is a valid semi-strong rejection of market efficiency. When semi-strong tests of efficiency are carried out in this manner, the econometric models become a norm with which to compare the futures markets.

Fama's (1970) third category, the strong form test, contains tests of efficient markets that are concerned with whether current prices "fully reflect" all available information. Fama (1970, p. 415) noted that, "The strong efficient markets model, in which prices are assumed to reflect all available information, is probably best viewed as a benchmark against which deviations from market efficiency (interpreted in its strictest sense) can be judged." Tests that fall into this category would be concerned with above average returns being generated by such factors as monopolistic access to information. Niederhoffer and Osborne (1966) and Scholes (1969) indicated that such market inefficiencies do occur by showing that above average returns are earned by New York Stock Exchange specialists and corporate officers.

Since Fama (1970), there have been many articles dealing with the concept of efficiency and the characteristics of efficient markets. The conventional Fama (1970) approach to efficiency was taken by this author, so little discussion will be made of later approaches. It is pertinent to note, however, that later works do indicate that there may be some problems with Fama's (1970) definition of efficiency since no account is taken of the costs of acquiring information and/or changes in the variability of the price series (Grossman and Stiglitz, 1980). In fact, Grossman and Stiglitz (1980) showed that, for the property of efficiency to hold, costless information is not only a sufficient condition, but also a necessary condition. This implies that, even if a particular model's forecast is more accurate than the forecasts of the futures market, inefficiency does not necessarily follow. For a market to be inefficient, it is necessary to have a model that forecasts more accurately than the market; however, this is not sufficient for market inefficiency. To be sufficient for market inefficiency, the risk adjusted returns must be large enough to cover all modeling costs.

Efficient Futures Market Research

Both the efficient market model and the special random walk model discussed in the previous section imply that no mechanical trading rules can be used to increase profits. A large body of research that followed Fama's (1970) article attempted to reject efficiency by constructing successful trading rules or by testing for serial correlations with the idea that serial correlations indicate the possibility of profitable trading rules. Since this will largely be the approach taken in this study, the articles discussed in the following section will be congregated around these ideas. Other approaches to efficiency tests of futures markets do exist and will be briefly summarized at the end of this section.

Cargill and Rausser (1975, p. 1049) weak form efficiency tested 464 futures contracts from seven commodities (corn, oats, soybeans, wheat, copper, live beef cattle, and pork bellies) and obtained weak-form rejections of efficiency for the set of results as a whole: "the results of this analysis clearly indicate that there are a significant number of departures from randomness. Thus the random walk model must be rejected." They did note in their paper that this was a rejection of a random walk and therefore did not necessarily imply that the markets tested were inefficient. In fact, in an interesting aside in their paper, they applied a g-percent filter (a quite popular trading rule that gives buy-sell signals based upon percentage changes in price) to computer produced random series of market prices and succeeded in generating substantial profits. Cargill and Rausser (1975) felt that this was strong evidence in support of the contentions that the random walk model was not an accurate explanation of efficient commodity markets and that positive profits from the g-percent filter were not necessarily indications of serial correlation as previously believed.

Leuthold and Hartmann (1979) performed a semi-strong form test for efficiency on the Chicago Board of Trade's hog futures market by constructing an econometric forecasting model to serve as a norm with which to compare the Chicago Board of Trade's hog futures market. The econometric model was a two equation demand-supply model using monthly data and closely following the well known cobweb model. Leuthold and Hartmann (1979, p. 484) stated that, "By design, the econometric model is kept simple because, if a simple model shows the market to be inefficient, further elaboration becomes unnecessary to test the efficient market hypothesis." On the basis of RMSE, Leuthold and Hartmann (1979) were able to reject (semi-strong form test) the efficiency hypothesis. They chose to use RMSE as the statistic of comparison because of the importance of weighting large errors greater than small errors in a forecasting model.

Rausser and Carter (1983) performed a semi-strong test of efficiency on the Chicago Board of Trade's soybean complex. They followed fairly closely the framework set forth by Leuthold and Hartmann (1979) by building an econometric forecasting model with which to compare the futures market and succeeded in obtaining a semi-strong rejection of market efficiency. However, they did not feel that this was in fact a true rejection of efficiency; rather, they felt that the necessary condition for efficiency rejection had been met. The sufficient condition for efficiency rejection would require that the cost of constructing and utilizing their model did not exceed the incremental benefits appropriately adjusted by risk (relative cost/benefit condition). Bias was also added as a comparison statistic in Rausser and Carter's (1983) analysis because they felt that for a model to meet the necessary condition for efficiency rejection it had to do so in both terms of volatility (RMSE) and bias. They referred to this concept of meeting both a bias and a volatility constraint as "relative accuracy." In concluding their article, Rausser and Carter (1983, p. 477) pointed out that, while only the necessary condition for efficiency rejection had been quantitatively met by their research, they had deliberately kept the predictive models simple, thereby minimizing the marginal cost of use and giving a high probability of meeting sufficiency requirements for efficiency rejection: "It appears that opportunities exist in the soybean complex for excess returns, i.e., returns which exceed normal returns adjusted for risk." They did indicate that, in later research, they planned to do market trading simulations with their model to test if actual excess returns do exist. A simple trading rule using their model as an indicator of market direction was to be used in developing a trading strategy.

Kamara (1984) summarized other research that had occurred in the futures market efficiency area over the last twenty years. As a whole, the results he found were fairly disconcerting since different researchers asking the same or similar questions often reached different conclusions. In the area of price forecasting ability the general consensus was that the speculator, especially the large speculator (defined as a speculator who traded in large enough quantities that reports on market position and intent had to be filed with the Commodity Futures Trading Commission), could forecast price better than the futures market. This result would be consistent with a Fama (1970) semi-strong efficiency rejection. However, it should be noted that the majority of the studies reviewed by Kamara (1984) did not take into account the cost of the speculator's forecasting information or the possibility that the speculators were being rewarded for bearing risk. Therefore, these results represent only the necessary condition for efficiency rejection and do not meet sufficiency requirements. Also, it should be noted that Hartzmark, in a 1987 study based upon the Commodity Futures Trading Commission's confidential files, was unable to find any evidence to support the contention that speculators could forecast price.

As for the special case of the random walk efficiency tests, most of the research on random walk models of the futures markets that was summarized by Karama (1984) found some evidence of serial correlation, especially short run serial correlation. While this result is consistent with a Fama (1970) weak form rejection of efficiency, again the results aren't very compelling. The mere existence of some nonrandom components is not sufficient evidence to reject general efficiency unless some unexploited opportunities for above average profits are created by this lack of randomness in price.

A 1980 argument by Grossman and Stiglitz probably best summarizes the current thoughts on futures market efficiency. They argued that if futures prices reflected all available information, then traders would have no incentive to gather information. If information is costly to obtain, then, in equilibrium, prices will reveal only part of the information held by informed traders, so that those who acquire information earn a higher return. Costly information will result in market prices that do not reflect all available information even though no traders behave suboptimally. This again emphasizes current theoretical trends towards redefining Fama's (1970) efficiency rejection tests as tests for only the necessary conditions for efficiency rejection and not tests that satisfy general market efficiency rejection criterion.

To meet both necessary and sufficient criterion for efficiency rejection, the potential expected returns from exploitation of the perceived failings in the market price must be greater than the cost and risk of gathering and utilizing the necessary information.

Wheat Price Forecasting Models

This section reviews some of the recent models that are used for forecasting wheat prices. Only models that were published in commonly read or easily available publications were considered as relevant literature. This was done to insure that the cost of acquiring and using these models was minimal.

Westcott et al. (1984) and Westcott and Hull (1985) built wheat price forecasting models for the United States Department of Agriculture (the USDA is the largest publisher of agricultural commodity and price forecasts). The model they developed was based on the general hyperbolic function, $(P-a)(S-d) = c$, where P is the quarterly wheat price, S denotes quarterly ending stocks of wheat, and a, c, and d are parameters. To avoid nonlinearities in estimation, the parameter d was assumed to equal zero. Solving the above equation for price gives $P = a + cS^{-1}$. To represent the different effects of stocks through the year, a separate c parameter was assumed for each quarter. It is important to note that stocks, S, were measured relative to amount of usage, U, in the wheat industry. Westcott et al. (1984) felt that, since the wheat market had grown sharply over time, it was necessary to develop this "relative usage" measurement of stocks because a larger market required a greater level of stocks to keep marketing channels filled. Lagged price was also included as an independent variable to reflect short term "stickiness" of quarterly wheat prices. Price "stickiness" was thought to reflect partial adjustments caused by relative bargaining positions of market participants and/or expectations based upon incomplete market information, which thereby prevented complete price adjustments in the short run. The preceding adjustment resulted in the following general equation:

$$(11) \qquad P = a + b\ \mathrm{lag}(P) + \sum_{i=1}^{4} c_i D_i (S/U)^{-1}.$$

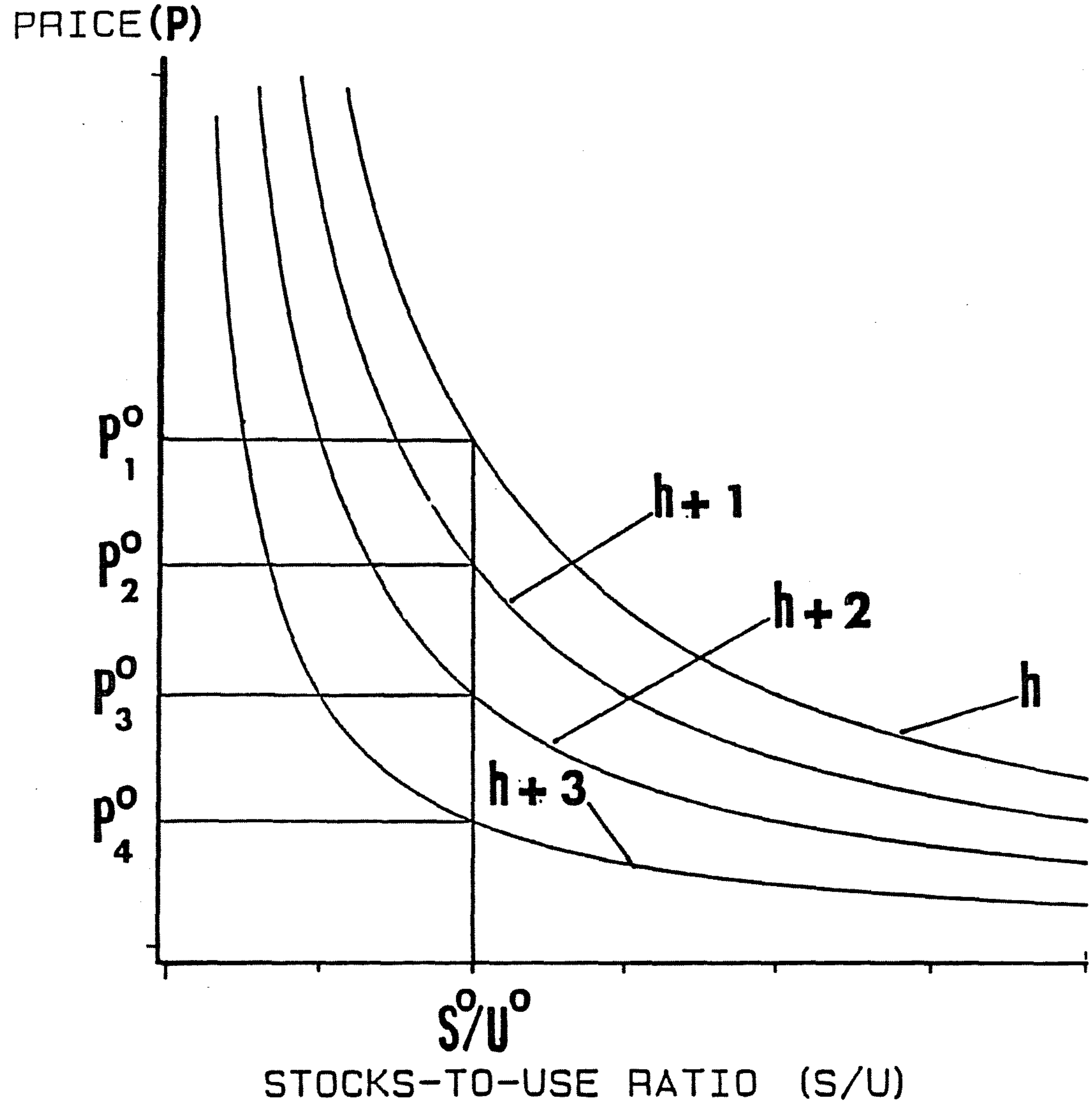
Where D_i are quarterly dummy variables (equal to 1 in the i-th quarter, 0, elsewhere), lag(P) is the one quarter lag of price (P), and a, b, and c_i, i=1,...,4, are parameters to be estimated. The subscripts "i" denote quarters, where i=1 is the January-March quarter, i=2 is the April-May quarter, i=3 is the June-September quarter, and i=4 is the October-December quarter. Westcott et al. (1984) included the $c_i D_i (S/U)^{-1}$ terms to allow a different effect of stocks on prices in each quarter. Thus, equation (11) is expected to yield a family of four hyperbolic curves that represent price's relationship to the stock-to-use ratio for each quarter (see Figure 1). For any given stock-to-use ratio, such as S^o/U^o, the resulting prices would be expected to be smaller as the time from harvest increases. This is indicated by a movement from one hyperbolic curve to the next. The actual model was estimated from 1971-81 (44 observations).

The final empirical results were:

$$(12) \qquad P = \underset{(0.2)}{0.041} + \underset{(12.7)}{.830}\ \mathrm{lag}(P) + \underset{(1.9)}{1.071}\ D_1(S/U)^{-1} + \underset{(0.9)}{.389}\ D_2(S/U)^{-1} +$$

$$\underset{(2.6)}{2.385}\ D_3(S/U)^{-1} + \underset{(3.1)}{2.401}\ D_4(S/U)^{-1}.$$

R^2 = .875 MAE (mean absolute error) = .270



h = harvest quarter
h + 1 = 1 quarter after harvest
h + 2 = 2 quarters after harvest
h + 3 = 3 quarters after harvest
P = price per bushel of wheat
P_h^o = harvest quarter price for a given stock-to-use ratio (S^o/U^o)
P_{h+1}^o = harvest + 1 quarter price for a given stock-to-use ratio (S^o/U^o)
P_{h+2}^o = harvest + 2 quarter price for a given stock-to-use ratio (S^o/U^o)
P_{h+3}^o = harvest + 3 quarter price for a given stock-to-use ratio (S^o/U^o)
S^o/U^o = a given stock-to-use ratio

Figure 1. Relationship Between Quarterly Price and Stocks-to-Use Ratio

The sign of the coefficients on the stock-to-use ratios were positive and tended to diminish as the time from harvest increased. This met with the expectations of Westcott et al. (1984).

To assess the predictive capabilities of their model, Westcott et al. (1984) forecasted quarterly price for the years 1982 and 1983. For 1982 a mean absolute error (MAE) of 24.2 cents per bushel was obtained and for 1983 an MAE of 31.1 cents per bushel was obtained. This was felt to be acceptable performance for a wheat forecasting model although they noted that some problems with forecasting may have been caused by the 1983 PIK program and the 1983 drought.

Another publicly available source of commodity forecasting models is the many books and pamphlets published by futures traders and analysts. Schwager (1984) contributed to this body of information when he published the book A Complete Guide to the Futures Markets. While not explicitly creating and testing a wheat forecasting model, Schwager presented theoretical arguments for a general model form. Since this book represented a fairly new and available publication on wheat market models, it was chosen as a literature source that met the general cost-availability framework discussed earlier. The following section will develop Schwager's (1984) general wheat model.

The basic model proposed by Schwager is:

$$DP = a + b(D5/ES). \tag{13}$$

Where DP is the average deflated cash wheat price for the period in question, a and b are parameters to be estimated by regression, and D5/ES is a ratio of five period average disappearance of grain stocks to ending grain stocks. The five period moving average of grain stock disappearance, D5, was used to normalize stocks since Schwager felt that this would be a more representative measure of the size of the market. A single period, D, could make the model unstable by making it prone to being affected by short period abnormalities that can occur in any market. It was suggested, however, that the length of the moving average on stock disappearance be varied until "best model fit" is obtained.

Schwager viewed the general model (13) as a logical starting point for constructing price forecasting models of the grain markets. Once this basic model was tested, the analyst can then experiment with the addition of other variables. Two potential right-hand side variables that were suggested are: (appropriately lagged) wheat-to-corn price ratios and trade dollar values. Schwager stated that some very impressive model fits (R^2 of .89 to .98) had been obtained using these methods, but did not explicitly show the actual models.

There are many other wheat price forecasting models in publications. However, those reviewed by this author followed the general framework of Schwager (1984) and/or Westcott et al. (1984). All models had lagged wheat price or wheat-to-feed grain price ratios and either lagged or forecasted supply-disappearance variables on the right-hand side. Therefore, the two wheat price models discussed above are felt by this author to be representative of the literature available.

General Auto-regressive Integrated Moving Average Modeling Theory

Box and Jenkins (1976) are generally considered the creators of a form of time series analysis that is referred to as autoregressive integrated moving average (ARIMA(p,d,q)) modeling. The (p,d,q) is defined as follows: the p represents the order of the autoregressive (AR) lag, the d represents the number of times the data were differenced, and the q represents the order of the moving average (abreviated MA) error term. (The (p,d,q) will not be presented unless a specific model structure is being discussed.) In this approach to time series analysis the goal is generally prediction; therefore, little emphasis is placed on explanation. As a result, ARIMA modeling has a much more limited application than most forms of time series econometric modeling; econometric models are often as concerned with explanation as with prediction.

ARIMA modeling is generally broken down into a four-fold iterative exercise. The four basic exercises are: (1) identification, (2) estimation, (3) diagnostic checking, and (4) forecasting. The first three steps are iterative. The fourth step is taken only when satisfactory results are obtained from steps 1 through 3. The rest of this section will discuss the characteristics that a data series need exhibit to be a candidate for ARIMA modeling, and will present a brief discussion of each of the steps involved in ARIMA modeling. Brevity was considered reasonable since ARIMA modeling is a well known and accepted process. For an in-depth discussion refer to <u>Time Series Analysis: Forecasting and Control</u> (Box and Jenkins, 1976).

Candidate data processes for ARIMA models must have some basic characteristics. These characteristics are: (1) the data set must contain data that was measured in equally spaced, discrete time intervals (Box and Jenkins (1976) suggest at least 50 observations),

(2) the mean of the data series must be constant through time, (3) the variance of the data series must be constant through time, and (4) the autocorrelation function must be constant through time; autocorrelation must be a function of lag length only, i.e. relative position in the series cannot have any effect on autocorrelation.

If a candidate data set satisfies all the preceding characteristics, then it is referred to as second order stationary (SOS) and is a good candidate for univariate, Box and Jenkins ARIMA. If a data set does not satisfy these characteristics, then the accepted methodology is to difference the series to try to obtain SOS. A data series that cannot meet SOS criterion is not a candidate for ARIMA modeling.

If a data set meets the requirements for ARIMA modeling, the next step is the identification stage. Identification is the step in which one or more possible ARIMA models are chosen as candidates for building the forecasting model. Two graphical devices are used to measure correlations between observations within a single data series. These devices are called an estimated autocorrelation function (acf) and an estimated partial autocorrelation function (pacf). The estimated acf and pacf measure the statistical relationships within a data series and are helpful in giving a feel for the patterns available in the data.

The estimated acf and pacf are then used as guides in choosing one or more ARIMA models that seem appropriate. Thus, the basic idea is that every ARIMA model has a theoretical acf and pacf associated with it. At this stage the theoretical acfs and pacfs are compared with the estimated acfs and pacfs in order to select a model whose theoretical acfs and pacfs most closely match the estimated acfs and pacfs. The data is not approached with a preconceived idea about what model to use, as in the case of econometric models; rather, the data is expected to "talk" through the estimated acfs and pacfs and thereby reveal the model of choice. Models are only chosen tentatively at the identification stage; a tentative model will not be accepted as a final model unless it proves adequate in the estimation and diagnostic checking stages. Otherwise the identification stage must be repeated.

The estimation stage is where precise estimates of the coefficients of the chosen model are obtained. This stage provides some warning signals about the adequacy of a model. In particular, the estimated coefficients must meet certain mathematical constraints (size and sign) or the tentative model is rejected. A model that doesn't meet these constraints will not satisfy stationarity and/or invertibility requirements. For a more detailed explanation of stationarity and/or invertibility see Pankratz (1983).

The third stage of ARIMA modeling is the diagnostic checking stage. Box and Jenkins (1976) suggested some diagnostic checks to help determine if an estimated model is statistically adequate. This stage is mainly concerned with looking at the residuals in order to determine if only white noise remains. If a model is shown to be inadequate in this stage, then stage 1 (identification) must be returned to.

The fourth and final step in ARIMA modeling is forecasting. Assuming that all the requirements of steps 1 through 3 are satisfied, the model is then used to derive forecasts. If the ARIMA model chosen is indeed the correct one, then forecasts made with this model are said to be optimal. This means that no other univariate forecasts have a smaller mean-squared forecast error (MSE).

Development of an Efficiency Test for the Wheat Futures Market

The following section traces the general ideas and concepts behind the efficiency test that is undertaken by this study. All references to efficiency in this section refer to the Fama (1970) definition of efficiency.

The market that is tested for efficiency in this study is the Chicago Board of Trade's wheat futures market. The contract tendered on the Chicago Board of Trade's wheat futures market is for number 2 soft red winter wheat deliverable upon contract expiration to any of several designated delivery points. One such point of delivery that is not subject to location premiums or discounts is Chicago, thereby making cash price for number 2 soft red winter wheat at Chicago a logical choice for a data series to be used in this study.

The next step is to choose a time interval to forecast since the Chicago Board of Trade's wheat futures market is capable of making forward price predictions of any length less than 15 months. However, close examination of the relationship between the length of the price prediction (contract length) and the number of predictions made (contracts traded) indicates that near term contracts (short length predictions) experience the greatest trading volume. Since there are five contracts (December, March, May, July, and September) traded per given year, each contract spends approximately two and one-half months being the near term contract. The closest any readily available, cash, number 2 soft red winter wheat data set could come to matching this prediction interval was in quarterly format. As a result, quarterly intervals were chosen to be the standard by which efficiency tests were made; a quarterly, cash price, number 2 soft red winter wheat data series was obtained for the period from the first quarter 1966 to the 2nd quarter 1986.

After selection of the prediction interval and data set, the next step becomes selection of the appropriate efficiency test. The efficiency tests used in this study closely follow the framework proposed by Fama in 1970.

The version of the Fama (1970) efficiency test that is undertaken requires the creation or selection of a standard (norm) with which to compare the price prediction capabilities of the market in question. Conclusions on market efficiency or, at least, conclusions about market efficiency relative to the model chosen for comparison, can then be reached. Logically, "simple" (easily constructed and utilized) models should be chosen first since an efficiency rejection by a "simple" model precludes the necessity of creating a more complex model. It must also be recognized that a Fama (1970) form rejection of efficiency represents only the necessary condition for general efficiency rejection. Therefore, since the sufficient condition for efficiency rejection requires that model cost be taken into account, the cost of creating and utilizing complex models often makes them fail sufficiency criterion.

Perhaps the most simple model of a market proposed is that of a random walk; it takes minimal knowledge and time to test the hypothesis that a data set is a random walk. If the data set does not follow a random walk, then this indicates that it may be possible to build a model or follow some other trading rule that will allow better predictions than those generated by the market. The general cash wheat random walk model is:

(14) $$WP_t = \alpha + \beta WP_{t-1}.$$

Where WP_{t-i} represents cash, number 2, soft red winter wheat price at Chicago in the (t-i)th quarter, α is an intercept parameter to be estimated, and β is a slope parameter to be estimated.

The random walk model has β equal to one and α equal to whatever number best represents the market drift, i.e. a market with no drift would have α equal to zero, whereas a market with positive growth would have α greater than zero. Therefore, the hypothesis to be tested is that $\beta = 1$. The T test is the appropriate test with n-2 degrees of freedom (n is the number of observations). A rejection of the hypothesis that $\beta = 0$ is a Fama (1970) weak form rejection of efficiency.

If the wheat price series do not follow a random walk, then this indicates the possibility of building an ARIMA model to compete with the wheat futures market. A random walk model is an AR(1) process; therefore, the rejection of a random walk model poses the possibility of creating a model that has an AR(p) process with p>1. An ARIMA(p,d,q) model where the exact form is not ARIMA(1,0,0) indicates that current price does not "fully reflect" available information. If such a model succeeds in rejecting wheat futures market efficiency, then this would represent a Fama (1970) semi-strong rejection of market efficiency.

Models other than ARIMA can be used to serve as a norm for efficiency comparisons; any model or rule that allows for either actual price prediction or predicts direction of price change is a viable candidate for an efficiency test. Two other competing models were selected from the literature to serve as comparison norms in this study. The general form of and theory behind the models selected (model (11) and model (13)) are given in a previous section. Model selection is chosen over model creation to allow for tests of models that are currently in the literature. This is especially relevant in the case of model (11) since this model is one that the USDA advocates. The USDA is possibly the largest, most easily available source of commodity price predictions. Another benefit of model selection over model creation is that with model selection the right-hand side variables don't have to be derived and defended.

The statistics that will be used for comparison between models of the wheat market and the wheat futures market are RMSE and bias. The selected statistic of comparison is RMSE since it effectively penalizes large prediction errors more than small prediction errors. This is important since it is the large errors in wheat price prediction that could more effectively lead to resource allocation problems. Bias is also chosen as a statistic of comparison to effectively rate how the wheat futures market fared against the other chosen models in the area of consistent resource allocation. A biased model or futures market will consistently misallocate resources through time. Both bias and RMSE are commonly accepted measures for tests such as these.

The final empirical step taken in this study only occurred because one of the preceding models (ARIMA) succeeded in obtaining a Fama (1970) semi-strong rejection of market efficiency. Since a Fama rejection of efficiency meets only the necessary condition for general market efficiency rejection, the sufficient condition for efficiency rejection must be examined. In order to meet sufficiency requirements for a rejection of market efficiency, a competing model must generate high enough returns (risk adjusted) to cover the cost of building and utilizing the competing model. Returns from trading the model that met the necessary criterion will be measured, the cost of building the model will be estimated, and the opportunity cost of money invested in the model will be figured at a 10% discount rate. However, the returns from speculating with a price predictive model need to be adjusted for risk before comparing them to returns from other investments. Since risk adjustment is a function of personal preference, no attempt will be made to adjust returns for risk. Individuals that review this study will have to choose a method of adjusting returns to reflect their risk preferences and thereby reach a conclusion as to whether the sufficient condition for wheat market efficiency rejection is met.

Data Availability and Requirements

Quarterly measures of the following variables from 1966 to 1986 were required: number 2 Chicago cash price for soft red winter wheat, producer price index (PPI), total grain usage, ending grain stocks, trade weighted dollar values, and cash corn prices. All the data were readily available from the following government publications: <u>Wheat</u>

Outlook and Situation Report, _Feed Outlook and Situation Report_, _Agricultural Outlook_, and _The Economic Report of The President_.

Efficiency tests require that an accounting of the costs of data gathering be kept in mind; however, the data required for this study did not represent a problem in this area. All the data sources are easily obtained from libraries or can be ordered on an annual basis for fees that total less that $100.

CHAPTER 3

EMPIRICAL RESULTS

The previous chapters presented the theoretical basis for this study. This chapter summarizes the actual empirical results. The estimation of the models used in this study is completed using the statistical package DYNREG (Burt et al., 1986).

This chapter is divided into five sections. The first section presents the results of fitting ARIMA models to the cash wheat market. The second section gives the results obtained from efficiency testing with model (11). The third section gives the results obtained from efficiency testing with model (15). The fourth section provides the results acquired from modeling the producer price index. The fifth section presents the costs of utilizing and the potential returns from speculating with the best competing model.

Soft Red Winter Wheat ARIMA Models

Random Walk Model Results

An ARIMA modeling process begins with a visual examination of the candidate data series to check for obvious problems that the series may exhibit regarding SOS; visual examination (see Figure 2) of both the nominal and real cash wheat series raises some real questions as to whether the series has constant mean and/or constant variance. The nominal data series appears to exhibit a slight growth rate, and both

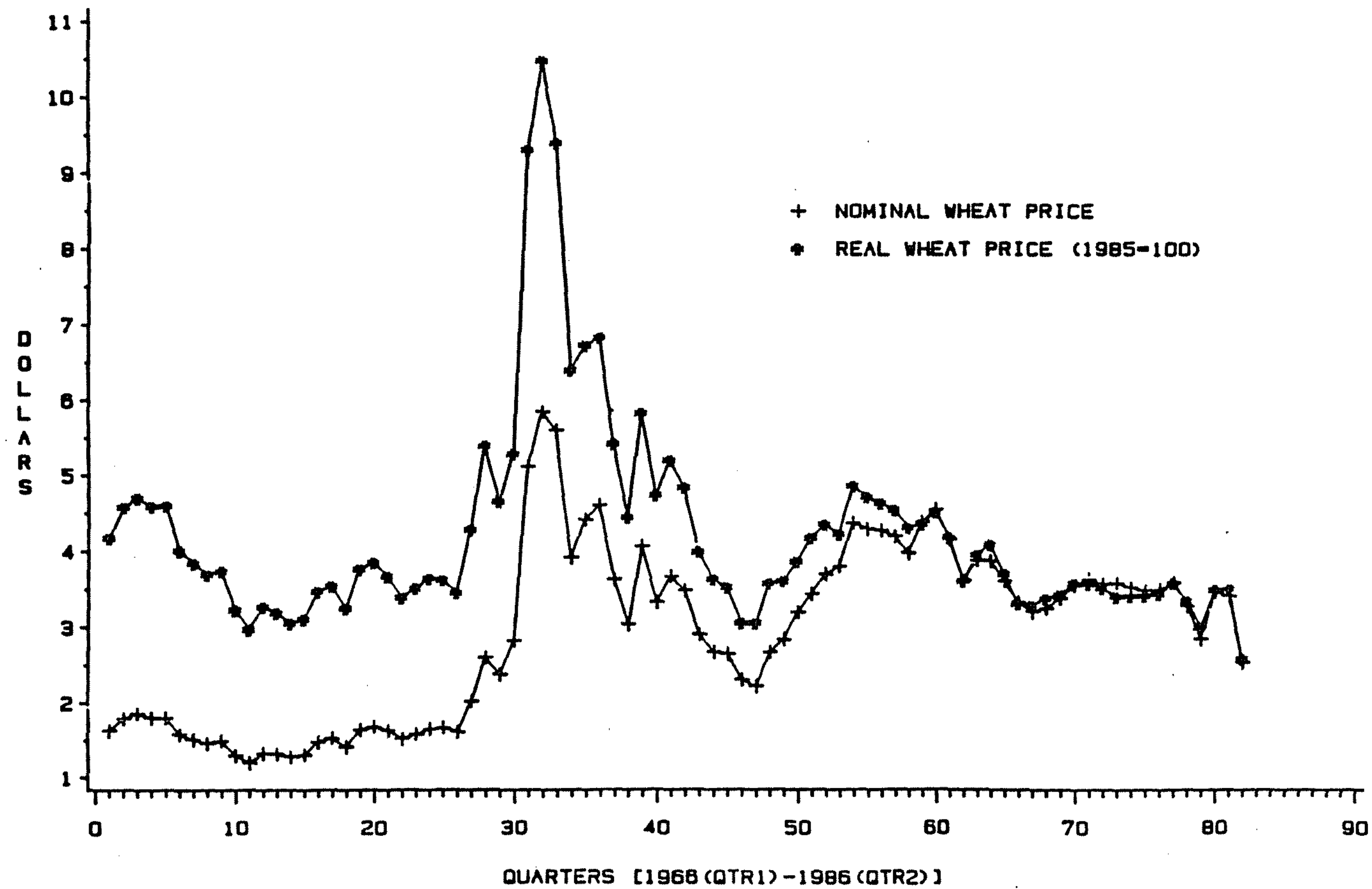


Figure 2. Nominal and Real Cash Soft Red Winter Wheat

the nominal and real data series appear to exhibit some structural variance changes in the quarters of 1973-1974 (specifically the 4th quarter of 1973 and the first two quarters of 1974). At this point it became necessary to choose to work with either the nominal or real price series. Since the futures market's price predictions are made on a nominal basis, the nominal data series were chosen as the appropriate series to work with to create the ARIMA model. The nominal series were then split in half (41 quarters per half) in order to compare the mean and variance of the two halves. The mean of the first half of the data set equals \$2.39, whereas the mean of the second half of the series equals \$3.41. The variance of the first half of the data set is equal to \$1.64 whereas the variance of the second half the the data set equals \$0.35.

The mean and variance statistics indicate a problem with SOS. Box and Jenkins (1976) suggest differencing to deal with problems of this nature, so this is initially the approach taken. The differenced series became constant mean; however, the constant variance problem caused by the 1973-1974 quarters did not improve. In fact, as the degree of differencing increased, the constant variance problem actually worsened. At this point either a time series approach other than ARIMA or a dummying of the problem quarters in 1973 and 1974 became necessary. Visual examination of a quarterly price chart for wheat from 1900 through 1988 indicates that the large variance appearing in the 1973-1974 time frame is an anomaly in this longer (352 quarter) series. Historically, there exists an explanation for the violent price changes of this period. In 1972 the Commodity Credit Corporation (CCC), eager to unload grain stocks in government storage, struck a bargain with drought stricken Russia which completely emptied the CCC stocks of grain (400 million bushels) by 1974. Also, in this time frame, the Organization of Petroleum Exporting Countries (OPEC) embargoed oil, thereby bringing an end to the era of cheap energy. Both these factors contributed strongly to the tremendous price variance experienced in this time period. However, it can be inferred from the 1900-1988 quarterly wheat chart (indicating the 1973-1974 time frame as an anomaly) that both the OPEC oil embargo and the Russian wheat deal were uncommon occurrences and unlikely to reoccur.

Given, then, that the price variance of the fourth quarter of 1973 and of the first and second quarters of 1974 can be described as an abnormality, it seems reasonable and prudent to take the dummying approach to stationarity. A zero/one dummy is regressed as a right-hand side variable where the fourth quarter of 1973 and the first and second quarter of 1974 are dummied out. The dummy variable is included in the difference equation (distributed lag effects) to allow for a gradual timing out of the 1973-1974 variance effects since this better represents the gradual disappearance of the real world market influences occurring during this time frame. The zero/one dummy should effectively compensate for the variance problems of the 1973-1974 period, thereby making an ARIMA representation of this data series possible (DYNREG, a nonlinear least squares algorithm for distributed lag models, is capable of dealing with the slight drift in the data series (Burt et al., 1986).

Because seasonality exists in the quarterly wheat data series, one other modification is made in the basic ARIMA process. The approach taken to this problem is to dummy out the seasonal component. This is a quite straightforward and well accepted procedure for seasonal models (Johnston, 1984). Zero/one dummies are used for the second, third, and fourth quarter of each year which results in the intercept coefficient carrying any seasonality information that is present in the first quarter.

The first ARIMA(p,d,q,) model to be considered is the ARIMA(1,0,0) model (random walk model). Tests of whether markets follow random walk models are Fama (1970) weak form efficiency tests. Model (14) presented the general form (ARIMA(1,0,0)) of a wheat market random walk model. The SOS requirements resulted in the general form having to be modified slightly to deal with the seasonality and variance problems (SOS problems) of our particular data set, i.e. seasonal dummies and a dummy for the fourth quarter of 1973 through the first two quarters of 1974 were added as previously discussed. The result of these modifications on the general random walk model is:

$$(15) \qquad PW_t = \alpha + \beta_1 D2 + \beta_2 D3 + \beta_3 D4 + \beta_4 D73 + \alpha PW_{t-1} + U_t,$$

$$\text{with} \qquad U_t = \varepsilon_t.$$

Where PW_{t-i} is the cash price of number 2 soft red winter wheat in the (t-i)th quarter, D2-D4 are the seasonal dummy variables for the second, third, and fourth quarters of the year respectively, D73 is a dummy variable for the fourth quarter 1973 through second quarter 1974 time period, and U_t is the error structure (MA(0)).

To be a random walk with a drift, the coefficient on the PW_{t-1} term, α, has to be equal to one (the other coefficients will pick up the drift effects); the null hypothesis tested is that β equals 1 versus the alternative hypothesis that β is not equal to 1. The appropriate test is the T test with n-6 degrees of freedom (n is the number of observations).

The empirical results of estimating model (15) are:

$$PW_t = \underset{(2.98)}{.37572} - \underset{(2.26)}{.18374}\,D2 - \underset{(1.07)}{.0010047}\,D3 + \underset{(1.21)}{.097382}\,D4 + \underset{(4.65)}{1.1155}\,D73 + \underset{(21.35)}{.8638}\,PW_{t-1} + U_t, \quad (16)$$

with $U_t = \varepsilon_t$,

$R^2 = .88.$

The null hypothesis that model (16) represents a random walk is tested at the 1 percent level of confidence. The calculated T-statistic to test the significance of the estimated parameter of the lagged price of wheat (PW) regressor is:

$$T_{(.01,76)} = 3.36.$$

At the 1 percent level of significance the hypothesis that the cash wheat market follows a random walk is rejected.

The rejection of the ARIMA(1,0,0) model (random walk with a drift) of the cash wheat market introduces the possibility of other ARIMA(p,d,q) forms better modeling this market. However, before leaving this section on random walk models, it is pertinent that the so-called "simple" random walk model be discussed since the "simple" random walk model of futures markets is quite popular in the efficiency literature.

The general model that represents the "simple" random walk is:

(17) $$PW_t = adj(PW_{t-i}) + U_t.$$

Where PW_{t-i} is wheat price in the (t-i)th quarter, and the (adj) prefix represents adjustments made for predicted inflation.

Model (17) is used to forward predict wheat price (the inflation adjustments, (adj), are acquired by using the ARIMA(1,0,0) PPI model discussed in a following section to obtain one step ahead forecasts of the PPI which are then used to adjust price). Table 1 presents the results of the forward price predictions of the simple random walk model (from first quarter 1982 through second quarter 1986) and the calculated RMSE and bias statistics.

Table 1. Price Predictions with a Random Walk Model

Time Period	Cash Price	Prediction	Residual
1982 I	3.59	3.70	0.11
1982 II	3.31	3.54	0.23
1982 III	3.18	3.35	0.17
1982 IV	3.23	3.12	-0.11
1983 I	3.36	3.14	-0.22
1983 II	3.53	3.34	-0.19
1983 III	3.62	3.54	-0.08
1983 IV	3.55	3.72	0.17
1984 I	3.57	3.64	0.07
1984 II	3.51	3.79	0.28
1984 III	3.47	3.65	0.18
1984 IV	3.49	3.57	0.08
1985 I	3.58	3.58	-0.00
1985 II	3.27	3.60	0.33
1985 III	2.83	3.22	0.39
1985 IV	3.46	2.70	-0.76
1986 I	3.40	3.45	0.05
1986 II	2.52	3.32	0.80

RMSE = .3193952
Bias = 8.220535E-02

When compared to predictions made by the actual Chicago Board of Trade's wheat futures market, the "simple" random walk models predictions don't appear to fare too badly. In fact, the random walk model's predictions had a 32 percent lower bias while only measuring 11 percent higher RMSE. Table 2 presents the wheat futures markets predictions.

Table 2. Predictions made by the Wheat Futures Market

Time Period	Cash Price	Prediction	Residual
1982 I	3.59	4.20	0.61
1982 II	3.31	3.66	0.35
1982 III	3.18	3.58	0.40
1982 IV	3.23	3.47	0.24
1983 I	3.36	3.37	0.01
1983 II	3.53	3.45	-0.08
1983 III	3.62	3.58	-0.04
1983 IV	3.55	3.95	0.40
1984 I	3.57	3.55	-0.02
1984 II	3.51	3.44	-0.07
1984 III	3.47	3.62	0.15
1984 IV	3.49	3.52	0.03
1985 I	3.58	3.47	-0.11
1985 II	3.27	3.36	0.09
1985 III	2.83	3.28	0.45
1985 IV	3.46	2.93	-0.53
1986 I	3.40	3.43	0.03
1986 II	2.52	2.78	0.26

RMSE = .2868507
Bias = .1205556

Graphically, the "simple" random walk model appears to consistently lag behind the market by a small amount (see Figure 3). Since cash wheat price in the time frame examined had about the same amount of up and

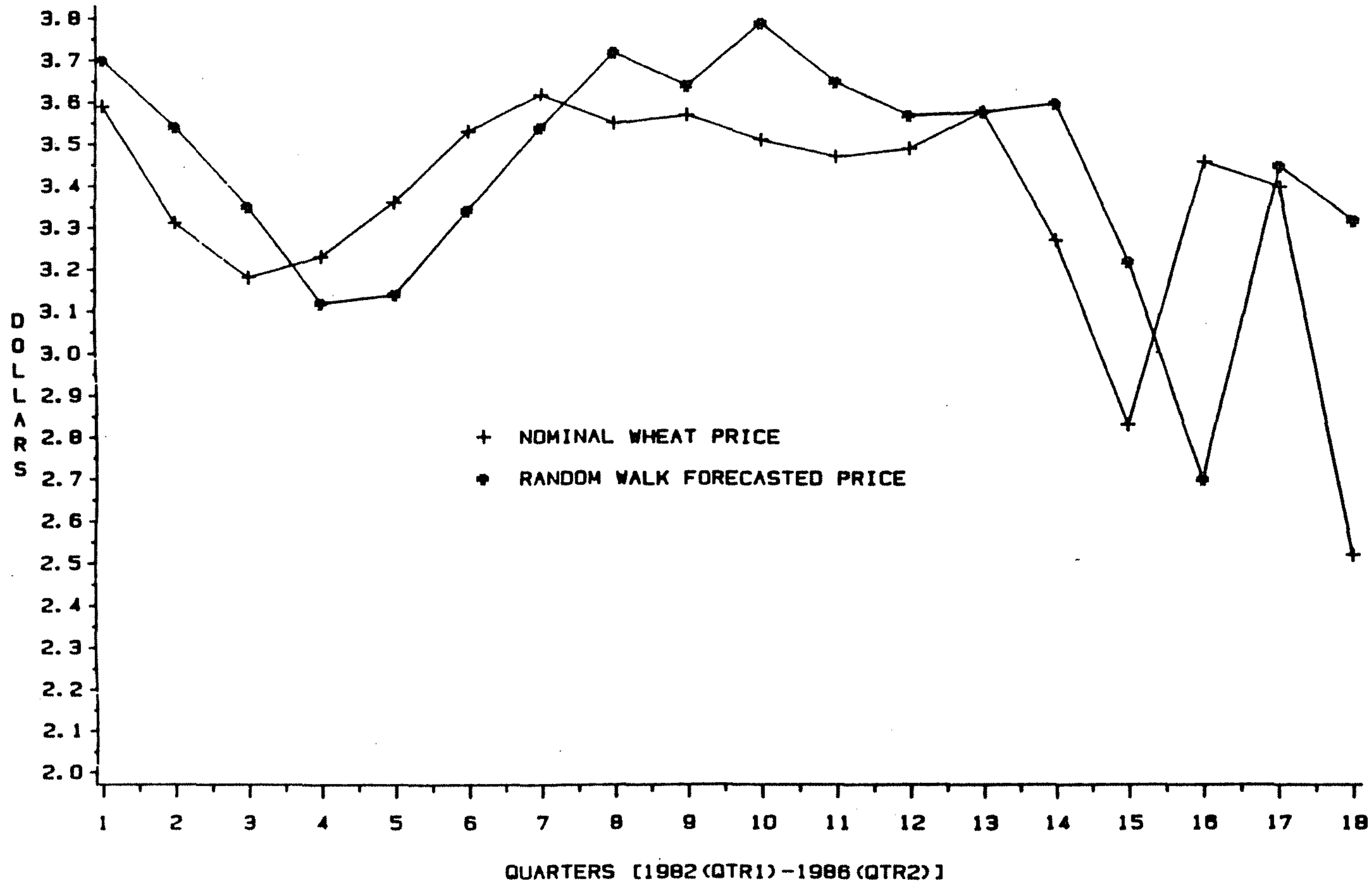


Figure 3. Random Walk Model's Forecast versus Cash Price

down trends, the lower bias of the "simple" random walk model can be explained. The random walk model tends to underestimate an up-trending market and overestimate a down-trending market so, if a time frame where the up-trending period is about equal to the down-trending period is examined, the bias of the random walk model's predictions will be small. The futures market's price predictions didn't appear to lag behind as consistently as the random walk model's price predictions. However, the futures market's price predictions had an occasional extremely large error (see Figure 4).

Since this study did not establish which statistic of comparison is of greater value, any inferences made as to which model is "better" are left to the reader. When comparing these two models it must be kept in mind that only a short prediction period was analyzed, and that there is a definite cost savings in using the futures market to predict price since this eliminates modeling the PPI.

ARIMA(3,0,3) Model Results

Since the ARIMA(1,0,0) model form of the wheat market is rejected, the next step is to identify other ARIMA(p,d,q) model forms that may be more representative of the wheat market. Figures 5 and 6 present the acf and the pacf which are the main tools for identification. The acf rapidly tails off and the pacf cuts off at lag = 3. Thus, at the identification stage, a preliminary model of ARIMA(3,0,0) is indicated. However, this model is rejected at the diagnostic stage because of autocorrelation problems in the residuals. The identification step is returned to, and thus the procedure iterates.

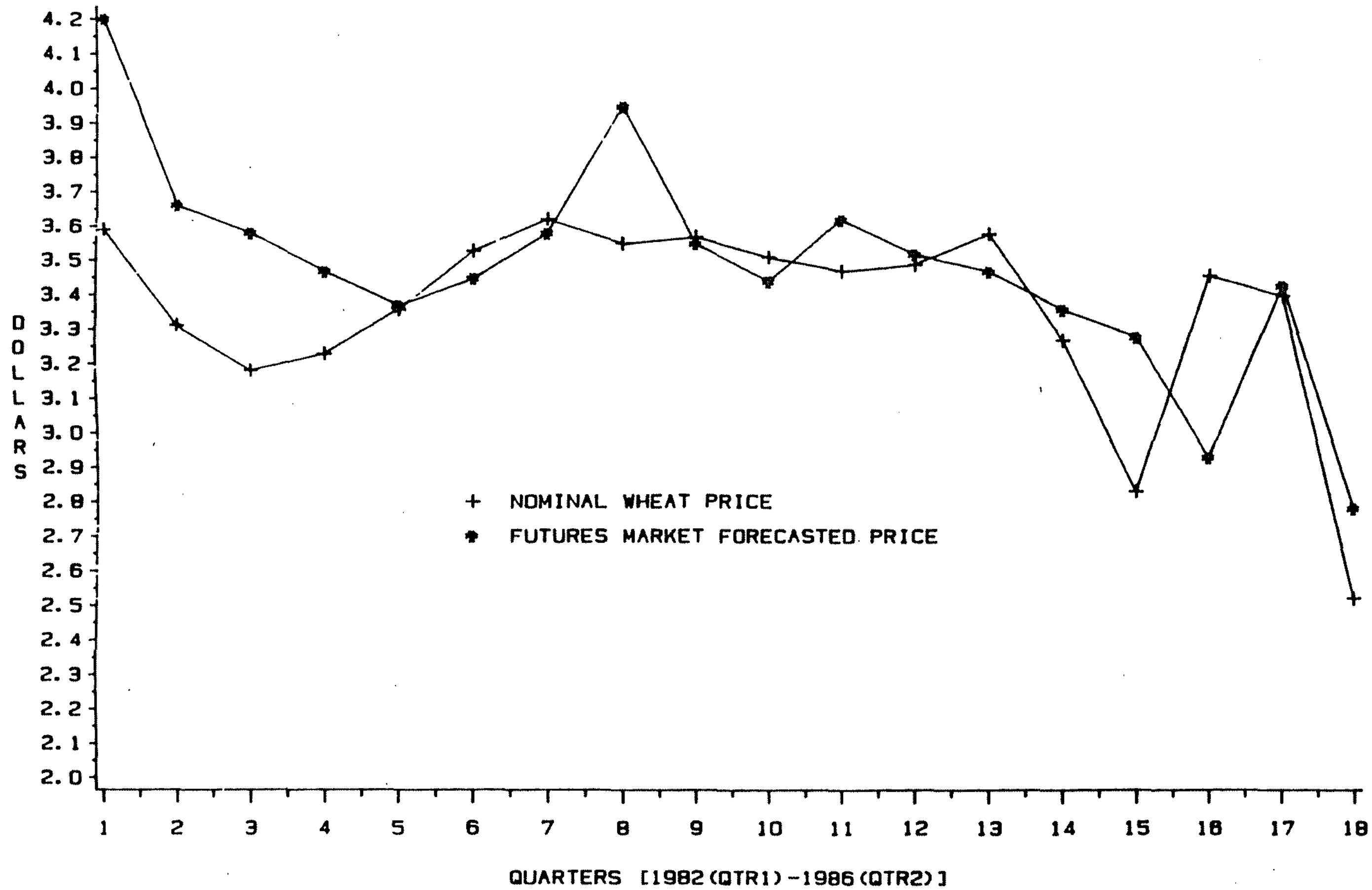


Figure 4. Wheat Futures Market's Forecast versus Cash Price

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LAG COVARIANCE CORRELATION -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0    1.85037    1.00000 |                   |********************|
  1    1.57016    0.84857 |               .   |*****************   |
  2    1.23148    0.66553 |             .     |*************       |
  3    1.05088    0.56793 |            .      |***********         |
  4   0.878363    0.47470 |           .       |*********           |
  5   0.591566    0.31970 |           .       |******  .           |
  6    0.35232    0.19041 |          .        |****     .          |
  7   0.219312    0.11852 |          .        |**       .          |
  8   0.147348    0.07963 |          .        |**       .          |
  9 0.00366617    0.00198 |          .        |         .          |
 10  -0.129182   -0.06981 |          .       *|         .          |
 11   -0.21352   -0.11539 |          .      **|         .          |
 12  -0.294936   -0.15939 |          .     ***|         .          |
 13   -0.38413   -0.20760 |          .    ****|         .          |
 14  -0.445252   -0.24063 |          .   *****|         .          |
 15  -0.444216   -0.24007 |          .   *****|         .          |
 16  -0.426661   -0.23058 |          .   *****|         .          |
 17  -0.423582   -0.22892 |          .   *****|         .          |
 18  -0.391886   -0.21179 |          .    ****|         .          |
 19  -0.317129   -0.17139 |          .     ***|         .          |
 20  -0.272567   -0.14730 |          .     ***|         .          |
 21  -0.249191   -0.13467 |          .     ***|         .          |
 22  -0.184567   -0.09975 |          .      **|         .          |
 23  -0.109745   -0.05931 |          .       *|         .          |
 24 -0.0847079   -0.04578 |          .       *|         .          |
 25 -0.0877323   -0.04741 |          .       *|         .          |
 26 -0.0521646   -0.02819 |          .       *|         .          |
 27 -.00209514   -0.00113 |          .        |         .          |
 28  0.0363057    0.01962 |          .        |         .          |
 29  0.0242609    0.01311 |          .        |         .          |
 30 -0.0328679   -0.01776 |          .        |         .          |
 31 -0.0586484   -0.03170 |          .       *|         .          |
 32 -0.0612425   -0.03310 |          .       *|         .          |
 33   -0.10677   -0.05770 |          .       *|         .          |
 34   -0.17065   -0.09222 |          .      **|         .          |
 35  -0.191801   -0.10366 |          .      **|         .          |
 36  -0.198048   -0.10703 |         .       **|          .         |

'.' Marks Two Standard Errors
```

Figure 5. Autocorrelation Function (ACF) for Cash Wheat

```
LAG CORRELATION -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1    0.84857 |                .   |*****************   |
  2   -0.19483 |               *****|   .                |
  3    0.21715 |                .   |****                |
  4   -0.12950 |                .***|   .                |
  5   -0.21590 |                ****|   .                |
  6    0.03731 |                .   |*  .                |
  7   -0.01012 |                .   |   .                |
  8    0.07198 |                .   |*  .                |
  9   -0.15443 |                .***|   .                |
 10    0.00254 |                .   |   .                |
 11   -0.08264 |                . **|   .                |
 12   -0.08011 |                . **|   .                |
 13    0.00650 |                .   |   .                |
 14   -0.04542 |                .  *|   .                |
 15    0.06273 |                .   |*  .                |
 16   -0.04855 |                .  *|   .                |
 17   -0.01333 |                .   |   .                |
 18    0.01769 |                .   |   .                |
 19    0.00842 |                .   |   .                |
 20   -0.03990 |                .  *|   .                |
 21   -0.00482 |                .   |   .                |
 22    0.06038 |                .   |*  .                |
 23   -0.03827 |                .  *|   .                |
 24   -0.03405 |                .  *|   .                |
 25   -0.03357 |                .  *|   .                |
 26    0.02206 |                .   |   .                |
 27   -0.00280 |                .   |   .                |
 28    0.05123 |                .   |*  .                |
 29   -0.08317 |                . **|   .                |
 30   -0.12814 |                .***|   .                |
 31    0.03920 |                .   |*  .                |
 32   -0.02338 |                .   |   .                |
 33   -0.02867 |                .  *|   .                |
 34   -0.03198 |                .  *|   .                |
 35    0.00039 |                .   |   .                |
 36   -0.04876 |                .  *|   .                |

'.' Marks Two Standard Errors
```

Figure 6. Partial Autocorrelation Function (PACF) for Cash Wheat

The ARIMA(3,0,3) form is accepted as satisfactory for the following reasons: (1) the estimation stage ARIMA criterion appear fulfilled since the coefficients on the AR terms sum to less than one (Pankratz, 1983), and (2) the diagnostic stage is fulfilled because the autocorrelation test on the residuals can't reject the hypothesis that the residuals are uncorrelated. The test used on the residuals is a statistic whose approximate distribution is chi-squared under the null hypothesis that the residual series is white noise (Pankratz, 1983). The exact form of the test used on the residuals is:

$$Q^* = n\,(n + 2)\sum_{j=1}^{k} r^2(j)/(n - j)$$

Where n is the number of observations, r(j) is the estimated autocorrelation at lag j, and k can be any positive integer. Table 3 presents the results of letting k = 6, 12, 18, and 24.

Table 3. Autocorrelation Check of Residuals

To Lag	Chi Square	DF	Prob	<------AUTOCORRELATIONS---------------->					
6	0.00	0	0.000	0.020	0.029	-0.031	0.108	-0.126	0.061
12	5.43	5	0.366	-0.133	0.045	-0.045	0.013	0.031	-0.059
18	8.14	11	0.701	-0.079	-0.128	-0.015	-0.030	0.051	0.019
24	11.49	17	0.830	0.035	0.050	0.097	0.068	0.053	0.093

The general form of the final ARIMA(3,0,3) is:

(18) $$PW_t = \alpha + \gamma_1 D2 + \gamma_2 D3 + \gamma_3 D3 + \gamma_4 D73 + \beta_1 PW_{t-1} + \beta_2 PW_{t-2} + \beta_t PW_{t-3} + U_t,$$

with $$U_t = \varepsilon_t - \lambda_1 \varepsilon_{t-1} - \lambda_2 \varepsilon_{t-2} - \lambda_3 \varepsilon_{t-3}.$$

Where PW_{t-i} is the cash price of wheat in the (t-i)th quarter, D2-D4 are seasonal dummy variables (α contains the information for D1), D73 is a dummy variable for the fourth quarter of 1973 through the second quarter of 1974, and U_t represents the error process (MA(3)). The coefficients to be estimated by regression are α, γ, β, and λ.

A comparison of the price predictions made by the ARIMA(3,0,3) model developed and the wheat futures market's price predictions constitutes a Fama (1970) semi-strong test for market efficiency. The null hypothesis tested is that the wheat futures is efficient, i.e. the wheat futures market has the lowest bias and RMSE forward price forecaster. The alternative hypothesis is that the wheat futures market is not the lowest RMSE and bias forward price predictor.

The general ARIMA(3,0,3) model (18) is estimated over the first quarter 1966 through second quarter 1986 time frame and is then used to recursively forecast the last 18 quarters of this time period. While recursively forecasting, the model structure is observed to see if model structure updating would improve fit since structural updating for best fit is allowable in ARIMA modeling, i.e. this study uses an ARIMA model to forecast price and not to explain structural relationships, thereby making model updating through time to best fit a necessity. The choice of changing ARIMA model structure through time is also consistent with real world behavior since one would expect ARIMA model users to update their model's structure to best fit through time. The empirical results of estimating model (18) over the entire period are:

$$(19)\quad PW_t = \underset{(2.27)}{.47534} - \underset{(3.98)}{.000000127}\ D2 - \underset{(2.39)}{.00000000442}\ D3 + \underset{(1.07)}{.00365}\ D4 +$$

$$\underset{(9.02)}{2.3416}\ D73 + \underset{(6.68)}{.37671}\ PW_{t-1} - \underset{(5.00)}{.28826}\ PW_{t-2} + \underset{(15.55)}{.71819}\ PW_{t-3} + U_t,$$

$$\text{with}\quad U_t = \varepsilon_t - \underset{(4.02)}{.50331}\ \varepsilon_{t-1} - \underset{(11.88)}{1.0459}\ \varepsilon_{t-2} - \underset{(2.85)}{.38171}\ \varepsilon_{t-3},$$

$$R^2 = .94.$$

Where the variables are as defined for model (18).

The coefficients that resulted from this estimation are all statistically significant with the exception of the coefficient on D4. Since this is a seasonal model, D4 is kept in as a regressor. The coefficient estimates and error structure satisfies the ARIMA criteria for a forecasting model, i.e. the coefficients on the AR terms sum to less than one. This suggests stationarity; therefore, the hypothesis that the error structure is uncorrelated can't be rejected (see Table 3 preceding).

Model (19) is then used to recursively forecast 18 quarters. The empirical results of the shortest model (first quarter 1966 through fourth quarter 1981) are:

$$(22)\quad PW_t = \underset{(2.66)}{.43498} - \underset{(3.20)}{.000000129}\ D2 - \underset{(.340)}{.00000000194}\ D3 + \underset{(.644)}{.003885}\ D4 +$$

$$\underset{(8.19)}{2.411}\ D73 + \underset{(4.55)}{.37073}\ PW_{t-1} - \underset{(3.06)}{.28518}\ PW_{t-2} + \underset{(9.08)}{.69436}\ PW_{t-3} + U_t,$$

$$\text{with}\quad U_t = \varepsilon_t - \underset{(1.90)}{.48960}\ \varepsilon_{t-1} - \underset{(6.81)}{1.7131}\ \varepsilon_{t-2} - \underset{(1.40)}{.36785}\ \varepsilon_{t-3},$$

$$R^2 = .98.$$

Where the variables are as defined for model (18).

The coefficients obtained from this estimation are all reasonably significant with the exception of the coefficients on D3, D4, and ε_{t-3}.

The seasonal dummies, D3 and D4, are left in since this is a seasonal model and, while removal of the third order MA lag would be permissible in this situation, doing so proved detrimental to model fit. Since the coefficients on the right-hand side variables appeared to be fairly stable through time, and the model structure did not require updating through time, the indications are that this model fits this time frame fairly well.

Forecasts obtained from using the ARIMA(3,0,3) model to one step ahead predict, along with the summary statistics RMSE and bias, are presented in Table 4. The ARIMA(3,0,3) model's price predictions had a 62 percent smaller RMSE and a 68.5 percent smaller bias than the wheat futures market's price predictions for the first quarter 1982 through second quarter 1986 time frame. This constitutes a Fama (1970) semi-strong rejection of wheat futures market efficiency.

The ARIMA(3,0,3) model's forecasts do appear to lag the actual market price during trends, as did the random walk; however, the size of the lags are quite small, thereby explaining the small RMSE of this model (see Figure 7). Other than this slight lagging problem, the results of using the ARIMA(3,0,3) model for forecasting are quite good. Caution needs to be taken when interpreting these results as they relate to the quality of the ARIMA(3,0,3) model as a forecaster of wheat prices over longer or other time frames since this model was fit for this time period and may not perform as well in other time periods.

A discussion of the potential incremental returns from speculating with this model will be presented in the final section of this chapter.

Table 4. Price Predictions with an ARIMA(3,0,3) Model

Time Period	Cash Price	Prediction	Residual
1982 I	3.59	3.57	-0.02
1982 II	3.31	3.36	0.05
1982 III	3.18	3.24	0.06
1982 IV	3.23	3.16	-0.07
1983 I	3.36	3.24	-0.12
1983 II	3.53	3.36	-0.17
1983 III	3.62	3.54	-0.08
1983 IV	3.55	3.54	-0.01
1984 I	3.57	3.52	-0.05
1984 II	3.51	3.41	-0.10
1984 III	3.47	3.43	-0.04
1984 IV	3.49	3.47	-0.02
1985 I	3.58	3.49	-0.09
1985 II	3.27	3.25	-0.02
1985 III	2.83	3.01	0.18
1985 IV	3.46	3.24	-0.22
1986 I	3.40	3.30	-0.10
1986 II	2.52	2.72	0.20

RMSE = .1092907
Bias = -3.444443E-02

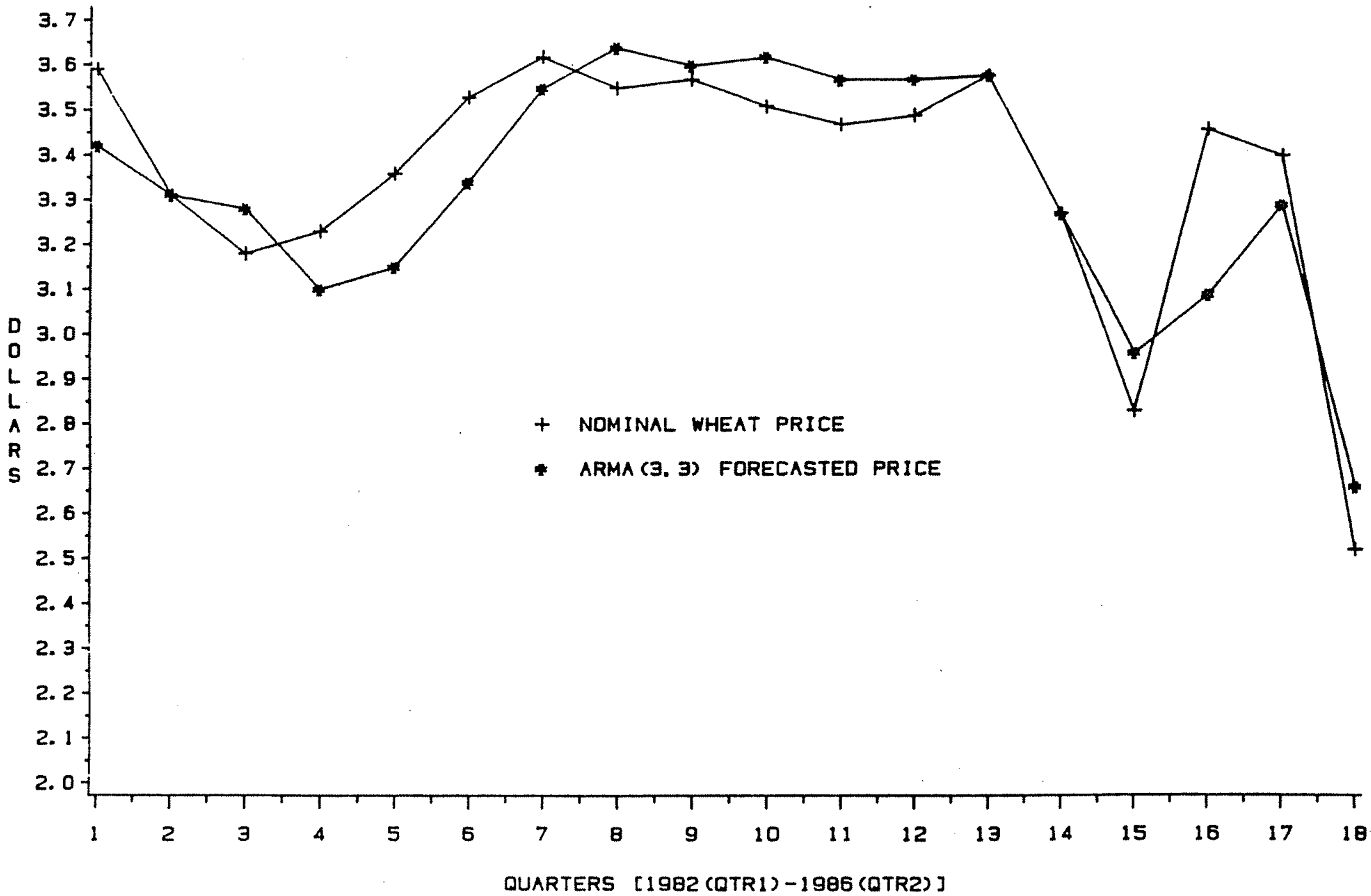

Figure 7. ARIMA(3,0,3) Model's Forecast versus Cash Price

USDA Model Results

The first structural model that this study examined is based upon the general USDA model (11). The term "based upon" means that the same right-hand side variables as those found in model (11) are present in the model that is used for the efficiency test. However, lag lengths on the right-hand side variables and error structure are adjusted to obtain best fit. This is justifiable because the prediction periods and the data series time frame used in this study are different from those used by the USDA studies. Any general postulated cause/effect relationships proposed by the general USDA model (11) will be unaffected by these adjustments; only the lead/lag time relationships and error structure will change (changes are limited to those which improved model fit). The changes made resulted in the following general model form (referred to hereafter as the USDA model):

$$PW_t = \alpha + \beta PW_{t-1} + \sum_{j=1}^{4} c_i D_i (U/S)_{t-1} + U_t , \tag{21}$$

with $$U_t = \varepsilon_t - \lambda_1 \varepsilon_{t-1} .$$

Where PW_{t-i} is the cash price of wheat in the (t-i)th time period, D_i is a dummy variable representing the (i)th quarter (i=1 for the January through March quarter, i=2 for the April through June quarter, etc.), $(U/S)_{t-1}$ is the quarterly use-to-wheat ending stocks ratio lagged 1 time period, and U_t is the error structure (MA(1)).

The first step taken with this model is an attempt to match the USDA's results by estimating the model over the same time period as the one used by Westcott et al (1984), i.e. 1971 through 1983. An exact match is not expected since Westcott et al. (1984) did not identify exactly what wheat series they were working with and it is unlikely that it was number 2 soft red winter wheat nor; did they publish exactly what error structure is used in their model. The model form obtained is:

$$(22)\quad PW_t = \underset{(2.74)}{.619} + \underset{(2.74)}{.400}\, PW_{t-1} + \underset{(2.44)}{3.937}\, D_1(U/S)_{t-1} + \underset{(4.30)}{6.836}\, D_2(U/S)_{t-1} +$$

$$\underset{(3.90)}{7.289}\, D_3(U/S)_{t-1} + \underset{(2.87)}{6.409}\, D_4(U/S)_{t-1} + U_t,$$

with

$$U_t = \varepsilon_t - \underset{(5.17)}{.731}\, \varepsilon_{t-1},$$

$$R^2 = .85.$$

While the coefficients of model (22) don't exactly match those of the USDA model (12), the coefficients of model (22) are significant and the fit is reasonable for a structural model, thereby justifying the relationships proposed by Westcott et al. (1984) for this time frame.

A comparison of the price predictions made by USDA model (21) and price predictions made by the wheat futures market constitutes a Fama (1970) semi-strong test of market efficiency. The null hypothesis is that the wheat futures market is efficient, i.e. the lowest RMSE and bias forward price prediction available is made by the wheat futures market. The alternative hypothesis is that the wheat futures market is not efficient, i.e. the lowest RMSE and bias forward price predictor is not the wheat futures market.

USDA model (21) is estimated over the first quarter 1966 through 2nd quarter 1986 time frame and then used to recursively forecast 18 quarters in order to obtain forward price predictions (real values). Since these predictions are in real values they have to be changed, using the predicted PPI, to nominal values. As this model is based upon proposed relationships among variables, no structural updating through time is considered. The empirical results of estimating model (21) are:

$$\begin{aligned}(23)\qquad PW_t = {} & \underset{(1.90)}{.68055} - \underset{(.1387)}{.11830}\, D1(U/S)_{t-1} + \underset{(2.248)}{1.7466}\, D2(U/S)_{t-1} + \\ & \underset{(1.75)}{1.5797}\, D3(U/S)_{t-1} + \underset{(.655)}{.77304}\, D4(U/S)_{t-1} + \underset{(7.87)}{.75023}\, PW_{t-1} + U_t ,\end{aligned}$$

with $$U_t = \varepsilon_t - \underset{(3.94)}{.46252}\, \varepsilon_{t-1} ,$$

$$R^2 = .82.$$

Where the variables are as defined for model (21).

The coefficients obtained from estimating this model are very disappointing. Only two of the right hand-side variables, PW_{t-1} and $D2(U/S)_{t-1}$, have coefficients that are statistically significant. The low significance of the coefficients is reflected in the marginal model fit as defined by the R^2 statistic. Clearly the extended time frame of first quarter 1966 through second quarter 1986 is not modeled as well by this structural model as is the shorter time frame of first quarter 1971 through first quarter 1983. This indicates that the relationships (model (21)) proposed by Westcott et al. (1984) may be a function of the period of time for which the market is examined. However, since this model is one that USDA publications present as representative of the wheat market, it is used to forecast wheat price. Table 5 presents the results of this forecast (predictions have been converted to nominal values).

Table 5. Price Predictions with Model (23)

Time Period	Cash Price	Prediction	Residual
1982 I	3.59	3.72	0.13
1982 II	3.31	3.26	-0.05
1982 III	3.18	3.86	0.68
1982 IV	3.23	3.39	0.16
1983 I	3.36	3.25	-0.11
1983 II	3.53	3.23	-0.30
1983 III	3.62	3.96	0.34
1983 IV	3.55	3.84	0.29
1984 I	3.57	3.49	-0.08
1984 II	3.51	3.41	-0.10
1984 III	3.47	3.97	0.50
1984 IV	3.49	3.90	0.41
1985 I	3.58	3.39	-0.19
1985 II	3.27	3.52	0.25
1985 III	2.83	3.39	0.56
1985 IV	3.46	3.05	-0.41
1986 I	3.40	3.58	0.18
1986 II	2.52	3.17	0.65

RMSE = .3559516
Bias = .1621556

Model (23)'s price predictions have a 24 percent larger RMSE and a 35 percent larger bias than the wheat futures market's price predictions; therefore, this model cannot reject the null hypothesis that the wheat futures market is efficient. Examination of the price predictions made by model (23) reveal large swings in the predicted price, thereby indicating model instability (see Figure 8). While this model may have adequately explained the first quarter 1971 through first quarter 1983 time frame, it certainly can't be advocated for the first quarter 1966 through second quarter 1986 time frame.

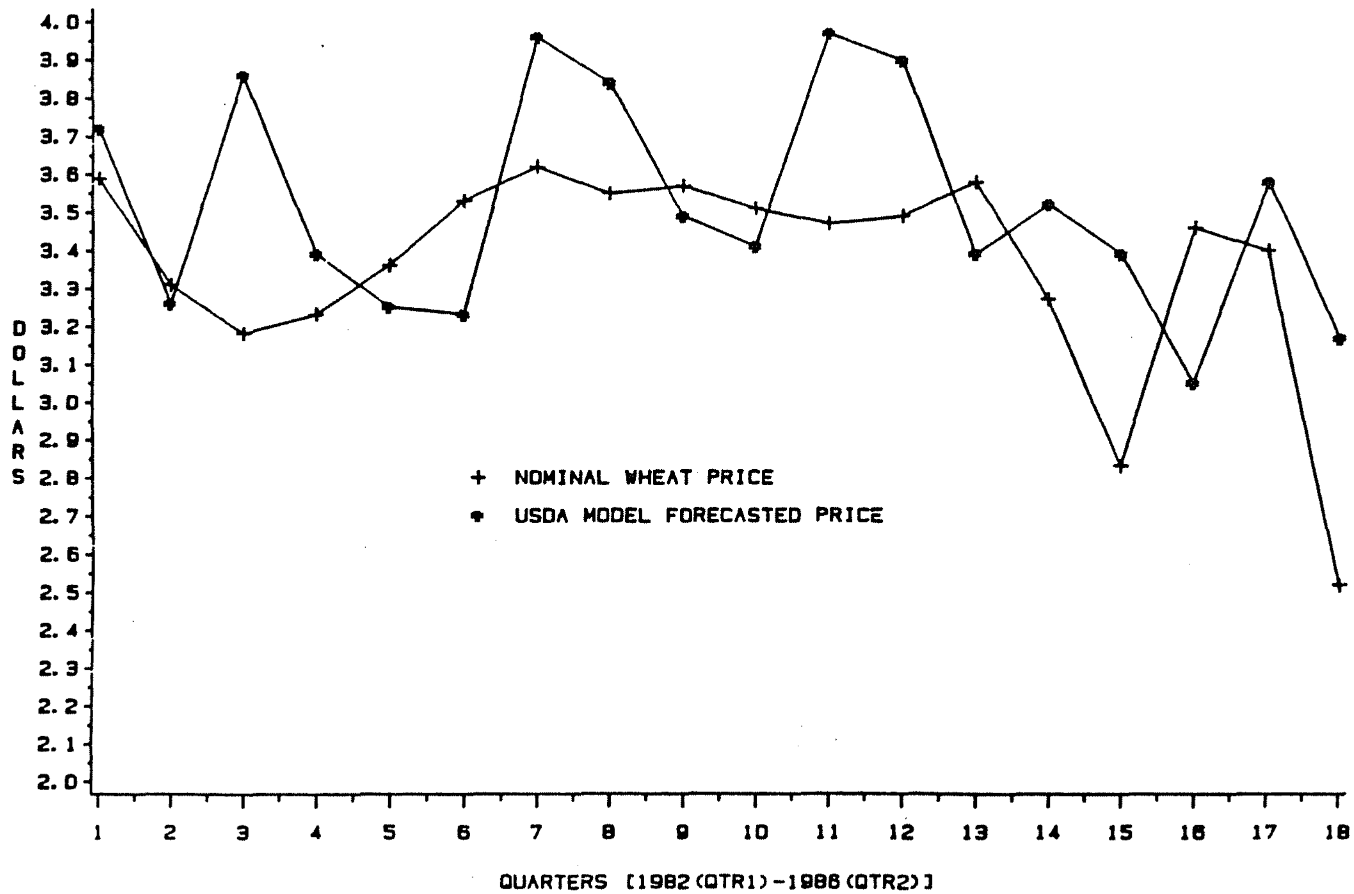

Figure 8. USDA Model's Forecast versus Cash Price

Market Trader's Model Results

The next structural model is "based upon" model (13). The term "based upon" is defined as discussed earlier. The exact model form obtained after adjustments is (referred to hereafter as the market trader's model):

$$PW_t = \alpha + \beta D_2 + \beta D_3 + \beta D_4 + \beta D73 + \alpha_1 (U4/S)_{t-1} + \alpha_2 (U4/S) + \delta_1 (PW/PC)_{t-1} + U_t, \tag{24}$$

with $$U_t = \varepsilon_t - \lambda_1 \varepsilon_{t-1} - \lambda_2 \varepsilon_{t-2} - \lambda_3 \varepsilon_{t-3}.$$

Where PW_t is the price of wheat in time period t, α is the intercept term (contains the seasonal effects of quarter 1), D_i is a seasonal dummy representing the (i)th quarter (i=1 represents January through March, i=2 represents April through June, etc.), D73 is a dummy variable for the 1973 through 1974 time frame, $(U4/S)_{t-1}$ is a variable representing the ratio in time period t-1 of the four quarter moving average total wheat use to total wheat ending stocks , $(PW/PC)_{t-1}$ is a variable representing the ratio in time period t-1 of cash white wheat to cash corn (corn and wheat price are deflated by the PPI), and U_t represents the error structure(MA(3)).

A comparison of the results of price predicting with market trader's model (24) and price predicting with the wheat futures market represents a Fama (1970) semi-strong test of market efficiency. Again, the null hypothesis is that the wheat futures market is efficient, i.e. the wheat futures market has the smallest RMSE and bias price forecaster versus the alternative hypothesis that the wheat market is inefficient, i.e. not the smallest RMSE and bias price forecaster.

Market trader's model (24) is estimated over the first quarter 1966 through second quarter 1986 time frame and then used to recursively forecast 18 quarters in order to obtain real price predictions. Again, these real price predictions are converted to nominal values using the predicted PPI values. Structural updating over time isn't considered for this model since it was designed to represent a relationship among variables. The empirical results of estimating this model are:

$$
\begin{aligned}
(25)\quad PW_t &= \underset{(3.05)}{1.7231} - \underset{(2.65)}{.39668}\, D2 - \underset{(2.66)}{.58775}\, D3 - \underset{(.247)}{.056751}\, D4 + \underset{(9.18)}{4.0399}\, D73 \; + \\
&\quad \underset{(4.01)}{1.7048}\, (U4/S)_{t-1} + \underset{(3.06)}{1.3028}\, (U4/S)_{t-2} + \underset{(2.70)}{.99146}\, (PW/PC)_{t-1} + U_t ,
\end{aligned}
$$

$$
\text{with} \qquad U_t = \varepsilon_t - \underset{(3.36)}{.44048}\, \varepsilon_{t-1} - \underset{(2.70)}{.33002}\, \varepsilon_{t-2} ,
$$

$$
R^2 = .90.
$$

Where the variables are as defined for model (24).

The coefficients on this model are all significant with the exception of the coefficient on seasonal dummy D4. This structural model appears to be much more structurally sound than the previous structural model (model (23)); model (25) fits this wheat data set and time frame relatively well as is indicated by the R^2 statistic, thereby suggesting that the variable relationships proposed by Schwager (1984) are fairly sound, at least for the period examined by this study. Table 6 presents the one step ahead forecasts obtained by recursively forecasting with model (25) and then converting the real price values to nominal values. The summary statistics, RMSE and bias, are also presented in Table 6.

Table 6. Price Predictions with the Market Trader's Model

Time Period	Cash Price	Prediction	Residual
1982 I	3.59	3.98	0.39
1982 II	3.31	3.63	0.32
1982 III	3.18	3.67	0.49
1982 IV	3.23	3.71	0.48
1983 I	3.36	3.50	0.14
1983 II	3.53	3.35	-0.18
1983 III	3.62	3.59	-0.03
1983 IV	3.55	3.96	0.41
1984 I	3.57	3.64	0.07
1984 II	3.51	3.57	0.06
1984 III	3.47	3.64	0.17
1984 IV	3.49	3.96	0.47
1985 I	3.58	3.87	0.29
1985 II	3.27	3.60	0.33
1985 III	2.83	3.43	0.60
1985 IV	3.46	3.28	-0.18
1986 I	3.40	3.67	0.27
1986 II	2.52	3.28	0.76

RMSE = .3677189
Bias = .2686888

Model (25)'s price predictions have a 28 percent larger RMSE and a 123 percent larger bias than price predictions made by the wheat futures market. Model (25)'s performance is not good enough to reject the hypothesis that the wheat futures market is efficient. Model (25), the market trader's model, is by far the worst biased model of the group examined since it consistently overestimated market wheat price (see Figure 9). In fact, out of 18 quarters of price predictions, model (25) only underestimated market price three times. Clearly, model (25) isn't a good choice for use as a price prediction model.

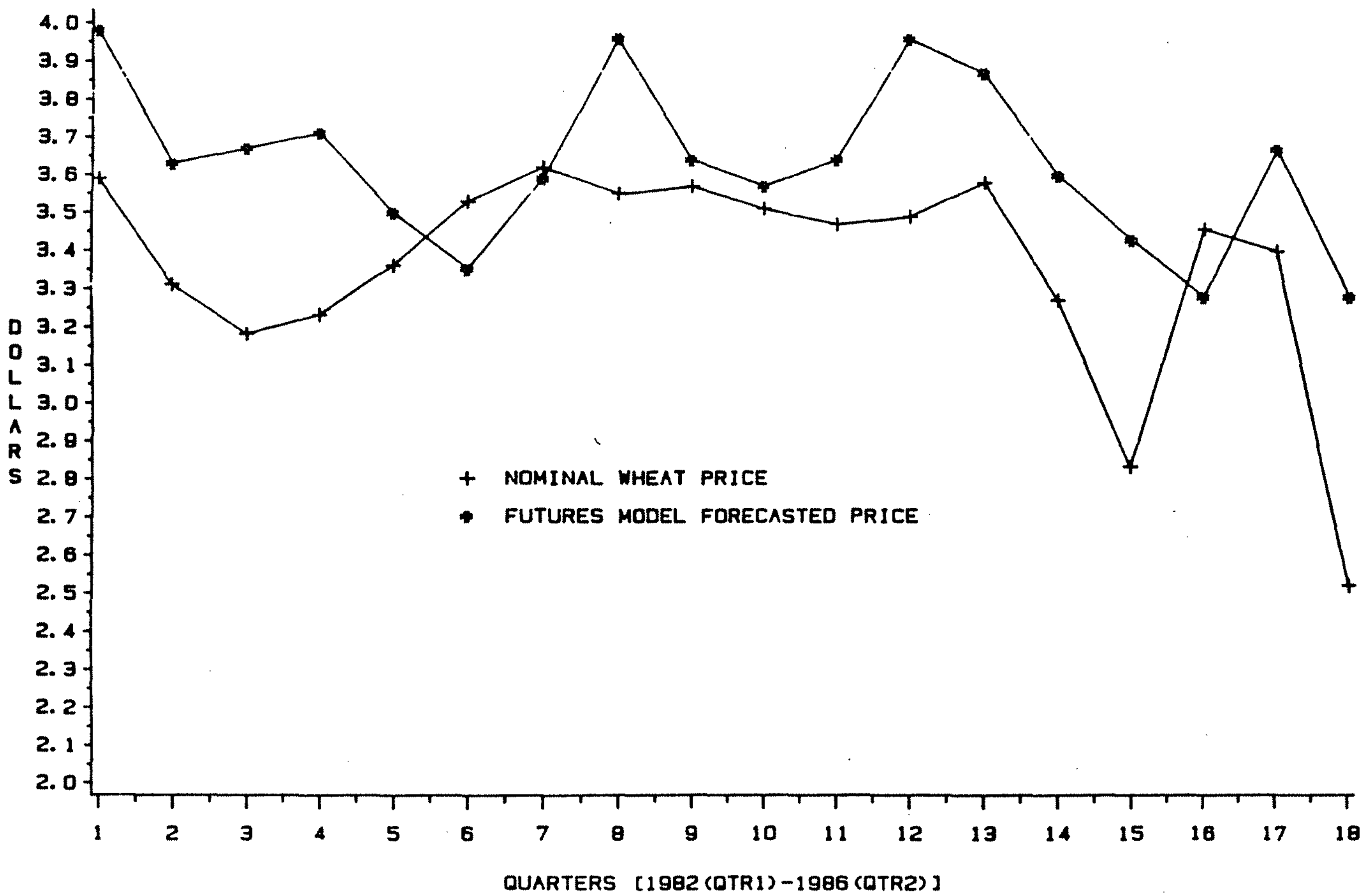

Figure 9. Market Traders Model's Forecast versus Cash Price

Predicting the PPI

An ARIMA approach is taken to build a model that would yield one step ahead forecast of the PPI. The actual PPI data series used to deflate the price variables in the structural models (23) and (25) is subjected to ARIMA modeling techniques. The result of this process is an ARIMA(1,0,0) model of the PPI. (Again the statistical package DYNREG is able to handle the slight trend in the data thereby, negating the need to difference.) This model form defines the PPI data series as a random walk with a positive drift of about 3.5 percent per year. The fact that the PPI series turned out to be a random walk is encouraging because deflating price data series with this PPI series doesn't introduce new serial correlation problems. The general model form is:

(26) $$PPI_t = \alpha + \beta\ PPI_{t-1} + U_t,$$

with $$U_t = \varepsilon_t.$$

Where PPI_{t-i} is the PPI in the (t-i)th time frame, and U_t is the error process (MA(0)).

This model is estimated over the 1966 through 2nd quarter 1986 time frame. PPI predictions are obtained from this model by recursively forecasting 18 quarters. These forecasted values are the ones that will be used to convert to nominal price predictions the real price predictions made by the structural models examined. The exact model form obtained from the estimation is:

(27) $$PPI_t = \underset{(1.80)}{.012949} + \underset{(103.51)}{.99243}\ PPI_{t-1} + U_t,$$

with $$U_t = \varepsilon_t.$$

Table 7 presents the predictions generated by this model.

Table 7. PPI Predictions with a Random Walk Model

Time Period	Actual PPI	Prediction
1982 I	97.21	95.80
1982 II	100.27	98.47
1982 III	97.21	101.29
1982 IV	96.15	98.12
1983 I	98.43	97.12
1983 II	99.18	99.39
1983 III	101.77	100.22
1983 IV	101.30	102.74
1984 I	105.22	102.41
1984 II	103.22	106.19
1984 III	101.96	104.08
1984 IV	101.81	102.78
1985 I	100.00	102.52
1985 II	97.84	100.62
1985 III	94.62	98.34
1985 IV	99.21	95.26
1986 I	97.13	99.74
1986 II	98.11	97.69

Utilizing the ARIMA(3,0,3) Model

The ARIMA(3,0,3) model's forecasts succeeded in obtaining a Fama (1970) semi-strong form rejection of market efficiency. However, as pointed out by Rausser and Carter (1983), this represents only the necessary conditions for general market efficiency rejection. To meet the sufficiency requirements for efficiency rejection, the cost of constructing and utilizing the ARIMA(3,0,3) must not exceed the incremental risk adjusted benefits. This section will attempt to quantify some of the costs of building and utilizing this model. A discussion of returns to price speculating with this model will also be presented; however, risk adjustment of the returns is left to the reader.

Since wheat price data and ARIMA procedures are quite straightforward, an ARIMA(3,0,3) model is relatively inexpensive to build. Computer charges for the time spent estimating and reestimating this model are approximately $500 and the opportunity cost of the time spent building this model is estimated at $1000. The marginal cost of running the ARIMA(3,0,3) model once it is constructed is so close to zero that it is assumed to be zero. Therefore, the total cost of building and running this model is estimated to be $1500.

The next step is to determine how much money would have to be invested to utilize this model's price predictions. The minimum margin requirement to trade one wheat contract (5000 bushels) at a brokerage house is approximately $750. However, an adverse price movement of more than $.05 would result in margin calls, i.e. more money would be required than $750 to hold the average contract one quarter. Since one contract of wheat is worth approximately $15,000 and the maximum cash wheat price change for any given quarter in the first quarter 1982 to second quarter 1986 time period was $.88 ($4400), an initial margin amount of $5000 is deemed sufficient.

The total cost of building and opening an account to operate this model sums to $6500. This model would have been utilized four and one-half years if the test prediction period is matched. The "safe" alternative for this $6500 would be to invest it in a bank CD for the four year period. If this were done with a 10 percent interest rate, the amount in the account at the end of four and one half years would be $9981.15.

Assume, that now, rather than investing the money in a CD, the ARIMA(3,0,3) model is built to be used as a price speculation tool for the first quarter 1982 through second quarter 1986 test period. The trading rule that will be followed with one wheat contract per quarter (18 trades) will be: If, in quarter t, the ARIMA(3,0,3) model's price prediction for quarter t+1 is greater than the wheat futures market's t+1 price prediction, then one (long) wheat futures contract with t+1 maturity will be purchased , i.e. a "long" position will be established and held until contract maturity is reached. If, instead, the ARIMA(3,0,3) model's price prediction for quarter t+1 is less than the wheat futures market's price prediction for t+1, then one (short) wheat futures contract with t+1 maturity will be purchased, i.e. a "short" position will be established and held until contract maturity is reached. Table 8 presents the quarterly breakdown of earnings and losses that are obtained from following this rule.

The gross return for trading this model is $17,250. If a commission of $70 per trade is charged, then the gross return is recalculated at $15,990.00. Assuming that no interest is paid on the brokerage house's accounts and that no money is removed from the account to be invested elsewhere, the total brokerage account dollar value at the end of the trading period would be $20,9900 (including the original amount invested).

It is pertinent to note at this point that the previous assumptions are quite restrictive, but the intent was to assume the worst possible investment scenario. In reality, most brokerage accounts pay interest, and, even if the brokerage account did not pay interest, any money above margin could be removed from the brokerage firm and placed in an interest bearing account. There also existed the possibility of increasing the number of contracts traded per quarter as the account value grew, thereby increasing returns.

Table 8. Returns to Market Price Speculation Using the ARIMA(3,0,3) Model

Time Period	Cash Price	ARIMA(3,0,3) Model's Prediction	Futures Market's Prediction	Position Established	Return
1982 I	3.59	3.57	4.20	S	3050.00
1982 II	3.31	3.36	3.66	S	1750.00
1982 III	3.18	3.24	3.58	S	2000.00
1982 IV	3.23	3.16	3.47	S	1200.00
1983 I	3.36	3.24	3.37	S	50.00
1983 II	3.53	3.36	3.45	S	- 400.00
1983 III	3.62	3.54	3.58	S	- 200.00
1983 IV	3.55	3.54	3.95	S	2000.00
1984 I	3.57	3.52	3.55	S	- 100.00
1984 II	3.51	3.41	3.44	S	- 350.00
1984 III	3.47	3.43	3.62	S	750.00
1984 IV	3.49	3.47	3.52	S	150.00
1985 I	3.58	3.49	3.47	L	550.00
1985 II	3.27	3.25	3.36	S	450.00
1985 III	2.83	3.01	3.28	S	2250.00
1985 IV	3.46	3.24	2.93	L	2650.00
1986 I	3.40	3.30	3.43	S	150.00
1986 II	2.52	2.72	2.78	S	1300.00

The resulting return to speculation is 19.5 percent per year even with the restrictive approach taken. Clearly there now needs to be a risk adjustment made to compensate for the fact that using an ARIMA model to trade is quite risky. As to the exact extent of the risk adjustment, no comments will be made since risk adjustment is a subject of personal judgment. If the risk adjustment is large enough that the real return after risk adjustment to speculation is less than 10 percent, then sufficiency criterion for efficiency rejection will not be met; however, if a risk adjusted return of greater than 10 percent is obtained, then sufficiency criterion for market efficiency rejection will be met. No matter what the conclusion is on the sufficiency criterion requirements, it must be remembered that this conclusion may only be valid for the time period examined by this study.

Another common approach taken in the literature to examine potential above average returns to a trading rule is to compare the returns generated by using the trading rule to naive buy and hold strategies. Following a naive buy and hold strategy for this 18 quarter time period results in a $10,850 loss. With a commission charge of $70 per trade, this loss become $12,110. Clearly, for this time period, the ARIMA(3,0,3) model's speculative approach is superior to a naive buy and hold strategy. However, the relatively poor performance of the buy and hold strategy can at least partially be explained by the fact that the wheat market's general overall trend was down in the period examined. If, instead, a naive sell and hold strategy is followed, the resulting return would be exactly opposite, i.e. a $10,850 profit is generated by a naive sell and hold strategy (with commission this is a $9590).

No matter which naive strategy is followed, the speculative return from using the ARIMA(3,0,3) is still superior. This indicates that the ARIMA model is capturing some relevant information which allowed for better than naive performance. These results fit into the framework of a Fama (1970) semi-strong market efficiency rejection; however, the problem of different risks for different strategies again prevents a judgment of whether sufficiency criteria for efficiency rejection are met.

The general conclusion of this empirics chapter is that only one model, the ARIMA(3,0,3), fully met the criteria for a Fama (1970) rejection of market efficiency. As for whether this model meets sufficiency criteria for efficiency rejection, only conditional conclusions can be made because of the problems with ranking risk.

CHAPTER 4

SUMMARY AND CONCLUSIONS

This chapter is broken into three sections. The first section briefly summarizes the steps undertaken by this study. The second section discusses any conclusions made from the results obtained by this study. The third section presents some suggestions for further research.

Summary

Futures market efficiency is of concern to both market traders and non-market participants since it relates the performance of a market in allocating resources through time. A problem exists in testing for market efficiency because the precise criteria for defining exactly what characteristics are consistent with market efficiency are obtuse, i.e. the tests taken for market efficiency are often limited to testing only one particular definition of efficiency and have little meaning beyond the particular definition chosen. In this study, the Chicago Board of Trade's wheat futures market was examined to see if the hypothesis of market efficiency, as defined by Fama (1970), could be rejected. The Fama (1970) approach to efficiency was taken because of its popularity in the relevant literature and because of its concisely defined tests.

The first step of this study was to determine if the quarterly cash wheat market followed a random walk model. The rejection of the hypothesis that the cash wheat market follows a random walk provided a Fama (1970) weak form rejection of market efficiency and indicated the possibility of developing an ARIMA model other than the ARIMA(1,0,0) model to forward predict price.

The subsequent steps that were taken in this study all find their basis in the concept that, if a forward price predicting model is shown to forecast future price "better" than the relevant futures market, then this constitutes a Fama (1970) semi-strong market efficiency rejection. The models that were used in this study were either built through ARIMA modeling procedures or selected from publicly available literature.

Box and Jenkin's (1976) ARIMA(p,d,q) modeling procedures were followed to create an ARIMA(3,0,3) model of the quarterly cash price wheat market. The ARIMA(3,0,3) model was used to one step ahead forecast wheat prices for the first quarter 1982 through second quarter 1986 time frame. The price forecasts obtained were compared, on the basis of RMSE and bias, to price predictions made by the Chicago Board of Trade's wheat futures market. A Fama (1970) semi-strong rejection of market efficiency was obtained on the basis of these comparisons.

Two other forward wheat price predicting models were chosen from the relevant literature in order to compare, on the basis of RMSE and bias, their forward price predictions to the Chicago Board of Trade's wheat futures markets forward price predictions. Although both models enjoy some popularity in the literature, neither was able to reject the hypothesis that the Chicago Board of Trade's wheat future's market is efficient. This can be partially explained by the fact that the creators of these models were probably as concerned with explaining market structural relationships as they were with forward price prediction.

Since Fama's 1970 work on efficiency is dated, this study undertook a final step to see if any conclusions on a later definition of efficiency could be obtained, i.e. a Fama (1970) rejection of efficiency represented only the rejection of the necessary conditions for efficiency rejection, and is not sufficient for a general rejection of market efficiency. To meet the sufficiency criteria for market efficiency rejection, costs and risk have to be accounted for. As a result, this study simulated price speculation with the ARIMA(3,0,3) model for the first quarter 1982 through second quarter 1986 time frame.

A 19.5 percent after cost rate of return was obtained by the ARIMA(3,0,3) for this time period. There is, however, a certain amount of risk involved in using an ARIMA model to forecast price, and the level of risk in using an ARIMA model to forecast price cannot be assumed equal to the level of risk faced by users of the futures market. As a result, the returns generated by the ARIMA(3,0,3) model need to be adjusted for risk before they are compared to returns generated by "safe" investments such as CDs. However, this study did not determine a satisfactory way to adjust for risk that would reflect individual risk preferences and the risk of using ARIMA models to forecast price. Not adjusting for risk made impossible any conclusions concerning whether or not the sufficient conditions for market efficiency rejection, as defined by Rausser and Carter (1983), were met.

Conclusions

Since efficiency studies are based only on a particular definition and/or test of efficiency, any general conclusions reached will be subject to limitations. This results in the tendency of rejecting the hypothesis of market efficiency when, in fact, the market may really be "efficient." As a result of the previously stated problems, implications of the wheat market efficiency rejection that will be subsequently presented are limited, and should not be inferred to imply more than the fact that a potental problem may exist.

For the first quarter 1982 through second quarter 1986 time period this study was able to reject the hypothesis of market efficiency. This implies that some objectionable resource allocations may have been present during this time frame. For example, farmers who based planting decisions on the Chicago Board of Trade's forecast of future wheat price could potentially have been misallocating too many resources to wheat production, i.e. the $.12 positive bias found to exist in the wheat future's market throughout this time period may have caused too many resources to be allocated to wheat production. The large RMSE of the Chicago Board of Trade's wheat futures market (relative to the ARIMA(3,0,3) model's RMSE) also indicates that the through time resource allocations initiated because of the forward price predictions of the futures market were consistently more inaccurate than resource allocations based upon the price predictions of the ARIMA(3,0,3) model would have been.

As to whether the resource misallocations that are potentially indicated by this study are just a function of the type of tests used or the time period examined, little can be said. Information is costly and price speculation is risky, so perhaps no objectionable inaccuracies exist. The wheat futures markets have, for approximately 100 years, provided a forward forecast of price at low cost to the user, and cannot be assigned the label of "inefficient" without a great deal more proof than was presented here. This study claims only to have rejected the Fama (1970) definition of efficiency, thereby indicating the slight probability that objectionable inaccuracies do exist in the wheat futures market.

Further Research

Even though the very definition of the word efficiency is obtuse to economists, the analysis of futures markets on the basis of variance and bias offers important contributions as to how well resources are being allocated. This study looked at but one futures market and one forecast length. There exist many markets and many forecast lengths that could benefit from some examination as long as the results from the examinations are taken at face value and not used to infer too much.

Some specific research that this author would like to see undertaken includes: (1) extension of the length of the forward price predictions of the wheat market to see at which forecast length the lagged price terms quit revealing market stickiness, i.e. finding what forecast length could be appropriately represented with a random walk model; (2) tests to see if any significance can be placed on price chart pattern formations that are advocated by technical market analysts as price prediction tools; (3) development of a test for efficiency that takes into account the risks of using trading rules to speculate and thereby allows an accurate measurement of the risk adjusted return received by speculators; and (4) measurements based on actual trading records of whether speculators, as a group or individually, can forecast price. If speculators are shown to be unable to forecast price and hence earn below average returns, then research needs to be done to explain why "rational" individuals chose to participate in a consistently losing endeavor.

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APPENDIX

Table 9. Original Data Set

Date	PPI	Cash Wheat	Total Use	Ending Stocks	Moving Average Use	Cash Corn
1966 I	39.04	1.63	419.00	917.30	000.00	1.19
1966 II	39.12	1.79	382.40	535.20	000.00	1.20
1966 III	39.55	1.86	411.40	1435.60	000.00	1.32
1966 IV	39.20	1.80	387.60	1049.10	400.10	1.28
1967 I	39.12	1.80	349.20	700.10	382.56	1.27
1967 II	39.36	1.58	275.40	425.00	355.90	1.26
1967 III	39.32	1.51	388.20	1559.30	350.10	1.15
1967 IV	39.55	1.46	347.40	1212.10	340.05	1.02
1968 I	40.06	1.50	372.90	839.50	345.98	1.06
1968 II	40.26	1.30	300.40	539.40	352.22	1.07
1968 III	40.38	1.20	430.90	1684.90	362.90	1.01
1968 IV	40.65	1.33	339.40	1345.70	360.90	1.02
1969 I	41.36	1.32	233.60	1112.40	326.07	1.09
1969 II	41.91	1.28	294.20	818.60	324.53	1.16
1969 III	42.07	1.31	403.90	1875.20	317.78	1.17
1969 IV	42.62	1.48	341.70	1534.50	318.35	1.09
1970 I	43.17	1.53	337.60	1197.70	344.35	1.13
1970 II	43.32	1.41	314.10	884.70	349.33	1.18
1970 III	43.60	1.64	870.80	1731.60	466.05	1.30
1970 IV	43.60	1.68	378.70	1410.00	475.30	1.33
1971 I	44.38	1.63	349.90	1060.40	478.38	1.43
1971 II	44.89	1.52	237.90	822.80	459.32	1.41
1971 III	44.97	1.58	568.10	1873.80	383.65	1.22
1971 IV	45.33	1.65	326.30	1547.60	370.55	1.02
1972 I	46.11	1.67	337.30	1210.70	367.40	1.09
1972 II	46.66	1.61	227.50	983.40	364.80	1.14
1972 III	47.21	2.02	659.10	1870.90	387.55	1.16
1972 IV	48.27	2.60	472.20	1399.00	424.02	1.27
1973 I	50.98	2.37	472.10	927.30	457.72	1.37
1973 II	53.42	2.82	330.40	597.10	483.45	1.67
1973 III	54.87	5.11	856.80	1451.60	532.87	2.29
1973 IV	55.70	5.84	523.60	928.30	545.72	2.25
1974 I	59.47	5.59	380.50	548.10	522.82	2.68
1974 II	61.15	3.91	209.60	340.10	492.62	2.48
1974 III	65.67	4.41	562.00	1562.10	418.92	3.19
1974 IV	67.36	4.60	455.20	1107.50	401.82	3.35
1975 I	66.93	3.62	445.80	662.10	418.15	2.86
1975 II	68.22	3.03	227.30	435.00	422.57	2.67
1975 III	69.80	4.06	676.70	1885.80	451.25	2.81
1975 IV	70.19	3.32	500.00	1386.60	462.45	2.44
1976 I	70.54	3.66	449.60	937.40	463.40	2.47
1976 II	71.92	3.47	272.40	665.60	474.67	2.60

Table 9. Continued

Date	PPI	Cash Wheat	Total Use	Ending Stocks	Moving Average Use	Cash Corn
1976 III	72.55	2.89	624.90	2190.40	461.72	2.69
1976 IV	73.49	2.66	407.20	1783.60	438.52	2.20
1977 I	74.98	2.63	393.00	1390.90	424.37	2.34
1977 II	75.22	2.29	278.80	1113.20	425.97	2.23
1977 III	72.27	2.20	755.10	2404.50	458.52	1.70
1977 IV	74.43	2.65	407.90	1997.00	458.70	1.84
1978 I	78.55	2.82	467.50	1529.90	477.32	2.06
1978 II	82.64	3.18	352.40	1177.80	495.72	2.27
1978 III	82.29	3.42	820.00	2133.90	511.95	2.05
1978 IV	84.88	3.68	503.60	1630.80	535.87	2.03
1979 I	89.95	3.79	401.90	1229.40	519.47	2.17
1979 II	89.95	4.36	305.60	924.10	507.77	2.37
1979 III	91.04	4.28	788.10	2270.80	499.80	2.56
1979 IV	92.14	4.26	555.10	1716.20	512.67	2.35
1980 I	92.26	4.18	491.60	1225.10	535.10	2.41
1980 II	92.03	3.96	323.50	902.00	539.57	2.42
1980 III	100.67	4.38	810.20	2473.50	545.10	2.89
1980 IV	100.75	4.54	569.90	1903.80	548.80	3.09
1981 I	99.57	4.15	575.80	1329.10	569.85	3.22
1981 II	99.88	3.60	340.40	989.10	574.07	3.22
1981 III	98.31	3.87	1074.70	2727.50	640.20	2.85
1981 IV	94.66	3.86	556.20	2172.10	636.77	2.39
1982 I	97.21	3.59	621.30	1551.20	648.15	2.48
1982 II	100.27	3.31	392.70	1159.40	661.22	2.57
1982 III	97.21	3.18	956.10	2969.50	631.57	2.45
1982 IV	96.15	3.23	466.30	2506.10	609.10	2.12
1983 I	98.43	3.36	646.90	1862.00	615.50	2.54
1983 II	99.18	3.53	347.60	1515.10	604.22	3.01
1983 III	101.77	3.62	981.20	2955.20	610.50	3.27
1983 IV	101.30	3.55	629.70	2326.40	651.35	3.16
1984 I	105.22	3.57	569.40	1758.10	631.97	3.16
1984 II	103.22	3.51	360.30	1398.60	635.15	3.34
1984 III	101.96	3.47	1258.80	2467.00	704.55	3.11
1984 IV	101.81	3.49	601.90	2139.80	697.60	2.59
1985 I	100.00	3.58	475.10	1667.10	674.02	2.64
1985 II	97.84	3.27	243.70	1425.20	644.87	2.67
1985 III	94.62	2.83	885.00	2971.10	551.42	2.44
1985 IV	99.21	3.46	450.30	2536.40	510.62	2.20
1986 I	97.13	3.40	397.90	2130.10	494.23	2.31
1986 II	98.11	2.52	227.90	1905.00	490.52	2.34