AN ANALYSIS OF MONTHLY WHEAT, FLOUR, AND BREAD PRICES IN A STRUCTURAL AND TIME SERIES FRAMEWORK

by

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ABSTRACT

Wheat, flour, and bread prices fluctuate at all levels of the market. Accurate forecasts of these prices are valuable to buyers and sellers that trade in the cash and futures markets. Rational distributed lag models of monthly prices from June 1977 to May 1984 for Kansas City No. 1 Hard Red Winter Wheat, Minneapolis Dark Northern Spring Wheat, Portland No. 1 Soft White Wheat, Kansas City flour, and retail bread prices are made to evaluate the economic or structural factors influencing price. Multivariate autoregressive-integrated-moving average error (ARIMA) models are also used to compare with the structural models price forecasting ability. Rational lags are estimated using a nonlinear least squares algorithm, incorporating the specification of nonstochastic difference equations so that the disturbance process is divorced from the systematic portion of the difference equations.

Certain economic factors are found to be significant in influencing the prices of wheat, flour, and bread. Partial derivatives and price flexibilities are calculated to estimate the short, intermediate, and long-run adjustments of prices in the structural models. In the structural models total wheat stocks are the most influential variable in determining wheat prices and the price of wheat was most influential in the flour price equation. Flour price is highly significant in influencing retail bread price, with the secular effects of income increasing over time. The price forecasting abilities of the structural and ARIMA are found to be relatively close when comparing the Root Mean Square Errors and the adjusted coefficients of determination.

CHAPTER 1

INTRODUCTION

United States wheat production and marketing is highly integrated with the international grain market. Currently the U.S. share of world wheat production is about 14 percent and its share of world wheat exports is about 43 percent. In general, U.S. wheat is used for food, feed, and seed, as well as exports, with changes in stocks accounting for the net disappearance. For the marketing years of June 1977 to May 1984, about 61 percent of U.S. wheat disappearance was exported; about 24 percent was used for human consumption; about 4.5 percent was used for seed; and about 7 percent was used for livestock and poultry feeding. However, there has been a relatively rapid increase in wheat fed during the last two years of that period.[1]

The process in which wheat moves into human consumption involves the wheat first being stored (public and private storage), processing into flour, and then further processsed into an edible retail product. Usually these retail products fall into the general categories of cereal products and bakery products. Considering these marketing stages of wheat, the final demand for the end product (i.e. cereal and bread) consists of the demand for the farm based component (wheat) plus the

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[1] U.S. Department of Agriculture. Economic Research Service. Wheat Outlook and Situation. Statistical Bulletins WS-247-273, Washington D.C. Government Printing Office. 1981-1983.

demand for the services component (i.e. storage, processing and distribution).

The market structure of the U.S. wheat industry at the production and initial marketing levels illustrates an example of a competitive market. Specifically, there are numerous local elevators buying wheat from many producers, with the farmers being a price taker since each individual demand is infinitely elastic. Local elevators are composed of many farmer owned cooperatives that handle most of the trade to the terminal elevators. The terminal elevators, which do most of the selling to foreign buyers, are relatively few in number so that the concentration ratio increases from the farm level to the terminal level.

Statement of the Problem

The complexity of the U.S. wheat market makes it difficult to predict certain variables in wheat production and marketing. This is a particular problem in predicting wheat prices since they are subject to economic, technical, institutional, and random factors in the market. However, if some of the important variables that influence price can be identified and used to form an efficient price forecasting model, buyers and sellers in the market would be able to predict price changes that could improve upon marketing strategies. Models of annual wheat prices are more common than either quarterly or monthly models, but the annual models are more useful for yearly production decisions than for marketing a current year's crop. Short term changes in wheat prices have more of an influence on producer marketing decisions. They also

have important implications for the flour and bread markets.

Previous studies dealing with the wheat, flour, and bread markets dealt more with time series analysis and have not considered the interrelationship of these markets in a structural framework. A study that provides estimates of structural parameters and response coefficients may be more useful in understanding the relationship of the wheat and processing markets, by measuring impacts of exogenous shocks to the wheat and wheat products industries.

Objectives

Three major objectives are addressed in this research. The first objective is to develop a monthly econometric model based on distributed lags for terminal wheat prices, flour price, and retail bread price. The terminal wheat prices include Kansas City Hard Red Winter (HRW), Minneapolis Dark Northern Spring (DNS), and Portland Soft White Wheat (SWW). Flour price is a Kansas City quotation and bread price is a U.S. average. The second objective is to analyze the dynamic interrelationships of these markets by calculating short, intermediate, and long term price flexibilities, and to interpret their meanings. The third objective is to estimate an alternative multivariate ARIMA model for each price series, and to compare their predictive performances with those of the structural model.

Procedures

The structural parameters for the first objective are estimated using a nonlinear least squares algorithm which incorporates

nonstochastic difference equations and a joint autoregressive/moving average error structure. The specification of the variables in the dynamic model is based on prior knowledge of the industry and economic theory. The short, intermediate, and long term price flexibilities are based on the distributed lags of the structural equations, and are estimated by a mathematical algorithm using a recursion formula. The ARIMA models are estimated by the Box-Jenkins integrated method, accounting for trend and seasonality. Finally, the relative predictive performances of the structural and ARIMA models are evaluated via calculated Root Mean Square Errors of forecast (RMSE). Predictions are period by period for a sample of twelve months.

Literature Review

No previous work, known to the author, has estimated a monthly dynamic model that interlinks the wheat, flour, and bread markets. Most of the work completed in this area involves using structural and time series methods to forecast farm wheat prices in either annual or quarterly periods.

A Kansas study conducted by Kahlon (1961) primarily investigated the competitive and complementary nature of the different classes of wheat by comparing their respective price and consumption ratios. Least-square regression lines were fitted to log price ratios of wheat (the dependent variable) and log consumption ratios (the independent variable) for the interwar period (1929-1938) and the postwar period (1946-1957). Kahlon concluded that hard winter and spring wheats were substitutes for each other and that all wheat price movements were

positively correlated. However, his results showed that the soft and hard wheats were not statistically significant as being competitive products.

Wang (1962) estimated structural parameters for price functions of various classes of wheat in the U.S.. An annual model incorporating data from 1929-1957 was hypothesized and the regression coefficients were estimated by ordinary least squares. Domestic wheat price was estimated as a function of the adjusted supplies of each class of wheat and per capita disposable income. Results showed that at least 89 percent of the variation in domestic wheat prices could be explained by these variables, with the adjusted supply of wheat being the more significant variable.

Vannerson (1969) estimated monthly U.S. wheat prices using postwar data and an annual wheat price model. Parameters estimated in the annual model were incorporated in the monthly model. The monthly model included the effects of government support price and loan programs, stocks of wheat remaining in commercial holdings, exports of wheat, and domestic food and feed consumption. The monthly model was determined to be useful for inventory control of wheat stocks, although some autocorrelation was felt to be present in the error structure.

A study by Barr (1973) estimated annual average farm price of wheat from 1964-1972 by using a ratio of normal food use to total ending stocks on July 1. The ratio of food use to stocks was specified to the fifth power so that a curvilinear relationship between the two variables existed. The results showed that average wheat price rose sharply when total ending stocks were less than 600 million bushels.

Arzac (1979) estimated an annual structural model of U.S. wheat supply with data from 1947-1975. The purpose was to evaluate a stabilization policy for the U.S. grain market. The endogenous variables included in the model were domestic consumption, commercial inventories, domestic supply, and the market price of wheat. Exports, government stocks, support prices, diversion rates, disposable income, weather, and a time trend were treated as exogenous variables. The most influential variables were the market and support prices of wheat, an index of weather conditions, and trend in the domestic supply of wheat.

A study by Westcott, Hull, and Green (1984) estimated an aggregate U.S. wheat price model by using three classes of wheat stocks, lagged wheat price, and quarterly binary seasonal variables. The following three wheat stocks were considered: (1) total wheat stocks (all private and government wheat in storage); (2) total stocks less Commodity Credit Corporation (CCC) wheat in storage less farmer owned reserve (FOR) in storage (SFONE); and (3) SFONE less CCC wheat on loan (SFTWO). Hyperbolic curves relating quarterly wheat prices to stocks-to-use ratio variables, for a given lagged price, were constructed for the years 1971-1981 and then were used to predict prices for 1982-1983. The mean absolute error of prediction for total stocks, SFONE, and SFTWO for 1982-1983 was .278, .261, and .246 respectively. The results indicated that the less aggregated wheat stocks (SFONE and SFTWO), compared to total wheat stocks, were slightly better at predicting the turning points in wheat prices.

CHAPTER 2

MODEL DEVELOPMENT

This chapter presents the theoretical and practical framework for modeling the wheat, flour, and bread price model equations. The framework is essentially twofold; describing the nature of the interrelationships between the market levels and the specification and justification of the individual variables at each level of the market.

It is hypothesized that the monthly price interrelationships between the U.S. wheat, flour, and bread markets are of a recursive nature. That is, wheat prices at the terminal markets are established by economic forces specific to that level and then feed forward into the flour and bread markets. The flour and bread market prices are further determined by economic variables specific to their industries. Such a framework is hypothesized since, on such a short-term basis, the concentration of economic power at the terminal markets and the importance of the international market may reduce the effect of the domestic flour and bread trades on wheat prices. However, if the time period were expanded to quarterly or annual observations, more feedback would be expected from the flour and bread markets, representing more of a jointly dependent relationship among prices.

Since the model is formulated on a monthly basis, the variables that determine wheat, flour, and bread prices are specified with distributed lags. Such dynamics indicate that a change in an

economic variable spreads its effect (on price) over several monthly periods (discussion in Chapter 3). This seems reasonable since there may be delayed adjustments in the markets due to formation of expectations, and institutional and technical constraints.

Terminal Wheat Markets

The first price level considered is the terminal wheat market. Terminal wheat prices are defined for Kansas City, Hard Red Winter; Minneapolis, Dark Northern Spring; and Portland, Soft White Winter and Spring. Each wheat price equation is treated as a reduced form relation, and all prices together are considered a set of jointly determined random variables. Consequently, each equation has a common set of independent variables since it is believed that the different wheats are relatively good substitutes with the present milling technology. However, it is not hypothesized that the magnitude of each independent variable will be the same in each wheat market.

In general, each class of wheat is considered to be a function of seasonality, wheat exports, feedgrain exports, wheat stocks, and estimated wheat production. Specifically, the equation for the terminal market price of the rth class of wheat is:

$$PWH_{rt} = f_1\,[D, QEXFG_{t-j}, QEXWH_{t-j}, K_{t-j}, PROD_{t-j}, E(PWH_r)_{t-i}, \epsilon_{rt}] \quad (1)$$

$$r=1,2,3, \quad j=0,1,\ldots,k \quad i=1,2,\ldots,p \quad k \leq p$$

where

PWH_1 = Price of No. 1 Kansas City Hard Red Winter Wheat ($/bu.).

PWH_2 = Price of Minneapolis Dark Northern Spring Wheat ($/bu.).

PWH_3 = Price of No. 1 Portland Soft White Wheat ($/bu.).

K = Beginning stocks of government and private wheat storage, (all classes of wheat (million bushels)).[1]

QEXFG = Quantity of U.S. feed grain exports, (corn, sorghum, oats, and barley (mil. metric tons)).

QEXWH = Quantity of U.S. wheat exports (all classes of wheat (thousand bushels)).

PROD = United States Department of Agriculture (U.S.D.A.) monthly projected harvest (crop year from March to August (mil. metric tons)).

D = Seasonal binary variables specific to eleven months with the month of January omitted.

E = Expectation operator. Refers to the lagged expectation of the rth wheat price.

ϵ = Random disturbance term with mean zero, constant variance, and serial independence.

All prices are deflated by the Consumer Price Index (1967 = 100). The sample period for the variables is based on monthly time series data from June of 1977 through May of 1984. The reduced form model is specified as a set of difference equations (with the justification of the lagged expectation of the dependent variables given in Chapter 3). Difference equations are specified since, in small samples, all the necessary information to explain wheat prices cannot be contained in the specified set of independent variables.

Over the sample period, wheat exports averaged about 44 percent of the total disappearance of U.S. wheat supplies. Consequently, inclusion of this variable in the structural equations is crucial. The quantity of wheat exported each month reflects factors such as

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[1] Since only quarterly stock figures are published by the U.S.D.A., the remaining months were linearly interpolated from the quarterly figures.

international relations, exchange rates, ocean freight rates, tariffs, and general foreign affairs. Since some of these variables are difficult to quantify, if not impossible, the export variable itself would tend to proxy the sum of these effects.

Monthly exports of feedgrains were also included as an indirect measure of the substitution relationship between wheat and feedgrains. Generally, corn is the key component in the feedgrain market with other feedgrains reacting to economic changes in the corn market. Usually consumption of corn, barley, and sorghum in livestock feeding exceeds that of wheat. Nevertheless, in periods when feedgrain prices increase relative to wheat prices, utilization of wheat as feed increases. Thus, changes in feedgrain exports would be expected to influence the level of wheat price.

Wheat stocks are assumed to have a strong influence on wheat prices since they measure the net balance that occurs between production and disappearance. Thus, for example, if wheat stocks are building up because of an increase in production and/or a decrease in wheat use, economic logic implies that wheat prices would reflect these changes.

After completion of a wheat harvest for a given crop year, the expectation of next year's crop production is important. Producer expectations play an important role here since anticipated changes in future wheat production will have an impact on current wheat prices. For example, if next season's crop production is projected to increase, less grain will probably be stored and more marketed. The production figures used are a forecast of total U.S. wheat production from the beginning of March until the harvest has been completed. After

completion of harvest, the U.S.D.A. figures are estimates of actual U.S. wheat production. Such projections usually reflect weather conditions as well as government farm programs which are implemented or will be enacted.

The binary variables are specified to account for monthly seasonal patterns in wheat prices over the course of a crop year. At times, seasonal variables may capture other factors in the model, thus, casting doubt on their meaning and interpretation. However, this is usually an inherent risk with seasonal time series data (Sims 1974), making the binary method legitimate for the purposes of this study. The expected signs or the partial derivatives in equation (1) indicate the a priori relationships among the variables. They are given as:

$$\frac{\partial PWH_r}{\partial QEXFG} < 0 \qquad \frac{\partial PWH_r}{\partial K} < 0 \qquad (2)$$

$$\frac{\partial PWH_r}{\partial QEXWH} < 0 \qquad \frac{\partial PWH_r}{\partial PROD} < 0 \qquad (3)$$

Ceteris paribus, an increase (decrease) in the quantity demanded of a commodity decreases (increases) its price. If the quantity demanded of a substitute increases (decreases), the price of the substitute decreases (increases) and consequently reduces (increases) own price through the demand response process. Therefore it is hypothesized that monthly changes in export quantities of wheat and feedgrains will display a negative relationship with wheat prices. Stocks and the production of wheat represent supply variables, thus, it is expected that changes in their levels would demonstrate a negative correlation with wheat prices.

Kansas City Flour Market

In the monthly model, the price of wheat interacts with the flour market and is thus one of the factors responsible for determining flour price. It is recognized that consumer demand represents primary demand at the retail level, with the demand for flour and wheat being derived demands (Tomek and Robinson 1972). However, in this study it is hypothesized that one month is not a sufficient time period for changes in the flour market to significantly impact terminal prices, but rather the reverse occurs. In addition, other economic variables specific to the flour market level are important. The following equation specifies the determinants of Kansas City flour price:

$$PKCF_t = f_2[D, PWH_{1t-j}, DINC_{t-j}, QFLM_{t-j}, W_{t-j}, E(PKCF)_{t-i}, \epsilon_t] \qquad (4)$$

$$j=0,1,\ldots,k \quad i=1,2,\ldots,p \quad k \leq p$$

where

PKCF = Price of Kansas City Flour ($/cwt.).

PWH_1 = Price of No. 1 Kansas City Hard Red Winter Wheat ($/bu.).

DISP = Disposable income per capita ($/thousand people).

QFLM = Quantity of flour milled per capita (mil. cwt/thousand people).

W = Wage index of flour mill workers (1967 = 100)

D = Seasonal binary variables specific to eleven months with the month of January omitted.

E = Expectation operator. Refers to the lagged expectation of flour price.

ϵ = Random disturbance term with mean zero, constant variance, and serial independence.

All price and income variables are deflated by the CPI (1967=100).

The contemporaneous price of K.C. HRW enters the flour equation recursively as an exogenous variable because it is believed that on a monthly basis, the world wheat market is the primary influence on K.C. wheat (rather than the K.C. wheat price jointly determined with the K.C. flour price).

The expected signs of the partial derivatives in equation (4) are given as:

$$\frac{\partial PKCF}{\partial PWH_1} > 0 \qquad \frac{\partial PKCF}{\partial QFLM} < 0 \qquad (5)$$

$$\frac{\partial PKCF}{\partial DINC} > 0 \qquad \frac{\partial PKCF}{\partial W} < 0 \qquad (6)$$

Flour is made with wheat as the major raw material resource. Bread and related products made from flour are a relatively small portion of consumer expenditures, therefore the consumption of these products is fairly constant and not highly price responsive. The milling industry is a fairly competitive industry so that we would expect the profits in the industry to be yielding a normal rate of return. With these concepts in mind, it appears logical that the price of flour will be highly influenced by the price of wheat rather than the price of bread (in a monthly time framework). Such reasoning implies that an increase (decrease) in the price of K.C. HRW wheat would result in an increase (decrease) in the price of K.C. flour.

Per capita quantity of flour milled would be expected to display a negative relationship with the price of K.C. flour. That is, ceteris paribus, additional supplies of flour would only be sold to domestic market users at lower prices. The partial derivative of flour price with respect to income is expected to be positive, however, not of

great magnitude. The positive sign is consistent with theoretical reasoning that flour (and particularly its end products) are normal goods.

The flour mill wage is used as a proxy for the processing margin in flour production. Such marketing costs affect the derived demand for the raw product. For example, if there were an increase in the flour mill wage the result would be a decrease in the derived demand on wheat prices. The extent of its reduction would depend upon the relative elasticities of supply and demand for wheat (Tomek and Robinson 1972).

Retail Bread Market

The specification of the retail price of bread is based on similar logic used in modeling the flour market. The retail bread price equation is given as:

$$PBR_t = f_3[D, PKCF_{t-j}, DINC_{t-j}, PPOT_{t-j}, E(PBR)_{t-i}, \epsilon_t] \qquad (7)$$

where

PBR = Retail price of bread (cents/lb.).

PKCF = Price of K.C. flour ($/cwt.).

DINC = Disposable income per capita ($/thousand people).

PPOT = Indexed price of potatoes (1967 = 100).

D = Seasonal binary variables specific to eleven months with the month of January omitted.

E = Expectation operator. Refers to the lagged expectation of the price of bread.

ϵ = Random disturbance term with mean zero, constant variance, and serial independence.

The expected signs of the partial derivatives in equation (7) are given as:

$$\frac{\partial PBR}{\partial PKCF} > 0 \qquad \frac{\partial PBR}{\partial PPOT} > 0 \qquad (8)$$

$$\frac{\partial PBR}{\partial DINC} > 0 \qquad (9)$$

All price and income variables are deflated by the CPI (1967 = 100). Cost statistics indicate that about 13 percent of the final cost of a loaf of bread is due to the price of the flour.[1] Consequently, other variables constant, the effect of a change in the price of flour on the price of bread is expected to be positive. Bread is presumed to be a normal good as well, so that an increase in per capita disposable income would result in an increase in the demand for bread, hence the price of bread. However, it is hypothesized that the income effect would be minimal.

A price index of potatoes is included in the bread equation as a measure for a substitute commodity. The substitution relationship between bread and potatoes is not expected to be very large, particularly since the proportion of consumer expenditures allocated to potatoe purchases is small. However, a positive sign is expected since an increase in the demand for potatoes would increase the price of potatoes relative to bread, leading consumers to substitute more bread in the diet.

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[1] U.S. Department of Agriculture. Economic Research Service. Wheat Outlook and Situation. Statistical Bulletins WS-247-273. Washington, D.C., Government Printing Office. 1981-1983.

CHAPTER 3

ECONOMETRIC THEORY

This chapter discusses the statistical concepts and econometric methods used in parameter estimation of the models developed in Chapter 2. Included are (1) distributed lags, (2) stochastic and nonstochastic difference equations, (3) recursive systems, and (4) Box-Jenkins multivariate ARIMA models. Elementary aspects of market demand and supply theory are assumed to be understood.

Distributed Lags

Oftentimes the dependent variables in demand and supply functions respond to changes in independent variables over several time periods. For example, the time adjustment between a change in price and its effect on quantity may not occur instantaneously due to the nature of the commodity, imperfect knowledge, habits and technology, and/or time required to make changes in consumption and production decisions. This particular form of dynamics (i.e. time lags in the adjustment of demand and supply) is the basis of distributed lags. In general, distributed lag models can be classified as either finite or infinite. The difference refers to whether a change in an independent variable influences the dependent variable over a finite or infinite length of time.

A finite lag model can be specified as follows:

$$Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \beta_k X_{t-k} + \epsilon_t \quad (10)$$

where Y is the dependent variable, X is an independent (exogenous) variable and ϵ_t is a white noise disturbance term. The equation indicates that the order of lag coefficients higher than β_k are assumed to be zero, so that the independent variable X does not affect Y beyond k time periods. Examples include the arithmetic lag, inverted V-lag, and Almon polynomial lag. Finite distributed lag models are difficult to statistically estimate because of the problems of defining the proper end of the adjustment process, degrees of freedom, and multicollinearity. Usually, defining the end of the adjustment process becomes arbitrary, since there is little theoretical basis and/or precise knowledge of the industry to identify the length of the lag period period. If the order of lag structure is large, degrees of freedom are lost and multicollinearity between the lagged coefficients may result in small coefficient estimates relative to their standard errors (Rucker 1980).

Three weighted lag structure models, the geometric, Pascal, and Jorgenson's rational lag are common examples of infinite lags. A geometric weighted lag model with one dependent variable Y and one independent (exogenous) variable X is specified as:

$$Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \epsilon_t \quad (11)$$

where ϵ_t is white noise and the sum of the β's is finite. This model cannot be directly estimated due to an infinite number of parameters and multicollinearity between the β's. However, the geometric series can be estimated via a Koyck transformation (Kmenta 1971), which

transforms equation (11) into the following three parameter function:

$$Y_t = \alpha(1-\lambda) + \beta X_t + \lambda Y_{t-1} + \epsilon_t - \lambda\epsilon_{t-1} \qquad (12)$$

The difference equation parameter, λ, indicates the time rate of adjustment of the dependent variable Y given a change in the independent variable, X. Thus, higher values of λ indicate a slower rate of adjustment and lower values of λ indicate a more rapid rate of adjustment. Such results are illustrated in figure 1. Note also that the error term is transformed into a first order autocorrelated process.

Distributed lag models with geometrically declining weights may not always be appropriate. It may be more reasonable to expect that current changes in an independent variable would display more of a polynomial weighted effect (i.e. an inverted V-lag distribution) rather than a geometric decline from the current period. Two ways of allowing for this distribution are by using the Pascal lag and Jorgenson's rational lag. The Pascal lag model is specified as

$$Y_t = \beta W(L) X_t + \epsilon_t \qquad (13)$$

where L is a lag operator, and W(L) represents a power series in the lag operator L. Specifically,

$$W(L) = w_0 + w_1 L + w_2 L^2 + w_3 L^3 + \ldots \qquad (14)$$

Each weight corresponding to the model is

$$w_i = [(i+r-1)! \,/\, i!(r-1)!]\,(1-\lambda)^r \lambda^i \quad (i=0,1,2,\ldots), \qquad (15)$$

where i is the time period in question, r is some positive integer, and λ is a parameter to be estimated (Kmenta, 1971). For r equal to one the Pascal distribution is a geometric lag distribution. For r greater than one the result is an inverted V-lag distribution with the peak

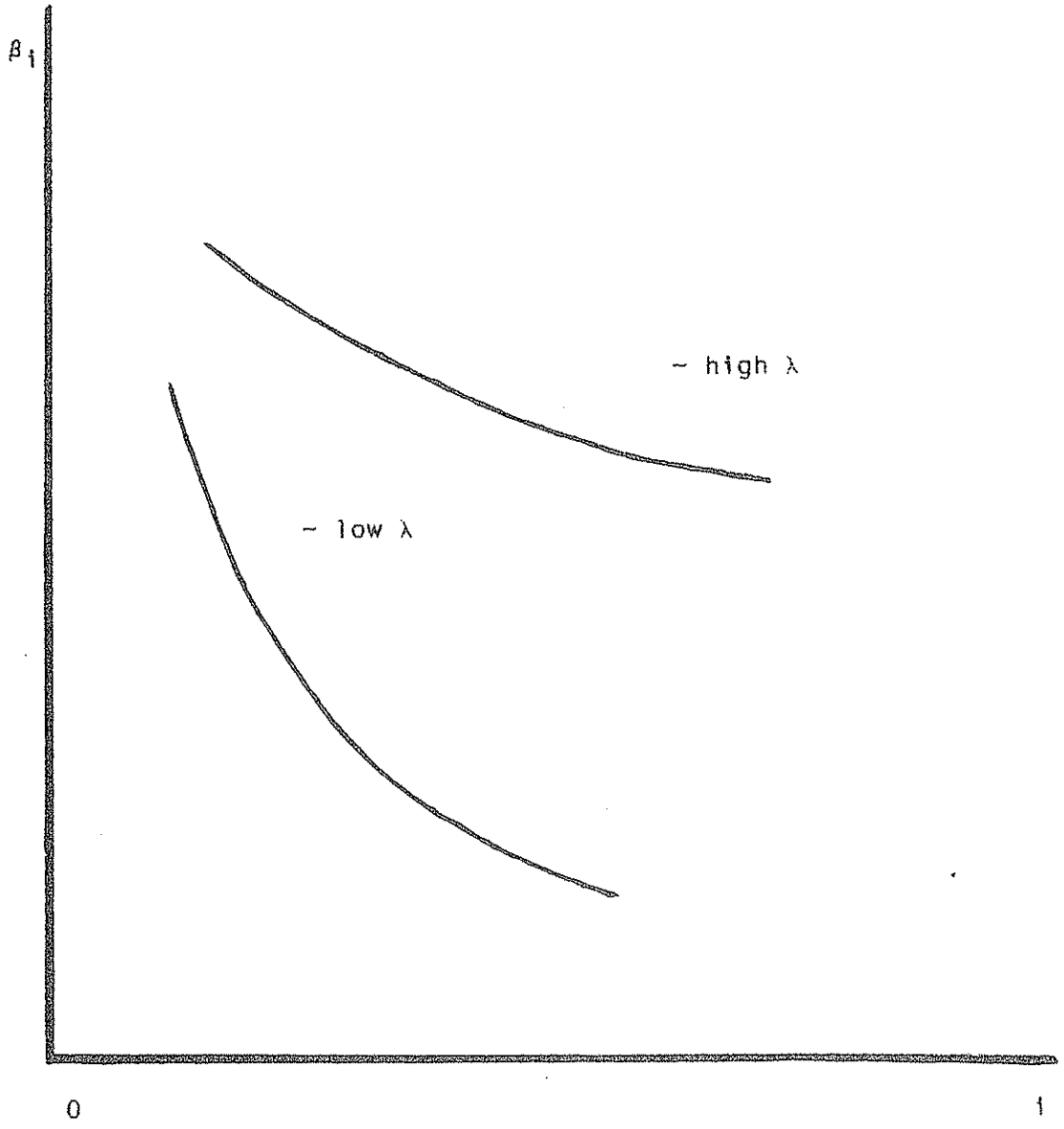


Figure 1. Geometric Distributed Lags

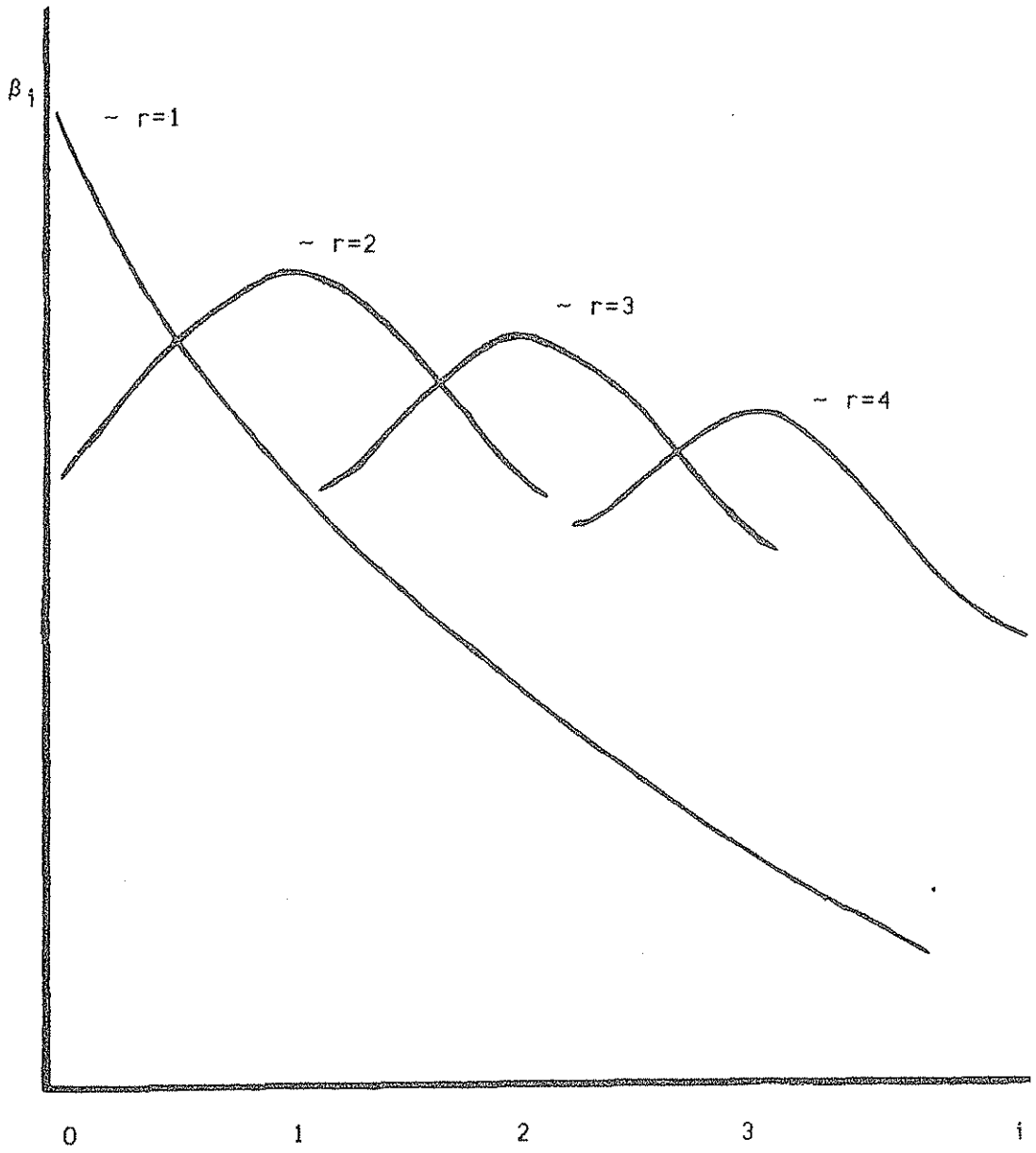


Figure 2. Pascal Density

weight occurring at period r-1. Figure 2 shows the relationship of the Pascal distribution for different values of r with a given λ. In essence, r determines the order of the difference equation and the order of correlation in the error term when the latter is transformed in equation (13) (Kmenta 1971). Its estimated value determines the rate of adjustment of the dependent variable, with the restriction that all roots of the difference equation are real, positive and equal. Both r and λ enter the estimation process nonlinearly, and generally maximum likelihood procedures are used to estimate the Pascal lag (Judge, et al. 1982).

A less restrictive distributed lag structure that allows for an inverted V-lag is Jorgenson's (1966) rational lag model. This model is specified as

$$Y_t = bT(L)X_t + \epsilon_t \qquad (16)$$

with the rational generating function

$$T(L) = A(L)/\beta(L). \qquad (17)$$

As given by Jorgenson, $A(L) = a_0 + a_1L + a_2L^2 + \ldots + a_mL^m$ and $\beta(L) = \beta_0 - \beta_1L - \beta_2L^2 - \ldots - \beta_nL^n$, with β_0 normalized at a value of one. Thus, A(L) is an mth order polynomial lag on the independent variable, and $\beta(L)$ is an nth order polynomial lag on the dependent variable. $\beta(L)$ also determines the order of the difference equation and correlation of the error structure. For example, multiplying equation (16) through by the numerator $\beta(L)$ yields;

$$Y_t + \beta_1Y_{t-1} + \ldots + \beta_nY_{t-n} = \alpha + \alpha_1X_{t-1} + \ldots + \alpha_mX_{t-m} + \epsilon_t + \beta_1\epsilon_{t-1} + \ldots + \beta_n\epsilon_{t-n}. \qquad (18)$$

$m \leq n$

The result is an nth order difference equation with an nth order moving average error process. Jorgenson's model is less restrictive than the Pascal lag since the roots may be imaginary, or real and unequal. If the order of m and n are of sufficient magnitude, Jorgenson showed that any arbitrary lag function can be approximated by the rational lag. This implies that the geometric and the Pascal functions are special cases of the rational lag. However, if not too constraining, the use of the Pascal or geometric lag may be more suitable in dynamic models due to the estimation of fewer parameters.

Stochastic and Nonstochastic Difference Equations

When there is a joint presence of a stochastic difference equation and an autocorrelated error process, ordinary least squares regression results in inconsistent parameter estimates. This inconsistency is due to statistical correlation between the error structure and the lagged dependent variable(s). One method that can be used to alleviate this problem is nonstochastic difference equations (Burt, 1980). Following Burt's definition, a first order nonstochastic difference equation can be written as:

$$Y_t = \alpha + \beta X_{t-1} + \lambda E(Y_{t-1}) + \mu_t \quad (19)$$

where $\mu_t = \rho\mu_{t-1} + \epsilon_t$, $E(Y_{t-1}) = Y_{t-1} - \mu_{t-1}$, and ϵ_t is a white noise error term. The mean of the nonstochastic difference equation is purely exogenous since the observed lagged dependent variable is replaced by its lagged expected value. That is, the lagged dependent variable, $E(Y_{t-1})$ is minus its random component. If the error structure is misspecified in such a model, consistent and unbiased

coefficient estimates are still obtainable since the disturbance process is removed from the systematic part of the equation. Further advantages in specifying nonstochastic difference equations are; (1) the disturbance structure does not have to be correctly estimated as in the stochastic difference equation; (2) the disturbance structure is usually simpler because it does not have to be transformed; and (3) a distinction is made between the exogenous and endogenous components of the model. The major advantage is that the parameter estimates of any autocorrelated disturbance are asymptotically uncorrelated with other parameters in the model (Burt 1980). Perhaps a minor weakness in using nonstochastic difference equations is that ordinary least squares is not appropriate since the specification of $E(Y_{t-1})$ and/or an autocorrelated error structure yields nonlinearities in the parameters. Therefore, for the model developed in this paper, a modified Marquadt nonlinear least squares algorithm (maximum likelihood under normality) is used to estimate the parameters.

Recursive Systems

Oftentimes in agriculture, particularly with short time periods, supply-demand interaction can be described by recursive systems (Wold, 1953). For example, a price determined at one market level often determines price at another market level. A recursive system can be illustrated as follows:

$$P_{1t} = a_1 + b_1 X_{1t} + e_t \qquad (20)$$

$$P_{2t} = a_2 + b_2 X_{2t} + c_1 P_{1t} + \epsilon_t \qquad (21)$$

$$P_{3t} = a_3 + b_3 X_{3t} + c_2 P_{2t} + c_3 P_{1t} + \mu_t \qquad (22)$$

where the error terms (e_t, ϵ_t, and μ_t) are assumed to be uncorrelated, and the error term in each equation is uncorrelated with its relevant exogenous variable, X_t. Thus, a chain causality effect occurs where an endogeous variable determined in one equation feeds into the following equation as an explanatory variable. Such a system is technically described as having a triangular β matrix and diagonal error covariance matrix (Johnston 1972). As explained in Chapter 2, this structure is hypothesized in the wheat, flour, and bread markets. Terminal wheat price is determined by certain exogenous and predetermined variables. Wheat price then feeds into the flour price equation, and the flour price, in turn, feeds into the bread price equation.

Time Series

An alternative to structural price models is analysis of price behavior by time series methods. Arguments for pure time series analysis is that knowledge of the "true" structural model is uncertain, data collection is usually less costly, and for an efficient market, a history of past prices may accurately predict current and future prices. The time series method used in this study is the Box-Jenkins autoregressive-integrated-moving average process (ARIMA). The ARIMA model may start with a simple univariate autoregressive process of order q, given as AR(q):

$$Y_t = \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_q Y_{t-q} + \epsilon_t \qquad (23)$$

where ϵ_t is white noise. If the order of q is large, or if the error term is weighted differently across time, then a moving average (MA) process of order p is more appropriate (Judge, et al. 1982). A MA(p)

is denoted as

$$Y_t = \epsilon_t + \alpha_1\epsilon_{t-1} + \ldots + \alpha_p\epsilon_{t-p}, \quad (24)$$

where equation (24) is merely a moving average of the white noise error term, ϵ_t.

If both an autoregressive, and a moving average error structure are present, then an autoregressive-moving average (ARMA) process of order q and p is appropriate. An ARMA (q,p) is noted as:

$$Y_t = \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_q Y_{t-q} + \epsilon_t + \alpha_1\epsilon_{t-1} + \ldots + \alpha_p\epsilon_{t-p} \quad (25)$$

If we assume a process where $E(Y_t)$ follows a linear trend equal to $t\mu$, then the series is nonstationary since the mean is not constant. To solve this problem, Y_t can be differenced up to some order d so that stationarity is obtained. That is,

$$w_t = (1 - L)^d Y_t \quad (26)$$

where L is the lag operator and w_t is stationary. The result is that Y_t in equation (25) would represent an autoregressive-integrated-moving average process, denoted as ARIMA (q,d,p), where d is the order of differencing.

The time series method applied to the price model described in Chapter 2 approximates the Box-Jenkins method. That is, this study approximates the Box-Jenkins ARIMA model by accounting for seasonality with binary variables, accounts for data trend with a trend variable, and tests for an autocorrelated error structure. The primary difference is that seasonality is additive in this model but multiplicative in the Box-Jenkins method (Marsh, 1983). As an alternative, the wheat, flour and bread price equations are tested as multivariate ARIMA processes. The latter implies that various lagged

endogenous variables are specified in the time series system (Chow, 1983). The individual ARIMA equations are represented in the following form:

$$(PWH_{rt},\ PBR_t,\ PKCF_t) = f_4(D,T,PWH_{rt-i},PBR_{t-i},PKCF_{t-i},\mu_t) \qquad (27)$$

where

D = monthly binary variables.

T = trend variable.

PWH_{rt-i} = lagged price of the rth wheat.

PBR_{t-i} = lagged price of bread.

$PKCF_{t-i}$ = lagged price of flour.

$\mu_t = \rho_1\mu_{t-1} + \ldots + \rho_q\mu_{t-q} + \epsilon_t - \theta_1\epsilon_{t-1} - \ldots - \theta_p\epsilon_{t-p}$, which represents an autoregressive process of order q and a moving average process of order p.

Thus, each time series equation is expressed as a function of the past history of the endogenous variables (i.e., i=1,2,...,k lags) and an error process. If the markets are relatively efficient, lagged prices would reflect important market information and the order of lags would be expected to be small.

CHAPTER 4

EMPIRICAL RESULTS

This chapter presents the statistical results of the structural and multivariate ARIMA models of the wheat, flour, and bread markets. Determination of the final model estimates was based on the joint criterion of the adjusted R^2's, asymptotic t-ratios, standard errors of the equations, and consistency of the model with economic theory. Therefore, not all variables hypothesized in the initial equations (Chapter 2) are included in the final version of the model. Tables 1 through 4 present the statistical results of the structural equations and their respective price flexibilities. The latter are based on the distributed lag patterns of the endogenous variables with given changes in the exogenous variables. Table 5 presents the statistical results of the multivariate ARIMA models and Table 6 presents the Root Mean Square Errors of forecast (RMSEs) used to compare the relative predictive performances of the structural and ARIMA models.

Terminal Wheat Markets

The structural wheat prices of K.C. HRW, Minn. DNS, and Port. SWW are estimated with a common set of independent variables since they are hypothesized to be influenced by the same economic factors. For example, each wheat price would be determined by exports, domestic production, and stocks. Also, the wheat prices are closely

interrelated since they are substitutes in the milling process and are partially utilized in livestock feed rations.

The Pascal distributed lag was used to estimate all three classes of wheat prices. The final wheat price equations are estimated as functions of seasonal binary variables, exports of feedgrains (t and t-1), exports of wheat (t and t-1), the contemporaneous quantity of government plus private wheat stocks, and monthly wheat production estimates. The nonstochastic difference equations are estimated up to a fourth order lag and each equation is also estimated with positive first order serial correlation. Table 1 presents the regression coefficient estimates and statistical results for the three terminal wheat price equations.

The Pascal distributed lag facilitated parameter stability in the wheat price models in that the parameter estimates varied little with changes in model specifications. The order of the difference equation, determined by r in the Pascal density structure, is not the same in all equations. That is, r=4 for PWH_1 and PWH_2, and r=3 for PWH_3. This difference indicates that the distributed lag price effects peak one month earlier in the Portland market (i.e., Portland prices peak 2 months compared to 3 months for the Kansas City and Minneapolis markets). Although this difference is not large, one reason may be the role of white wheat in livestock feeding. Generally, more soft white wheat (lower grade) is fed to livestock compared to the hard wheats. Thus, the shorter price peak period may reflect its relatively quicker adjustments due to changing livestock feeding conditions in the Pacific Northwest, particularly since lower quality white wheat substitutes

with barley in concentrate rations.

The summation of the parameter estimates for wheat exports (t and t-1) is negative, indicating larger quantities of wheat entering the export market occur at a reduced price. This would be in agreement with negative quantity effects for inverse demand. Initially, the price flexibilities are positive since the contemporaneous parameter estimate for wheat exports is positive. In a 3 month period, a 10 percent increase in wheat exports leads to increases in K.C. HRW, Minn. DNS, and Port. SWW prices by .56, .16, and .44 percent, respectively (Table 2). These initial positive signs are likely due to an initial increase in demand for wheat at the terminal level. Beyond 3 months the effects of wheat exports are negative as the negative coefficient on wheat exports (t-1) dominates. However, the price flexibilities show relatively little impact until about 12 months, after which the coefficients demonstrate a more significant effect. Such cumulative effects appear to be more in line with an adjustment period of a full crop year or more. Note, also that soft white wheat prices are not as affected by wheat exports as are hard wheat prices. For example, over a 12 month period, a 10 percent increase in wheat exports reduces K.C. HRW price by 6.8 percent but Port. SWW price by only 1.8 percent. The smaller price flexibility may partly reflect white wheat's greater reliance upon livestock feeding, where the latter tends to cushion wheat price variability due to changes in exports.

The sum of the parameter estimates for exports of feedgrains (t and t-1) indicate that an increase in the quantity of feedgrains exported results in a decrease in all classes of wheat prices. Generally, this

reflects competition between wheat and feedgrains as wheat is partially utilized as livestock feed and some feedgrains are used in food production. Note, however, that a positive relation exists between feedgrain exports and the price of soft white wheat for the first 3 months and then the relationship becomes negative thereafter (Table 2). The initial positive relation is small and could mean that additional feedgrain exports temporarily reduces feed supplies in the Pacific Northwest, thus, boosting feed demand for lower quality white wheat. Extending the time analysis it can be seen that, over a 12 month period, a 10 percent increase in feedgrain exports reduces K.C. HRW, Minn. DNS, and Port. SWW prices by 9.96 percent, 10.37 percent, and 8.05 percent, respectively. These results confirm the fact that a dominating inverse demand relation exists.

The contemporaneous and lag parameters of both the wheat and feedgrain export variables appear to alternate in sign. A priori reasoning would indicate that unusually high or low exports one month (i.e., due to unusual international events or problems with loading and unloading ships at the dock) could be followed by opposite levels of exports the next month. Upon examining the sample data, the export observations seem to confirm this pattern for both wheat and feedgrains. However, in the statistical model the combination of other independent variables and the difference equation coefficients have more of a smoothening affect on the distributed lag patterns of wheat prices. The result is to preclude wheat prices from displaying corresponding month-to-month oscillations.

Government plus private wheat stocks display a negative correlation

with all three terminal wheat prices. This is in agreement with theoretical reasoning since additional wheat stocks augment total supplies, thus, tending to decrease wheat prices. As shown by the price flexibilities in Table 2, wheat stocks have a greater distributed lag impact on wheat prices compared to the impact of other variables. For example, over the long-run, a 1 percent increase in stocks decreases K.C. HRW price by about 2.2 percent compared to 1.2 percent and 1.3 percent, respectively, for wheat and feedgrain exports. Since total wheat stocks measure a net balance between wheat production and wheat disappearance, its dominating effect is not surprising. An alternative model included specifying only private wheat stocks as a separate explanatory variable. However, the statistical results were inferior compared to those including total wheat stocks. One reason is that there was an increase in the variance of the stock variable when government stocks were added, giving more explanatory power to the latter.

The forecast of next year's crop production ($PROD_t$) is also included as an independent variable in each wheat price equation. However, positive signs of the parameter estimates resulted, which are opposite of those hypothesized in Chapter 2. Monthly data reveal that wheat exports, feedgrain exports, and wheat stocks display considerable variations about their means. However, since the production variable is defined on a crop year basis (i.e., more nearly reflects yearly phenomena), relatively little variation exists in its monthly estimates. Such lack of variation may at least partly account for these unexpected coefficient signs. But due to strong theoretical

considerations, the production forecast variable was retained in the wheat price equations. In terms of demand and supply analysis, expectations of future wheat production (as given by U.S.D.A. wheat production estimates) should certainly be important in influencing current cash wheat prices.

Overall, the monthly seasonal binary variables are not highly significant. Calculation of F-ratios indicated that K.C. HRW was the only terminal wheat price significant at a 90 percent confidence level, indicating that the seasonal variables contributed only little to the regression sum of squares in the Minn. DNS, and Port. SWW equations. However, certain individual asymptotic t-ratios appear significant making these results difficult to interpret. Often, in dynamic models, seasonal coefficients lack precise meaning as the binary variables may be confounded with other economic and technical factors.

The nonstochastic difference equation coefficients in the Pascal model are relatively large (in absolute values) for all three wheat prices. These large values indicate that the distributed lag effects (i.e. the adjustment period of a dependent variable given a change in an independent variable) take a considerable period of time to dissipate. In the Pascal model, the time length of dissipation for at least 80 percent of the distributed lag affects to be realized on wheat prices due to changes in the independent variables averaged 14 months. This may not be unusually long since it only extends 2 months beyong a full crop year. The Pascal model also performs reasonably well in sample prediction performance as the standard error of the estimates divided by the respective means of the dependent variables are less

than 5 percent for all three wheat price equations.

Kansas City Flour Market

The Kansas City flour price equation is estimated as a function of lagged Kansas City wheat price, per capita U.S. disposable income, quantity of flour milled per capita, seasonal variables, trend, and a first order nonstochastic difference equation with a first order autoregressive error. Table 3 gives the parameter estimates and statistical results of flour prices, while Table 4 presents the time related price flexibilities. The structural equation was estimated by rational lags, yielding a Koyck geometric function. The value of the difference equation coefficient (.7033) indicates the length of the adjustment period (the distributed lag pattern) of the dependent variable given a change in an independent variable. On the average, flour prices tended to reach an equilibrium or dissipate within 6 to 8 months given a change in an independent variable.

The hypothesis that wheat price influences flour price was evaluated against the alternative of flour price determining wheat price in a structural and lagged price framework. The results of the t-ratios and adjusted R^2's indicated that changes in flour price were determined by wheat price movements with little feedback. Because little feedback occurred, wheat and flour prices were assumed not to be jointly dependent. Consequently, K.C. HRW price entered the flour price equation recursively in its original form. Entering the original K.C. HRW price data was also supported by the fact that there was no significant correlation (i.e., adjusted R^2's were less than .01)

Table 1. Statistical Results of the Kansas City Hard Red Winter Wheat, Minneapolis Dark Northern Spring Wheat, and Portland Soft White Wheat Price Equations.[a]

	Equations		
Variable	PWH_1	PWH_2	PWH_3
Intercept	.1499E+00 (.1974E+01)	.1149E+00 (.1482E+01)	.2173E+00 (.3721E+01)
$EXFG_t$	-.5928E-02 (-.1091E+01)	-.6521E-02 (-.1599E+01)	.9625E-02 (.7758E+00)
$EXFG_{t-1}$	.2258E-02 (.3951E+00)	.4178E-02 (.1019E+01)	-.1732E-01 (-.1325E+01)
$EXWH_t$	.2868E-06 (.1689E+01)	.1414E-06 (.1171E+01)	.2933E-06 (.8838E+00)
$EXWH_{t-1}$	-.4420E-06 (-.2260E+01)	-.2737E-06 (-.1920E+01)	-.3865E-06 (-.1133E+01)
K_t	-.1669E-04 (-.3030E+01)	-.8683E-05 (-.2848E+01)	-.2971E-04 (-.3055E+01)
$PROD_t$	.2242E-03 (.2389E+01)	.1557E-03 (.1933E+01)	.1829E-03 (.7919E+00)
D_2	-.9126E-01 (-.6533E+00)	-.1262E+00 (-.8771E+00)	-.1156E+00 (-.1462E+01)
D_3	-.9534E-01 (-.1069E+01)	-.4524E-01 (-.4948E+00)	-.1205E+00 (-.2107E+01)
D_4	-.6723E-01 (-.6217E+00)	-.4297E-01 (-.3858E+00)	-.5390E-01 (-.8787E+00)
D_5	-.1408E+00 (-.1331E+01)	-.1363E+00 (-.1252E+01)	-.1539E+00 (-.2495E+01)
D_6	-.3688E-01 (-.3471E+00)	-.7092E-01 (-.6482E+00)	-.7604E-01 (-.1204E+01)
D_7	-.1262E+00 (-.1160E+01)	-.5717E-01 (-.5125E+00)	-.8985E-01 (-.1415E+01)
D_8	-.1474E+00 (-.1425E+01)	-.2232E+00 (-.2087E+01)	-.1416E+00 (-.24522E+01)

Table 1 (continued).

Variable	PWH_1	PWH_2	PWH_3
	Equations		
D_9	.1048E+00 (.1245E+01)	.2431E+00 (.2812E+01)	-.4675E-01 (-.8095E+00)
D_{10}	-.2126E+00 (-.2391E+01)	-.2866E+00 (-.3211E+01)	-.9204E-01 (-.1415E+01)
D_{11}	.2157E-01 (.2494E+00)	-.3673E-01 (-.4211E+00)	-.3619E-01 (-.6308E+00)
D_{12}	-.1930E+00 (-.1364E+01)	-.9294E-01 (-.6378E+00)	-.1610E+00 (-.2037E+01)
E(DEP-1)[b]	.2761E+01	.2918E+01	.2182E+01
E(DEP-2)	-.2859E+01	-.3193E+01	-.1586E+01
E(DEP-3)	.1316E+01	.1553E+01	.3850E+00
E(DEP-4)	-.2270E+00	-.2830E+00	
ρ_1	.5731E+00 (.6215E+01)	.5933E+00 (.6551E+00)	.7902E+00 (.1153E+02)
Statistic[c]	Regression Results		
$\bar{R}^2$	.9347E+00	.9192E+00	.9380E+00
Sy/Y	.4260E-01	.4096E-01	.3891E-01
D.W.	.1872E+01	.1925E+01	.1852E+01

[a] The top figure represents the paramter estimate and the figures in parentheses represent the respective t-ratios for each variable.

[b] Represents the expected value of the lagged dependent variables, which are determined by the estimated Pascal parameter. The Pascal parameters and their asymptotic t-ratios for each equation are: PWH_1 = .6903, t-ratio = 20.462; PWH_2 = .7296, t-ratio = 27.281; PWH_3 = .7272; t-ratio = 17.530.

[c] $\bar{R}^2$ = adjusted multiple R-squared statistic.
Sy/Y = standard error of the estimate divided by the mean of the dependent variable.
D.W. = Durbin-Watson statistic.

Table 2. Estimates of Price Flexibilities for the Kansas City Hard Red Winter Wheat, Minneapolis Dark Northern Spring, and Portland Soft White Wheat Price Equations.[a]

	Length of Run (months)				
Variable	3	6	12	24	Long-Run
EXFG	-.137	-.445	-.996	-1.301	-1.329
	(-.144)	(-.455)	(-1.037)	(-1.454)	(-1.537)
	[.019]	[-.218]	[-.805]	[-1.214]	[-1.268]
EXWH	.056	-.075	-.682	-1.178	-1.228
	(.016)	(-.140)	(-.867)	(-1.719)	(-1.911)
	[.044]	[-.006]	[-.183]	[-.318]	[-.336]
K	-.167	-.623	-1.556	-2.122	-2.175
	(-.095)	(-.395)	(-1.173)	(-1.896)	(-2.051)
	[-.214]	[-.629]	[-1.312]	[-1.717]	[-1.768]

[a] The top figures represent the PWH_1 equation, the figures in parentheses represent the PWH_2 equation, and the figures in brackets represent the PWH_3 equation. The price flexibilities are calculated with respect to the means of each variable. Price flexibilities were not computed with respect to the production variable because the sign was not consistent with the original hypothesis.

between the residuals of the wheat price and flour price equations.

The effect of Kansas City wheat price is statistically significant in both the contemporaneous and first order lag periods. The one month lag could indicate the time period needed for wheat to be moved from storage to the point of processing. The distributed lag effect of hard red winter price on flour price indicates there is always a positive relationship between the two prices (Table 4). That is, as the raw material cost of wheat increases millers pass part of the cost on in

the form of higher flour prices. For example, the 6 month price flexibility indicates a 10 percent increase in wheat price yields a 7.7 percent increase in flour price. Note that the long-run price flexibility for K.C. HRW is about 3 times larger than that for either per capita quantity of flour milled or per capita disposable income. These economic results are consistent with the fact that wheat is the dominant input in the flour milling process.

Per capita disposable income has a positive affect on flour price, which is consistent with flour being a normal good. However, the magnitude of the disposable income coefficient indicates that the effect of income is relatively small and tends to increase rather slowly over time. Given a 1 percent increase in disposable income, flour price increases only about .3 percent over the long-run. Flour is a relatively small proportion of the cost of retail products in consumer budgets. Thus, the income effect is not expected to be strong. In addition, flour is utilized in numerous retail products that are income inelastic, precluding a strong income effect in the flour market.

The per capita quantity of flour milled is negatively correlated with flour price. Its effect is not particularly large as can be seen by the price flexibility coefficients in Table 4. For example, a 10 percent increase in per capita quantity of flour milled decreases the price of flour by only 1.6 percent over the long-run. One reason for its minor importance may be the dominating effect of the level of wheat prices. That is, if monthly processing costs for making bread remain relatively constant, the price of flour is largely affected by the

price of wheat. This is particularly true since the cost of wheat constitutes the largest share of miller raw material costs.

In the original hypothesis a flour mill wage variable was included to proxy the processing margin between the wheat and flour markets. However, the result was a positive relationship between the flour price and wage rate, which was contrary to the effect of marketing costs on derived demand (Tomek and Robinson 1972). Part of the reason for the positive relationship may be that milling technology and flour price jointly influence wage rates rather than wages impacting flour price. Also, in this case, using a monthly wage as a proxy for a processing margin might be inadequate for reflecting all processing costs. For example, about 85 percent of the final cost of flour (at the mill) is due to the cost of wheat and most of the processing costs are related to capital investment in plant and equipment.

The asymptotic t-ratios indicate that most of the seasonal binary variables are not statistically significant (different from zero) in determining levels of flour prices. Economic logic would bear this out since wheat is a nonperishable commodity with considerable storage life. Consequently, millers can continually draw upon wheat stocks to satisfy monthly flour processing requirements. In addition, seasonal retail consumption of flour based products is very weak at best.

The trend variable in the flour price equation indicates that real flour prices experienced an upward trend throughout the sample period. Though the variable is statistically significant, the magnitude of the coefficient (.0014) is relatively small, indicating its impact is overshadowed by the effects of other regressors.

Retail Bread Market

The retail bread price equation is also estimated by rational distributed lags (similar to that of the flour price equation). Retail bread price is estimated as a function of lagged Kansas City flour price, per capita disposable income, a price index of potatoes, seasonal binary variables, trend, and a first order nonstochastic difference equation with a first order autoregressive error. Table 3 presents the associated parameter estimates and statistical results.

The rational lag form for the bread price equation was reduced to a geometric function. The estimated difference equation coefficient, 0.907, indicates that the distributed lag effects adjust more slowly than those found in the flour price equation. More specifically, the average length of period for bread prices to dissipate or reach equilibrium (given a change in any independent variable) is about 10-12 months (6-8 months for flour). This may be due to the fact that bread price is not only subject to economic influences from the flour market, but also to the factors that determine purchasing behavior of consumers. The result could be to produce an underlying structure that delays the distributed lag process. Such distributed lag effects are reflected in the price flexibilities for different lengths of run in Table 4.

The causal relationship of flour price influencing retail bread price was evaluated against the opposite alternative to verify the hypothesized recursive structure (i.e., similar to the relationship of wheat and flour prices in the flour price equation). Results of the t-

ratios and adjusted R^2's showed that, on a monthly basis, there was no significant joint dependency between the two markets, but rather that flour price only impacted bread price. The regression results show that the Kansas City flour price is significant in both the contemporaneous period and in the period lagged one month. The lag may be due to an adjustment in price expectations from one month to the next or to a lag in the production process due to transportation and processing time. The price flexibilitiy of bread price with respect to flour price is .305 for a 3 month period and then decreases to .187 for the long-run. This time decrease in the price flexibility coefficients indicates that bread prices adjust to changes in flour prices quite rapidly in the initial months, which may be due to the very short time horizon in bread production and sales.

Per capita disposable income displays a positive correlation with the price of bread. This positive relationship supports the original hypothesis that bread is a normal good. The price flexibility coefficient of .13 for a 3 month time period indicates that the income effect is not very significant for shorter time periods, but increases over the course of a year to a value of .353. Although small, it is indicative that longer periods of time permit consumers to more freely adjust bread purchases from an income change. Also, the price flexibility coefficient is still relatively small over the long-run, reflecting the fact that bread is a relatively small proportion of total consumer food expenditures.

The price index of potatoes is included to measure potatoes as a substitute for bread. A priori the degree of substitutability is

hypothesized to be weak, which was confirmed withand a long-run price flexibility coefficient of only .027. The positive coefficient sign is theoretically correct; that is, for substitute commodities an increase in the price of potatoes would lead to an increase in the demand for bread (hence, increase its price).

The seasonal and trend variables show little statistical significance. The absence of seasonality in bread prices is due to continual available supplies of flour for bread manufacturing and the fact that consumption of bread is nonseasonal. The negative trend in real bread price could indicate there has been a steady increase in the efficiency of baking bread, but lack of information makes the argument weak at best.

Multivariate ARIMA Equations

Few theoretical considerations are used in the ARIMA models, consequently, terminal wheat prices, flour price, and bread price are estimated as a function of the same set of variables. They include lagged prices, seasonal binary variables, trend, and an autoregressive-moving average error structure. Final parameter estimates and statistical results for the time series equations are given in Table 5. Stochastic difference equations are used since the lagged observed values of the dependent variables are specified. The specification of binary variables and trend account for seasonality and time effects in the data, respectively. The autoregressive term (ρ) is estimated to account for the fact that the data is not first differenced as is conventionally done in the Box-Jenking framework. However, the

Table 3. Statistical Results of the Kansas City Flour Price and U.S. Bread Price Equations.[a]

	Equations	
Variable	PKCF	PBR
Intercept	.6639E-01 (.4083E+00)	.5683E+00 (.4384E+00)
PWH_{1t}	.1605E+01 (.1088E+02)	
PWH_{1t-1}	-.1040E+01 (-.3499E+01)	
$DINC_t$	.9378E-01 (.3403E+01)	.2869E+00 (.1930E+01)
$QFLM_t$	-.1690E+01 (-.1009E+01)	
$PKCF_t$		.1743E+01 (.5240E+01)
$PKCF_{t-1}$		-.1651E+01 (-.4749E+01)
$PPOT_t$		.4800E-03 (.2162E+00)
E(DEP-1)[b]	.7033E+00 (.5904E+01)	.9070E+00 (.1112E+02)
ρ_1	.3160E+00 (.2980E+01)	.7118E+00 (.9064E+01)
Trend	.1143E-02 (.2133E+01)	-.3141E-02 (-.6600E+00)
D_2	-.7880E-02 (-.1252E+00)	.1300E-01 (.5470E-01)
D_3	-.1836E-01 (-.3156E+00)	-.7768E-01 (-.3323E+00)
D_4	-.7210E-01 (-.1255E+01)	.2395E-01 (.1033E+00)

Table 3 (continued).

Variable	Equations PKCF	PBR
D_5	.7232E-01 (.1309E+01)	-.6253E-01 (-.2703E+00)
D_6	-.4488E-01 (-.7515E+00)	-.9063E-02 (-.3757E-01)
D_7	.1610E+00 (.2671E+01)	.6572E-01 (.2607E+00)
D_8	.8969E-02 (.1427E+00)	.1347E+00 (.5531E+00)
D_9	-.1962E-01 (-.3144E+00)	.1711E-01 (.7104E-01)
D_{10}	-.4443E-01 (-.7420E+00)	.3063E-01 (.1322E+00)
D_{11}	-.4174E-01 (-.7007E+00)	.2944E-01 (.1248E+00)
D_{12}	-.5243E-01 (-.8363E+00)	.2359E+00 (.9882E+00)
Statistic[c]	Regression Results	
$\bar{R}^2$	.9616E+00	.9587E+00
Sy/Y	.2481E-01	.1987E-01
D.W.	.1976E+01	.2178E+01

[a] The top figures represents the parameter estimates and the figures in parentheses represent the asymptotic t-ratios for each variable.

[b] Represents the expected values of the lagged dependent variables.

[c] $\bar{R}^2$ = adjusted multiple R-squared statistic.
Sy/Y = standard error of the estimate divided by the mean of the dependent variable.
D.W. = Durbin-Watson statistic.

Table 4. Estimates of Price Flexibilities for the Kansas City Flour Price and U.S. Bread Price Equations.[a]

	Length of Run (months)				
Variable	3	6	12	24	Long-Run
PWH_1	.726	.766	.784	.787	.787
QFLM	-.102	-.137	-.153	-.156	-.156
DINC	.180 (.130)	.243 (.227)	.272 (.353)	.276 (.462)	.276 (.512)
PKCF	(.305)	(.275)	(.236)	(.203)	(.187)
PPOT	(.007)	(.012)	(.019)	(.025)	(.027)

[a] The figures in parentheses represent the U.S. Bread Price Equation, and the figures without parentheses represent the Kansas City Flour Price Equation. Price flexibilities were calculated with respect to the means of the variables.

statistical results showed that an autoregressive error structure was not significant in any equation, and that the only error structure consisting of a moving average parameter in the soft white wheat price equation.

The lagged price variables that were not statistically significant (in terms of their asymptotic t-ratios) were excluded from the original ARIMA model (as given in Chapter 2). As a general result, it can be seen that most of the equations nearly reverted back to a univariate autoregressive structure. The individual fits of the ARIMA equations

are close to those of the structural equations, however, the adjusted R^2's and standard errors of estimates are slightly inferior.

Since the ARIMA and structural methods are highly different, comparison of their respective results is somewhat tenuous. Generalization of the results would indicate that in both models seasonality is very weak, no doubt due to lack of strong seasonal requirements in monthly production and consumption. Trend in the ARIMA models appears only strong in the soft white wheat equation, with marginal effects in the hard red winter wheat and bread price equations. Trend in the ARIMA may be reflecting some of the weaker structural arguments found in the structural equations. Finally, the statistical significance in the ARIMA models rests with the lagged dependent variables, which are merely incorporating historical information implicit in the sample.

Such results suggest that the wheat, flour, and bread markets are relatively efficient in that past prices readily capture important factors at work in the market. In the structural models, the difference equation coefficients are also reflecting past history in wheat prices, but emphasis is shifted toward independent effects by certain regressors that leads to understanding market structure.

Structural vs. Multivariate ARIMA

To evaluate the relative predictive performances of the structural and ARIMA models, Root Mean Square Errors of forecast (RMSE) were calculated. The most recent 12 months of the sample period were sequentially truncated and, thus, forecasts were made on a month by

month basis for each equation. During the truncating process, the parameter estimates remained stable for both the ARIMA and structural equations, suggesting that same models would have been chosen even if the sample had been shortened. The formula for the Root Mean Square Error is

$$RMSE = \left[\sum_{i=1}^{n} \hat{e}_i^2 / n \right]^{1/2}$$

where $\hat{e}_i$ is the difference between the actual and predicted value of the dependent variable, and n is the number of periods tested (i.e., sample size of 12). Table 6 presents the RMSE, adjusted R^2, and standard error of estimate associated with each equation in both the structural and ARIMA framework.

Generally when the size of RMSEs are large relative to the standard errors of forecast, it is indicative of the measure of specification errors in the model (Marsh, 1983). Such errors are usually revealed in that the estimated parameters are unstable with respect to a change in sample size. In this model, however, the RMSEs of both the structural and ARIMA price equations are less than their respective standard errors of forecast, and the parameter estimates remained quite stable in the truncation process. This would suggest, particularly for the structural model, that given the combination of data, sample size, and methodology, relative structural price stability is present in the wheat, flour, and bread markets.

Overall, the comparative results for the structural and ARIMA equations appear to be close and mixed. For example, in examining the price equation for hard red winter wheat, the RMSE statistical criteria are close for the structural and ARIMA methods when comparing .0416 in

the structural model with .0456 in the ARIMA method (i.e., only a slight advantage for the structural equation). However, in the soft white wheat and bread price equations the RMSE's favor the ARIMA model. Thus, one may conclude that if there is joint interest in structural information and price prediction in the market, the use of a structural model would serve relatively well. If one were merely interested in pure price forecasting in these markets, the ARIMA model would be a more efficient method since the costs of data collection and estimation would be less with little concession of statistical precision.

Table 5. Statistical Results for the ARIMA models of Wheat, Flour, and Bread Prices.[a]

	Equations				
Variable	PWH_1	PWH_2	PWH_3	PKCF	PBR
Intercept	.8096E-01 (.8439E+00)	-.1596E+00 (-.8614E+00)	.2647E+00 (.2398E+01)	.3357E+00 (-.7698E+00)	.1848E+01 (.1599E+01)
D_2	.1088E-01 (.2761E+00)	-.5214E-02 (-.1411E+00)	-.1684E-02 (-.5000E-01)	.1674E-01 (.1958E+00)	.3964E-01 (.1510E+00)
D_3	.1389E+00 (.3507E+00)	.1000E-01 (.2696E+00)	-.1857E-01 (-.4923E+00)	.1978E-02 (.2313E-01)	-.8112E-01 (-.3089E+00)
D_4	.3561E-01 (.9003E+00)	.6499E-01 (.1757E+01)	.1806E-01 (.4787E+00)	.3344E-02 (.3905E-01)	.1913E-01 (.7278E-01)
D_5	-.2252E-02 (-.5661E-01)	.5803E-01 (.1565E+01)	-.1846E-01 (-.4880E+00)	.8971E-01 (.1048E+01)	.8176E-01 (.3109E+00)
D_6	.2593E-01 (.6280E+00)	.4740E-01 (.1220E+01)	.5800E-02 (.1478E+00)	.1433E-01 (.1596E+00)	-.3914E-01 (-.1430E+00)
D_7	.8412E-02 (.2032E+00)	.3947E-01 (.1009E+01)	.2820E-01 (.7160E+00)	.1611E+00 (.1793E+01)	.1627E+00 (.5940E+00)
D_8	-.3514E-02 (-.8323E-01)	-.2721E-01 (-.6990E+00)	-.3443E-01 (-.8725E+00)	.1246E-01 (.1376E+00)	.7871E-01 (.2878E+00)
D_9	.4067E-01 (.1006E+01)	.4325E-01 (.1167E+01)	-.1581E-01 (-.4229E+00)	.3335E-01 (.3887E+00)	.6308E-01 (.2397E+00)
D_{10}	.4646E-01 (.1167E+01)	.7172E-01 (.1938E+01)	-.1581E-01 (-.4192E+00)	.1898E-01 (.2213E+00)	.4806E-01 (.1827E+00)
D_{11}	.7882E-01 (.1999E+01)	.4622E-01 (.1244E+01)	.1413E-01 (.3750E+00)	.9437E-01 (.1101E+01)	.1776E+00 (.6756E+00)
D_{12}	-.7192E-03 (-.1829E-01)	-.1688E-01 (-.4546E+00)	-.5291E-01 (-.1567E+01)	-.3048E-01 (-.3554E+00)	.1688E+00 (.6122E+00)
Trend	-.7155E-03 (-.1372E+01)	.1886E-03 (.2850E+00)	-.1325E-02 (-.2305E+01)	.6827E-03 (.4245E+00)	-.5961E-02 (-.1454E+01)
PWH_{1t-1}	.8117E+00 (.1048E+02)				

Table 5 (continued)

Variable	Equations				
	PWH_1	PWH_2	PWH_3	PKCF	PBR
PWH_{2t-1}		.8231E+00 (.1387E+02)			
PWH_{3t-1}	.1361E+00 (.1441E+01)		.8754E+00 (.1598E+02)		
$PKCF_{t-1}$				.7949E+00 (.1134E+02)	
PBR_{t-1}		.1993E-01 (.1860E+01)		.5228E-01 (.1925E+01)	.9157E+00 (.1879E+02)
θ_1			-.2094E+00 (-.1637E+01)		
Statistic[b]	Regression Results				
$\bar{R}^2$	.9224E+00	.9065E+00	.9278E+00	.8920E+00	.9384E+00
Sy/Y	.4629E-01	.4388E-01	.4182E-01	.4167E-01	.2425E-01
D.W.	.1831E+01	.1771E+01	.1955E+01	.2195E+01	.2053E+01

[a] The top figures represent the parameter estimate and the figures in parenthesis represent the asymptotic t-ratios for each variable.

[b] $\bar{R}^2$ = adjusted multiple R-squared statistic.
Sy/Y = standard error of the estimate divided by the mean of the dependent variable.
D.W. = Durbin-Watson statistic.

Table 6. Comparison of the Root Mean Square Errors of the Structural and ARIMA Wheat, Flour, and Bread Price Equations.[a]

	Statistic[b]		
Equation	RMSE	$\bar{R}^2$	Sy
PWH_1	.0416 (.0456)	.9347 (.9224)	.0675 (.0734)
PWH_2	.0400 (.0430)	.9192 (.9065)	.0645 (.0691)
PWH_3	.0642 (.0401)	.9380 (.9278)	.0642 (.0690)
PKCF	.0523 (.0782)	.9616 (.8920)	.0952 (.1599)
PBR	.1750 (.1325)	.9587 (.9384)	.4025 (.4912)

[a] The top figures represent the structural equations and the figures in parentheses represent the ARIMA equations.

[b] RMSE = Root Mean Square Error of forecast.
$\bar{R}^2$ = adjusted multiple R-squared statistic.
Sy = standard error of the estimate.

CHAPTER 5

SUMMARY AND CONCLUSIONS

The purpose of this study was: (1) to determine the dynamic structure of economic variables that impact short-term (monthly) levels of wheat prices (K.C. HRW, Minn. DNS, Port. SWW), flour prices, and retail bread prices; (2) to measure and analyze the distributed lag relationships both within and between these market level prices; and (3) to compare the price forecasting performance of each structural equation with an alternative multivariate ARIMA model. An econometric model incorporating rational distributed lags and nonstochastic difference equations was used to estimate the structural equations, while the time series equations were estimated by an approximation of the Box-Jenkins ARIMA method. Monthly data from June of 1977 to May of 1984 were used. The structural coefficient estimates were used to calculate 3 month, 6 month, 12 month, 24 month, and long-run price flexibilities. These price flexibilities reflected the distributed lag patterns of the endogenous price variables which facilitated analysis of their adjustment process. Statistical tests revealed that joint dependency was nonexistent between monthly wheat, flour, and bread prices, but rather that a recursive structure existed. That is, wheat price determined flour price and flour price, in turn, determined bread price. This stands in contrast to many agricultural commodities where economic conditions in the higher market levels (i.e., retail) feed

into the lower market levels (i.e., farm).

The terminal market wheat prices were estimated as a function of seasonal variables, lagged exports of wheat, lagged exports of feedgrains, U.S.D.A. monthly wheat production estimates, and third and fourth order nonstochastic difference equations. The third order difference equation was estimated for Port. SWW and fourth order difference equations were estimated for K.C. HRW and Minn. DNS. All equations were estimated as Pascal distributed lags with positive first order serial correlation. Exports of wheat and exports of feedgrains included contemporaneous values and lags of one period. Both the wheat and feedgrain export variables exerted a negative impact on the terminal wheat prices, indicating increases in quantity demanded occurred at lower market prices. However, the asymptotic t-ratios were relatively weak for feedgrain exports, probably due to wheats minor role in livestock feeding. The wheat production variable exerted a positive relationship with wheat prices, which was contrary to theoretical expectations. Total stocks of wheat was the dominant variable in determining monthly wheat prices. In particular, its price flexibility coefficient exceeded twice the value of those of other regressors.

Kansas City flour price was estimated as a function of seasonal variables, lagged Kansas City wheat price, per capita U.S. disposable income, quantity of flour milled per capita, a trend variable, and a first order nonstochastic difference equation. The structure was estimated by rational distributed lags with positive first order autoregression in the error structure. Kansas City Hard Red Winter

Wheat price (contemporaneous and one period lag) was the most important variable in determining flour price. This result is consistent with the fact that wheat is the dominant raw product input in the milling process and constitutes the largest portion of variable costs.

Retail bread price was estimated as a function of seasonal variables, contemporaneous and lagged Kansas City flour price, U.S. per capita disposable income, a price index of potatoes, a trend variable, and a first order nonstochastic difference equation. The equation was likewise estimated by rational lags with a positive first order autoregressive error. Basically, the statistical results showed that K.C. flour price was the most influential variable in determining levels of bread prices within a sixth month period. However, beyond six months disposable income was most important, indicating that secular effects of demand (i.e., as opposed to the input side of the market) are more important in establishing bread price.

All of the multivariate ARIMA models were estimated as a function of the same set of lagged stochastic price variables, accounting for seasonality and time effects in the data with binary variables and a trend variable, respectively. The lagged price variables that were not statistically significant were omitted from each price equation. The result was that the price equations for Port. SWW, and retail bread reverted back to a univariate autoregressive structure. The price equations for K.C. HRW, Minn. DNS, and K.C. flour more nearly reflected a multivariate autoregressive structure since an additional lagged price variable was included (Port. SWW price, retail bread price, and retail bread price, respectively). These results suggest that the ARIMA

models are relatively efficient since past wheat, flour, and bread prices appear to capture relevant economic and technical information in the market.

In the structural and ARIMA models, the 12 most recent sample observations were sequentially truncated and then monthly predictions were made for each estimation method. Their prediction performances were evaluated via calculated Root Mean Square Errors of forecast. Overall, the price prediction performances of the structural and multivariate ARIMA models were relatively close, with the structural model performing only slightly better. Both demonstrated parameter stability in the truncation process and all RMSEs were less than their standard errors of forecast. Since data collection and parameter estimation may be less costly for time series equations, it is concluded (for this model) that the ARIMA approach may be more efficient if short term prediction were the only goal of the researcher. However, if the effect of grain policy decisions must be analyzed (i.e., the impact of a change in the government storage program on wheat price) then a structural model is superior since there is a description of cause-effect relationships.

Several concluding remarks are in order. First, in this model the relationship of wheat, flour, and bread prices is cast in a relatively short run framework. Consequently, price studies based on longer periods, such as quarterly or annual models, might negate the recursive structure and yield more of a jointly dependent system. Second, a further refined model could provide additional information for terminal wheat prices determined by quantities divided into different classes of

wheat; however, the necessary data was not available. Third, the interpretation of the effect of wheat exports may be relatively obscure since it also captures the effects of other variables such as the income of importing countries, ocean freight rates, and indirectly, farm programs. Fourth, the Root Mean Square Errors of forecast were estimated on a month to month basis; however, longer forecast periods such as three and six months may be valuable because of the time involved in producer grain marketing and holding decisions. Lastly, overall, the parameter estimates in the structural wheat price equations were not highly significant though most of the coefficient signs were theoretically correct and the adjusted R^2's were high. The strength in these equations, according to the t-ratios, was the negative impact of stocks. However, its effect goes beyond the terminal market since wheat prices are instrumental in the flour market, and indirectly in the bread market. One can conclude that the structural equations would serve as a base for likely direction and magnitude in wheat price changes (due to changes in the independent variables), but such measurements need to be interpreted with caution.

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APPENDIX

Table 7. Original Data Used in the K.C. HRW, Minn. DNS, Port. SWW, K.C. Flour, and Retail Bread Price Equations.[a]

OBS	Consumer Price Index	K.C. HRW Price	Minn. DNS Price	Port. SWW Price	K.C. Flour Price
1	.18180E+03	.23100E+01	.24300E+01	.27900E+01	.55800E+01
2	.18260E+03	.23500E+01	.22900E+01	.28800E+01	.58500E+01
3	.18330E+03	.23100E+01	.22200E+01	.28800E+01	.59100E+01
4	.18400E+03	.24700E+01	.25100E+01	.28000E+01	.60900E+01
5	.18450E+03	.25600E+01	.26100E+01	.27500E+01	.63200E+01
6	.18540E+03	.28100E+01	.27100E+01	.29100E+01	.65800E+01
7	.18610E+03	.28000E+01	.26800E+01	.29700E+01	.64900E+01
8	.18720E+03	.28200E+01	.27300E+01	.31700E+01	.69900E+01
9	.18840E+03	.28400E+01	.27200E+01	.33300E+01	.66800E+01
10	.18980E+03	.30700E+01	.28600E+01	.34100E+01	.69600E+01
11	.19150E+03	.32100E+01	.30800E+01	.36200E+01	.72500E+01
12	.19330E+03	.31200E+01	.31000E+01	.36000E+01	.74600E+01
13	.19530E+03	.31200E+01	.30600E+01	.36000E+01	.72300E+01
14	.19670E+03	.31400E+01	.29500E+01	.37400E+01	.76000E+01
15	.19780E+03	.31400E+01	.29600E+01	.37200E+01	.75800E+01
16	.19930E+03	.32400E+01	.30700E+01	.37700E+01	.75500E+01
17	.20090E+03	.34200E+01	.32100E+01	.37600E+01	.76000E+01
18	.20200E+03	.34800E+01	.33200E+01	.37600E+01	.79200E+01
19	.20290E+03	.33900E+01	.31500E+01	.37100E+01	.77900E+01
20	.18720E+03	.34200E+01	.31200E+01	.37000E+01	.75500E+01
21	.18840E+03	.35000E+01	.31200E+01	.36500E+01	.77800E+01
22	.18980E+03	.35200E+01	.31800E+01	.37000E+01	.81800E+01
23	.19150E+03	.35300E+01	.32900E+01	.37000E+01	.81200E+01
24	.19330E+03	.36400E+01	.36200E+01	.39100E+01	.88000E+01
25	.19530E+03	.41700E+01	.42300E+01	.44600E+01	.90800E+01
26	.19670E+03	.43400E+01	.43100E+01	.46700E+01	.10390E+02
27	.19780E+03	.41200E+01	.41000E+01	.44500E+01	.10090E+02
28	.19930E+03	.42600E+01	.41800E+01	.43100E+01	.10080E+02
29	.20090E+03	.43900E+01	.43100E+01	.41300E+01	.10100E+02
30	.20200E+03	.45300E+01	.42700E+01	.41600E+01	.10600E+02
31	.20290E+03	.45100E+01	.41800E+01	.41000E+01	.10460E+02
32	.23320E+03	.43300E+01	.41600E+01	.41000E+01	.10000E+02
33	.23640E+03	.43200E+01	.41300E+01	.42600E+01	.10260E+02
34	.24490E+03	.40700E+01	.40400E+01	.41300E+01	.98100E+01
35	.24250E+03	.39000E+01	.39400E+01	.40200E+01	.94900E+01
36	.24490E+03	.41000E+01	.42100E+01	.39100E+01	.10010E+02
37	.24760E+03	.40700E+01	.41900E+01	.39200E+01	.98100E+01
38	.24780E+03	.42100E+01	.45400E+01	.41500E+01	.10000E+02
39	.24940E+03	.43100E+01	.42200E+01	.40600E+01	.10110E+02
40	.25170E+03	.44500E+01	.41700E+01	.42300E+01	.10480E+02
41	.25390E+03	.47000E+01	.46200E+01	.44800E+01	.10600E+02

[a] Observations 1-84 represent months of June 1977 to May 1984.

Table 7 (continued).

OBS	Consumer Price Index	K.C. HRW Price	Minn. DNS Price	Port. SWW Price	K.C. Flour Price
42	.25620E+03	.48900E+01	.47800E+01	.46800E+01	.10680E+02
43	.25840E+03	.45400E+01	.46200E+01	.44000E+01	.10350E+02
44	.26050E+03	.46000E+01	.46500E+01	.45200E+01	.10660E+02
45	.26320E+03	.44700E+01	.45300E+01	.45200E+01	.10400E+02
46	.26900E+03	.43500E+01	.43200E+01	.44100E+01	.10280E+02
47	.26680E+03	.44800E+01	.44100E+01	.45100E+01	.10530E+02
48	.26900E+03	.43600E+01	.44400E+01	.44100E+01	.10310E+02
49	.27130E+03	.42400E+01	.42900E+01	.42600E+01	.10530E+02
50	.27440E+03	.42500E+01	.41800E+01	.42700E+01	.10280E+02
51	.27650E+03	.41400E+01	.40300E+01	.42500E+01	.10300E+02
52	.27930E+03	.41900E+01	.40700E+01	.42100E+01	.10200E+02
53	.27990E+03	.43100E+01	.42200E+01	.43800E+01	.10020E+02
54	.28070E+03	.44600E+01	.42900E+01	.44200E+01	.10310E+02
55	.28150E+03	.43500E+01	.41500E+01	.40000E+01	.10050E+02
56	.28250E+03	.43300E+01	.42100E+01	.41200E+01	.10640E+02
57	.28340E+03	.42600E+01	.41700E+01	.40900E+01	.10700E+02
58	.28310E+03	.42500E+01	.41000E+01	.41200E+01	.10640E+02
59	.28430E+03	.42800E+01	.42100E+01	.41400E+01	.10420E+02
60	.28710E+03	.42200E+01	.41600E+01	.42400E+01	.10330E+02
61	.29060E+03	.40600E+01	.40800E+01	.41800E+01	.10260E+02
62	.29220E+03	.37400E+01	.40800E+01	.41300E+01	.10210E+02
63	.29280E+03	.37000E+01	.37800E+01	.41600E+01	.99800E+01
64	.29330E+03	.37500E+01	.37900E+01	.42900E+01	.10120E+02
65	.29410E+03	.36100E+01	.37800E+01	.42900E+01	.99600E+01
66	.29360E+03	.38600E+01	.38500E+01	.44400E+01	.99200E+01
67	.29240E+03	.39800E+01	.37600E+01	.44500E+01	.10300E+02
68	.29310E+03	.40000E+01	.38000E+01	.45200E+01	.10200E+02
69	.29320E+03	.40800E+01	.38200E+01	.45900E+01	.10490E+02
70	.29340E+03	.41800E+01	.40100E+01	.46800E+01	.10500E+02
71	.29550E+03	.42100E+01	.43400E+01	.46200E+01	.10160E+02
72	.29710E+03	.40500E+01	.42500E+01	.43500E+01	.10350E+02
73	.29810E+03	.39200E+01	.41500E+01	.41500E+01	.10390E+02
74	.29930E+03	.37100E+01	.40700E+01	.40800E+01	.10380E+02
75	.30030E+03	.38800E+01	.42100E+01	.40600E+01	.10340E+02
76	.30180E+03	.39000E+01	.43000E+01	.41200E+01	.10330E+02
77	.30260E+03	.38400E+01	.43300E+01	.40300E+01	.10300E+02
78	.30310E+03	.38200E+01	.42300E+01	.39000E+01	.10020E+02
79	.30350E+03	.38500E+01	.42100E+01	.38100E+01	.96800E+01
80	.30520E+03	.38100E+01	.41500E+01	.37900E+01	.98700E+01
81	.30660E+03	.37100E+01	.40600E+01	.36900E+01	.10030E+02
82	.30730E+03	.38500E+01	.42000E+01	.37300E+01	.10120E+02
83	.30880E+03	.39300E+01	.42800E+01	.40300E+01	.10070E+02
84	.30970E+03	.37200E+01	.43900E+01	.40500E+01	.10120E+02

Table 7 (continued).

OBS	Population	Quantity of Wheat Stocks	Quantity of Feedgrain Exports	Quantity of Wheat Exports	U.S. Wheat Production Estimate
1	.21667E+03	.11108E+04	.39000E+01	.77073E+05	.55100E+02
2	.21682E+03	.14322E+04	.41000E+01	.83657E+05	.55600E+02
3	.21699E+03	.17536E+04	.41000E+01	.93432E+05	.55600E+02
4	.21716E+03	.20750E+04	.46000E+01	.11063E+06	.55200E+02
5	.21733E+03	.23965E+04	.38000E+01	.69107E+05	.55200E+02
6	.21748E+03	.22623E+04	.46000E+01	.57565E+05	.55200E+02
7	.21761E+03	.21281E+04	.53000E+01	.87368E+05	.55200E+02
8	.21774E+03	.19938E+04	.42000E+01	.64819E+05	.55100E+02
9	.21784E+03	.18384E+04	.43000E+01	.94669E+05	.55100E+02
10	.21794E+03	.16830E+04	.51000E+01	.10547E+06	.48100E+02
11	.21809E+03	.15277E+04	.51000E+01	.10329E+06	.48100E+02
12	.21822E+03	.13522E+04	.60000E+01	.12006E+06	.48800E+02
13	.21836E+03	.11767E+04	.58000E+01	.10893E+06	.48800E+02
14	.21850E+03	.14168E+04	.50000E+01	.10611E+06	.49500E+02
15	.21867E+03	.16569E+04	.52000E+01	.13192E+06	.49500E+02
16	.21886E+03	.18970E+04	.48000E+01	.11961E+06	.48700E+02
17	.21903E+03	.21370E+04	.39000E+01	.11552E+06	.48400E+02
18	.21919E+03	.19686E+04	.44000E+01	.92392E+05	.48400E+02
19	.21934E+03	.18002E+04	.45000E+01	.90027E+05	.49000E+02
20	.21953E+03	.16318E+04	.42000E+01	.70400E+05	.49000E+02
21	.21967E+03	.14963E+04	.43000E+01	.67106E+05	.49000E+02
22	.21978E+03	.13606E+04	.49000E+01	.75548E+05	.49000E+02
23	.21993E+03	.12249E+04	.53000E+01	.76961E+05	.49000E+02
24	.22009E+03	.10747E+04	.58000E+01	.78306E+05	.49000E+02
25	.22025E+03	.92450E+03	.61000E+01	.10461E+06	.49000E+02
26	.22058E+03	.12611E+04	.60000E+01	.13328E+06	.57200E+02
27	.22078E+03	.15977E+04	.62000E+01	.11779E+06	.58100E+02
28	.22099E+03	.19343E+04	.54000E+01	.12962E+06	.57800E+02
29	.22118E+03	.22708E+04	.63000E+01	.14904E+06	.57500E+02
30	.22136E+03	.20859E+04	.65000E+01	.10888E+06	.57500E+02
31	.22155E+03	.19010E+04	.65000E+01	.11488E+06	.57500E+02
32	.22172E+03	.17162E+04	.59000E+01	.82683E+05	.58300E+02
33	.22187E+03	.15525E+04	.58000E+01	.89526E+05	.58300E+02
34	.22200E+03	.13888E+04	.61000E+01	.94735E+05	.58300E+02
35	.22217E+03	.12251E+04	.65000E+01	.98327E+05	.58300E+02
36	.22235E+03	.10635E+04	.51000E+01	.88579E+05	.61800E+02
37	.22261E+03	.90200E+03	.57000E+01	.96193E+05	.61800E+02
38	.22281E+03	.12946E+04	.57000E+01	.12360E+06	.63100E+02
39	.22301E+03	.16872E+04	.59000E+01	.14141E+06	.63300E+02
40	.22324E+03	.20798E+04	.58000E+01	.13732E+06	.64100E+02
41	.22345E+03	.24723E+04	.69000E+01	.11695E+06	.64300E+02
42	.22848E+03	.22826E+04	.70000E+01	.11220E+06	.64300E+02

Table 7 (continued).

OBS	Population	Quantity of Wheat Stocks	Quantity of Feedgrain Exports	Quantity of Wheat Exports	U.S. Wheat Production Estimate
43	.22865E+03	.20929E+04	.68000E+01	.13205E+06	.64300E+02
44	.22883E+03	.19032E+04	.62000E+01	.12998E+06	.64500E+02
45	.22898E+03	.17117E+04	.61000E+01	.12440E+06	.64500E+02
46	.22912E+03	.15202E+04	.60000E+01	.12877E+06	.64500E+02
47	.22928E+03	.13286E+04	.53000E+01	.12765E+06	.64500E+02
48	.22944E+03	.11587E+04	.60000E+01	.78030E+05	.73600E+02
49	.22962E+03	.98880E+03	.46000E+01	.12452E+06	.71800E+02
50	.22980E+03	.14254E+04	.47000E+01	.13817E+06	.76500E+02
51	.23003E+03	.18620E+04	.47000E+01	.14543E+06	.74800E+02
52	.23026E+03	.22986E+04	.49000E+01	.19415E+06	.74800E+02
53	.23048E+03	.27352E+04	.61000E+01	.15699E+06	.74800E+02
54	.23067E+03	.25495E+04	.51000E+01	.12749E+06	.74800E+02
55	.23084E+03	.23638E+04	.54000E+01	.13776E+06	.74800E+02
56	.23101E+03	.21780E+04	.48000E+01	.12416E+06	.76000E+02
57	.23118E+03	.19710E+04	.44000E+01	.13872E+06	.76000E+02
58	.23138E+03	.17640E+04	.56000E+01	.14908E+06	.76000E+02
59	.23154E+03	.15571E+04	.54000E+01	.14818E+06	.76000E+02
60	.23170E+03	.13605E+04	.58000E+01	.11660E+06	.72100E+02
61	.23188E+03	.11639E+04	.50000E+01	.14591E+06	.73900E+02
62	.23206E+03	.16197E+04	.37000E+01	.11791E+06	.73800E+02
63	.23228E+03	.20755E+04	.37000E+01	.12434E+06	.75400E+02
64	.23250E+03	.25313E+04	.34000E+01	.13099E+06	.76600E+02
65	.23270E+03	.29871E+04	.48000E+01	.98520E+05	.76500E+02
66	.23290E+03	.28315E+04	.49000E+01	.94638E+05	.76500E+02
67	.23308E+03	.26759E+04	.52000E+01	.88457E+05	.76500E+02
68	.23327E+03	.25210E+04	.53000E+01	.14314E+06	.76400E+02
69	.23343E+03	.23060E+04	.46000E+01	.14659E+06	.76400E+02
70	.23357E+03	.20920E+04	.49000E+01	.13113E+06	.76400E+02
71	.23374E+03	.18770E+04	.42000E+01	.11245E+06	.76400E+02
72	.23389E+03	.17090E+04	.41000E+01	.96235E+05	.64000E+02
73	.23407E+03	.15410E+04	.42000E+01	.11351E+06	.63800E+02
74	.23423E+03	.18973E+04	.36000E+01	.11670E+06	.66300E+02
75	.23467E+03	.22535E+04	.37000E+01	.87823E+05	.66000E+02
76	.23488E+03	.26098E+04	.46000E+01	.11926E+06	.65500E+02
77	.23522E+03	.29660E+04	.47000E+01	.11481E+06	.65500E+02
78	.23538E+03	.27527E+04	.57000E+01	.10288E+06	.65500E+02
79	.23555E+03	.25393E+04	.53000E+01	.12889E+06	.65500E+02
80	.23571E+03	.23260E+04	.53000E+01	.11836E+06	.66000E+02
81	.23588E+03	.21360E+04	.48000E+01	.11110E+06	.66000E+02
82	.23603E+03	.19460E+04	.54000E+01	.11871E+06	.66000E+02
83	.23620E+03	.17560E+04	.50000E+01	.97132E+05	.66000E+02
84	.23636E+03	.15660E+04	.46000E+01	.11281E+06	.69400E+02

Table 7 (continued).

OBS	Disposable Income	Retail Bread Price	Wage of Flour Mill Workers
1	.13026E+04	.40200E+02	.58300E+01
2	.13222E+04	.40600E+02	.59300E+01
3	.13317E+04	.40600E+02	.60300E+01
4	.13424E+04	.40700E+02	.62000E+01
5	.13558E+04	.40500E+02	.62100E+01
6	.13679E+04	.40400E+02	.64000E+01
7	.13799E+04	.40900E+02	.63900E+01
8	.13825E+04	.39900E+02	.64000E+01
9	.13949E+04	.40100E+02	.63800E+01
10	.14166E+04	.40200E+02	.64300E+01
11	.14330E+04	.40300E+02	.64400E+01
12	.14399E+04	.41200E+02	.64900E+01
13	.14493E+04	.41900E+02	.65300E+01
14	.14702E+04	.42000E+02	.66800E+01
15	.14825E+04	.42400E+02	.68500E+01
16	.14936E+04	.42400E+02	.71100E+01
17	.15131E+04	.42800E+02	.70800E+01
18	.15294E+04	.43500E+02	.71700E+01
19	.15504E+04	.44000E+02	.71100E+01
20	.15648E+04	.44400E+02	.69400E+01
21	.15785E+04	.44600E+02	.69900E+01
22	.15972E+04	.44900E+02	.69200E+01
23	.16024E+04	.45200E+02	.68300E+01
24	.16105E+04	.45400E+02	.68900E+01
25	.16254E+04	.45700E+02	.69000E+01
26	.16503E+04	.46600E+02	.70400E+01
27	.16664E+04	.47700E+02	.71700E+01
28	.16747E+04	.48200E+02	.73700E+01
29	.16944E+04	.48600E+02	.75000E+01
30	.17109E+04	.49100E+02	.76100E+01
31	.17251E+04	.49800E+02	.75800E+01
32	.17569E+04	.50100E+02	.73600E+01
33	.17633E+04	.50700E+02	.73600E+01
34	.17751E+04	.50200E+02	.74600E+01
35	.17756E+04	.50700E+02	.75800E+01
36	.17838E+04	.50400E+02	.75400E+01
37	.17930E+04	.50300E+02	.76200E+01
38	.18249E+04	.51100E+02	.78300E+01
39	.18377E+04	.50700E+02	.79100E+01
40	.18592E+04	.51100E+02	.79200E+01
41	.18802E+04	.51400E+02	.79200E+01
42	.18977E+04	.51900E+02	.81500E+01

Table 7 (continued).

OBS	Disposable Income	Retail Bread Price	Wage of Flour Mill Workers
43	.19131E+04	.51900E+02	.80200E+01
44	.19314E+04	.53100E+02	.80000E+01
45	.19466E+04	.53300E+02	.80100E+01
46	.19654E+04	.53800E+02	.79700E+01
47	.19756E+04	.51900E+02	.80400E+01
48	.19849E+04	.52500E+02	.80300E+01
49	.19963E+04	.52300E+02	.81900E+01
50	.20554E+03	.52100E+02	.82200E+01
51	.20432E+04	.51900E+02	.84400E+01
52	.20573E+04	.52400E+02	.85500E+01
53	.20804E+04	.52100E+02	.84600E+01
54	.20929E+04	.52700E+02	.84600E+01
55	.20921E+04	.52100E+02	.85500E+01
56	.21092E+04	.53700E+02	.86400E+01
57	.21175E+04	.53400E+02	.87500E+01
58	.21244E+04	.52600E+02	.87800E+01
59	.21463E+04	.52600E+02	.88300E+01
60	.21525E+04	.52900E+02	.87800E+01
61	.21556E+04	.52500E+02	.87200E+01
62	.21948E+04	.53400E+02	.91400E+01
63	.21967E+04	.53400E+02	.93100E+01
64	.22027E+04	.53600E+02	.94200E+01
65	.22119E+04	.53400E+02	.93600E+01
66	.22287E+04	.53400E+02	.94500E+01
67	.22323E+04	.53700E+02	.93800E+01
68	.22532E+04	.53800E+02	.93800E+01
69	.22482E+04	.54000E+02	.94400E+01
70	.22665E+04	.54400E+02	.94600E+01
71	.22868E+04	.54500E+02	.94400E+01
72	.23038E+04	.54600E+02	.95500E+01
73	.23124E+04	.54700E+02	.95500E+01
74	.23518E+04	.54900E+02	.97200E+01
75	.23644E+04	.54700E+02	.98700E+01
76	.23861E+04	.54600E+02	.99700E+01
77	.24103E+04	.55000E+02	.99400E+01
78	.24269E+04	.55500E+02	.10040E+02
79	.24487E+04	.55600E+02	.10110E+02
80	.24822E+04	.56000E+02	.10150E+02
81	.25045E+04	.55600E+02	.10130E+02
82	.25197E+04	.55900E+02	.10060E+02
83	.25452E+04	.55800E+02	.10180E+02
84	.25541E+04	.56200E+02	.99900E+01