ESSAYS ON TOTAL EVALUATION OF COLOMBIA WHEAT IMPORT DEMAND, FORECAST EVALUATION OF THE UNITED STATES TOTAL WHEAT TRADE IN COLOMBIA, AND THE IMPACT OF PRICE CHANGES AND TRENDS ON DEMAND FOR MEAT IN NIGERIA

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DEDICATION

I dedicate this piece of academic research thesis first and foremost, to our God Almighty ---Jesus Christ for His mercy endures forever. Second, to the entire members of Alliance Bible Church Stillwater, Oklahoma for their constant and unfailing love for me throughout the course of my studies here at Oklahoma State University. Finally, to those lives lost and living victims of Holocaust and at the Pentagon and World Trade Center in New York on September 11, 2001. What a great base of knowledge wasted!

PREFACE

This research study was conducted to provide further knowledge and insight with regard to the following economics issues:

(1) Determination of Colombia's total wheat import demand and effect of seasonality especially from the major exporters such as the United States and Canada.

(2) Forecasting the United States' total wheat exports to Colombia, with the specific objective to develop forecasting models that incorporate economic variables such as wheat prices and exchange rates on monthly trade flows in Colombia's wheat market.

(3) Estimating the responsiveness of demand for meat to variations in prices and incomes. In addition, determination of whether demand for meat is price-elastic on the basis of food demand data covering the period of 1980 to 1999, and provide recommendations for policies that can help create more stable meat consumption and prices for the nation.

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I.

TOTAL EVALUATION OF COLOMBIA WHEAT IMPORT DEMAND: ECONOMIC ANALYSIS AND PROJECTION

Introduction

Colombia, the fourth largest country in South America, occupies a strategic position as the gateway to the South American economy, with port facilities on both the Pacific Ocean and the Caribbean Sea.[1] Colombia's real Gross Domestic Product (GDP) grew only marginally in 1998, and growth is forecasted at 1.6 present in 1999 (USDA, 1999). Agriculture's share of the GDP is forecasted to decline to 14 percent in 1999 from 20.1 percent in 1995 (Agriculture and Agri-Food Canada, 2000). Per capita income increased marginally to US$2,261 in 1999, and the inflation rate is currently at approximately 30 percent (Table 1.1).

Colombia has emerged over the past six years as a stable growth market for the United States exports of agricultural products, in particular grain exports, and it continues to beckon with opportunity as interested agricultural exporters set forth to explore trade liberalization in beginning 1991 (USDA, 1996a). Colombian trade data show that the

[1] Economic growth in Colombia slowed significantly in 1998 and 1999. The downturn is attributed to low oil and coffee prices, the economic slowdown in neighboring countries especially Ecuador and Venezuela, devaluation of the peso, and economic difficulties in Brazil.

U.S. market share of Colombia's total agricultural imports has risen from 29 percent of total import value in 1991 to 42 percent in 1995 and to 45 percent in 1996 (USDA, 1998).

Major U.S. grain exports to Colombia consist of corn, wheat, and soybeans. After nearly a year of slow or negative growth, according to 1997 data provided by the Colombian government, the economy grew at a robust 4.7 percent in the third quarter of 1997. Government forecasters anticipated economic growth of 3 to 4 percent for calendar 1997 and anticipated 5 percent for 1998 (USDA, 1997).

Prior to 1991, the Colombian market was largely restricted to imports of most commodities, especially grains, as the government pressed a basic policy of food self-sufficiency. United States agricultural exports have benefited from virtual elimination of import quotas, a reduction in import tariffs and improvements in import licensing procedures (USDA, 1998).

With Colombia placing priority on its dairy, livestock and poultry industries, together with a growing population and a downward trend in grain and oilseed production, long-term sales opportunities are bright for U.S. grains and particularly wheat (USDA, 1996b). Colombia's wheat production has declined from a high of 117,000 tonnes in 1992 to 25,000 tonnes in 1999 (Table 1.2). As area seeded shifted to more profitable crops, such as fruits and vegetables, between 1988 and 1992, the United States was the largest supplier of wheat to Colombia (USDA, 1996b). Figure 1.1 shows that Colombia's total wheat imports grew with GDP per capita from 1980 through 1999. However, since the partial elimination of trade barriers [2], other countries, most notably

[2] Prior to 1992, before the advent of trade pacts such as the Andean Trade Pacts, the Colombian government agency Institute de Mercadeo Agropecuarira (IDEMA) controlled all wheat imports. *Andean Community and Mercosur Merger*: Colombia and the Andean community are hoping to sign a merger agreement during 1999 with the Mercosur trade bloc---Argentina, Brazil, Paraguay and Uruguay that will become effective January 1, 2000. The Government of

Canada, have increased their market share. Canadian wheat exports to Colombia have averaged 0.44 million metric tons (MMT) over the past five years. However, Canadian share is forecast to decrease to 0.25 MMT for 1999-2000, the Canadian wheat prices are higher due to high protein premiums (USDA, 2000).

Therefore, although the Colombian market is expected to grow, United States market share is being challenged by Canada and could face increased competition from other countries such as Argentina and Australia that are likely to receive duty preferences in the years to come as a result of the South American Trade Agreements (Hoffman Schwartz and Chomo, 1995). The United States share of Colombian total wheat imports fell from 52 percent in 1996 to 35 percent in 1998, while the Canadian share rose from 39 percent to 42 percent. Colombian wheat imports in marketing year 1995-1998 are estimated at 950,000 tons. This volume is expected to consist of almost 90 percent hard wheat and approximately 10 percent soft wheat (USDA, 1996b). The Colombian wheat market is part of a trend that is becoming apparent in terms of wheat export competition in many of the South American import markets.

Another factor influencing import demand is seasonality. Seasonality is a pattern in markets that generally repeats itself each year, although this pattern may drift or change in amplitude over time (Jaditz, 1994). Production of wheat in Colombia is often during the major harvest month July and is usually due to start from the fourth quarter. Hence, the bulk of the United States wheat is exported to Colombia during the second quarter of every year particularly between June and July. This view of seasonality is at the very core of the approach taken by the United States Department of Agriculture towards adjustment

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Colombia (GOC) hopes that the elimination of duties on agricultural products imported from Mercosur countries will of their data (Harwood and Bailey, 1990). The seasonality explores the question of the impact of weather, predictable and regular calendar events, transportation, domestic production, and social conventions on seasonal variations in data. There also tends to be more seasonality of demand in some shipping lanes due to trade patterns or prevailing conditions in bulk commodity markets particularly for grains (USDA, 1996a).

Another important reason for reduction of the United States' wheat market share in Colombia might be long-term trade agreements between an importer and exporter. These long-term trade agreements typically involve shipment periods of two or more seasons and often provide an upper and lower bound on purchases (Harwood and Bailey, 1990). Therefore, long-term trade agreements can decrease an importer's flexibility to respond immediately to market conditions. Long-term trade agreements are widely used in world wheat trade. In the 1980s, approximately 25 to 30 percent overall world wheat was traded through long-term trade agreements (Harwood and Bailey, 1990).

The Colombian wheat market exhibits a trend that is becoming apparent in terms of wheat export competition in import markets where United States and Canada are the major exporters of wheat. That is, increased Canadian competition on the one side, and trade policy agreements among the South American countries on the other, are complicating the environment in which the United States must operate to maintain steady market shares. Hence, the main objective of this research is to determine the impact of economic factors influencing Colombia's total wheat import demand. More specifically, this study will highlight the effects of seasonality on the Colombian wheat import demand from the United States and Canada. In other words, this study will attempt to determine

be phased in over an extended period for 7 or 8 years (Agriculture Canada, 1997).

how seasonality impacts various exporting countries differently. Also, differences in own-price demand elasticities as a result of seasonality will be determined.

Model Considerations

The empirical investigation of the import demand function has been one of the most active research areas in international economics. Perhaps one of the main reasons for its popularity is its application to a wide range of important macroeconomic policy issues (Abdelhak, 1998). More specially, the international transmission of domestic disturbances, where these elasticities are a crucial link between economies, the degree to which the external balance constraint affects trade competition.

The traditional import demand function is often specified as a log-linear function of relative price of imports and real income. Empirical researchers are generally interested in two statistical properties of their estimates of import demand elasticities. First, they are interested in the magnitude of these elasticities. A relevant question then is how close the small sample estimates are to their true value.
Second, they are interested in inference, that is, hypotheses testing, about these estimates. For example, are the price and income elasticities significantly different from one (Green, 1976)?

Yang and Koo (1994) specified a source differentiated AIDS model to estimate Japanese meat import demand. Block separability and product aggregation are rejected at conventional levels of significance. The model with the block substitutability restriction explains more than 95 percent of data variation. The empirical results indicated that the U.S. has the largest potential for beef exports to Japan. Taiwan is in a strong position in the pork market, and Thailand and China are strong in the poultry market. The U.S. competes with Canada and Taiwan in the pork market, but the competition between Taiwan and European countries is the strongest in the market. The U.S. competes with Thailand in the poultry market, where the U.S. is the most vulnerable.

Van, De Boer, and Harkema (1993) used a first-order autoregressive scheme in order to introduce dynamics into the AIDS model. They also considered the theoretical restrictions of additivity, homogeneity, and symmetry, and used two different specifications of the covariance matrix. They estimated the models using import allocation data for the U.K. 1952-1979 of five EEC countries and tested different specifications against each other.

In the case of wheat trade, the world wheat market is one of the most widely studied commodity markets (McCalla; Alaouze, Watson, and Sturgess; Wilson, Koo and Cater; and many others). Despite this, it remains one of the most controversial commodity markets because of its imperfectly competitive structure, including large grain trading companies and state trading enterprises (STES), product heterogeneity, and extensive government intervention in both exporting and importing countries. Among various aspects of the market, estimation of demand including exports and import demand has received significant attention in the past few decades (Mohanty and Peterson, 1999).

Most past studies estimating demand for wheat have either ignored or have failed to fully recognize two important factors: product differentiation of wheat and dynamics in the wheat demand function. With respect to product differentiation of wheat by source, past studies can be divided into three different groups. First, various studies such as

Konandreas, Bushell and Green; and Gallagher et al. have assumed perfect substitutability across classes and origins. The second group of studies has allowed for imperfect substitutability either in terms of origin or end uses (Wang; Chai; and Chang; and Agriculture Canada). The importance of product differentiation of wheat, where trade is the focus has been recognized by Sumner, Alston and Gray (1994). Furthermore, both Larue (1991), and Wilson (1989) argue that wheat should be differentiated also by country of origin. Larue (1991) found that the assumption of one form of differentiation or another would be appropriate if countries specialize in one product type or the given product type is exported by only one country.

Demand Specifications

In the literature, relatively few models have been used for import demand analyses. The Armington trade model is theoretically consistent and has been widely used (Abbott and Paarlberg; Babula; Penson and Babula; Sarris). The advantage of the Armington trade model is that it differentiates goods by sources; in other words, the model allows for imperfect substitutions among goods from different origins (Armington, 1978). However, this model suffers from the restrictive assumptions of homotheticity[3a] and single constant elasticity of substitution (Alston et al; Winters: Yang and Koo) and is no longer a popular model.

A traditional approach to identifying price responses in international trade is to employ the elasticity of substitution model. In this approach, logarithms of relative

[3a] A homothetic function is a monotonic transformation of function that is homogenous of degree 1. In other words, $f(X)$ is homothetic if and only if $f(X)$ can be written as $f(X) = g[h(X)]$ where $h(X)$ is homogenous of degree 1 and $g(X)$ is a monotonic function (Varian, 1992).

import ratios are regressed on the logarithms of income and relative prices. The functional form used in the specification has been widely criticized because it is not derivable from an underlying model of optimization behavior (Samarendu and Peterson, 1999).

Alternatively, Deaton and Muellbauer's (1980) AIDS model has an important feature that the expenditure levels are allowed to impact the distribution of shares. It has a flexible functional form, allowing testing of theoretical restrictions on demand equations.

The AIDS model is derived from a cost function representing a PIGLOG[3b] class of preferences. These preferences, represented by either a cost or an expenditure function, define the minimum expenditure necessary to attain a specific utility level at a given price (Chalfant, 1987). The cost function $c(u, P)$ for utility u and price vector P can be defined using the PIGLOG class of preferences by

(1) $$\log c(u,P) = (1-u)\log\{a(p)\} + u\log\{b(P)\}.$$

Where u lies between 0 (subsistence) and 1 (bliss) so that the positive linearly homogeneous function $a(P)$ and $b(P)$ can be regarded as the costs of subsistence and bliss, respectively (Theil, 1965). The functional forms for log $a(P)$ and log $b(P)$ are chosen such that the first and the second order derivatives of the cost function can be set equal to those of an arbitrary cost function, thus satisfying the necessary condition for flexibility of functional form.

(2) $$\log a(P) = \alpha_0 + \sum \alpha_k \log P_k + \tfrac{1}{2}\sum_k \sum_j \gamma_{kj}^* \log P_k \log P_j ,$$

[3b] PIGLOG is a special form of the price-independent, generalized (PIGL) class of preferences.

$$\log b(P) = \log a(P) + \beta_0 \prod_k P_k^{\beta_k}. \tag{3}$$

After the selection of a specific functional form, the cost function in the AIDS model can be written as

$$\log c(u,P) = \alpha_0 + \sum \alpha_k \log P_k + \tfrac{1}{2}\sum_k \sum_j \gamma_{kj}^* \log P_k \log P_j + \beta_0 \prod_k P_k^{\beta_k}. \tag{4}$$

The demand functions can be derived directly from the cost function equation (4) using Shepherd's lemma because a fundamental property of the cost function is that price derivatives are the quantity demanded $\partial c(u,P)/\partial P_i = q_i$. Multiplying both sides by $P_i/c(u,P)$, the left-hand side may be expressed as a budget share and the right-hand side may be expressed as a function of prices and utility. The cost function is then solved for u and the resulting term is substituted for u in the budget share equation (Theil, 1980). The budget shares as a function of P and X (total expenditure) can be represented as a single equation:

$$\frac{\partial \log c(u,P)}{\partial \log P_i} = \frac{p_i q_i}{c(u,P)} = w_i, \tag{5}$$

where w_i is the budget share of good i. Hence, logarithmic differentiation of equation (4) gives the budget shares as a function of prices and utility,

$$w_i = \alpha_0 + \sum_j \gamma_{ij} \log P_j + \beta_i u \beta_0 \prod_k P_k^{\beta_k}, \tag{6}$$

where

$$\gamma_{ij} = \tfrac{1}{2}\left(\gamma_{ij}^* + \gamma_{ji}^*\right), \tag{7}$$

for a utility-maximizing consumer, total expenditure X is equal to $c(u, P)$ and this equality can be inverted to give u as a function of P and X, the indirect utility function. Solving equation (4) and (6) and eliminating u, we obtain the budget shares as a function of P and X. These are AIDS demand functions in budget share form:

(8) $$w_i = \alpha_i + \sum_j \gamma_{ij} \log P_j + \beta_i \log\{X/P\},$$

where w_i is the expenditure share of commodity i, P_j is the commodity price, x is the total expenditure of the selected goods, and P is overall price index, which is defined by

(9) $$\log P = \alpha_0 + \sum_k \alpha_k \log P_k + \tfrac{1}{2} \sum_k \sum_j \gamma_{kj} \log P_k \log P_j,$$

Homogeneity, Slutsky symmetry and Adding-up can be imposed on the parameters of the AIDS equation (6) by the following (Alston and Chalfant, 1993):

Homogeneity:

(10) $$\sum_{i=1}^{n} \gamma_{ij} = 0.$$

Adding-up:

(11) $$\sum_{i=1}^{n} \alpha_i = 1 \; ; \sum_{i=1}^{n} \gamma_{ij} = 0 \; ; \sum_{i=1}^{n} \beta_i = 0 \; .$$

Symmetry:

(12) $$\gamma_{ij} = \gamma_{ji}.$$

If homogeneity, symmetry and adding up are not rejected, the estimated demand functions are homogenous of degree zero in prices and expenditure taken together (Deaton and Muellbauer, 1980). Provided equations (10), (11) and (12) hold, equation (8) represents a system of demand functions which add up to total expenditure $\sum w_i = 1$, and are homogenous of degree zero in prices and total expenditure, thus satisfying Slutsky symmetry. When there is no change in relative price and X/P, the budget shares are constants. Changes in relative prices take effect through γ_{ij}. Changes in expenditure operate through the β_i coefficients, which are summed to zero and are positive for luxuries and negative for necessities (Deaton and Muellbauer, 1980)[4].

An important feature of the AIDS model is that the expenditure levels are allowed to impact the distribution of shares. It is of flexible functional form, allowing testing of theoretical restrictions on demand equations. The AIDS model in share form for a group of n commodities can be written as

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln P_j + \beta_i \ln(X/P), \qquad i = 1, 2, \ldots, n \tag{13}$$

where w_i is budget share of source i, X is total expenditure on imported wheat and P_j is the price from source j in the system. α_i, γ_{ij}, and β_i are parameters. ln$P$ is defined as:

$$\log P = \alpha_0 + \sum_k \alpha_k \ln P_k + \tfrac{1}{2} \sum_k \sum_j \gamma_{kj} \ln P_k \ln P_j, \tag{14}$$

In practice, equation (13) is difficult to estimate because of its nonlinearity. A common alternative is to estimate a linear approximation version of the AIDS model. That is, instead of estimating the complete AIDS model in equation (13), its linear approximation is employed by replacing ln$P$ with lnP^*, where lnP^* is the Stone's index defined as:

$$\ln P = \sum_i w_i \ln P_i, \qquad i = 1, 2, \ldots, n. \tag{15}$$

therefore, (14) becomes:

[4] Deaton and Muellbauer (1980) summarized the advantages of the AIDS model as follows:
(1) It gives an arbitrary first-order approximation to any demand system
(2) It satisfies the axioms of choice exactly;
(3) It aggregates perfectly over consumers without invoking parallel linear Engel curves;
(4) It has a functional form that is consistent with known household-budget data;
(5) It is simple to estimate, largely avoiding the need for non-linear estimation; and
(6) It can be used to test restrictions of homogeneity and symmetry through linear restrictions on fixed parameters.

(16) $$w_i = \alpha_i + \sum_j \gamma_{ij} \ln P_j + \beta_i \ln\{X/P\},$$

Marshallian and Hicksian measures of elasticities were computed from the estimated coefficients of the AIDS model using derivation by Chalfant* as follows:

(17) $$\varepsilon_{ii} = -1 + \gamma_{ij}/w_i - \beta_i,$$

(18) $$\varepsilon_{ij} = \gamma_{ij}/w_i - \beta_i(w_j/w_i),$$

(19) $$\delta_{ii} = -1 + \gamma_{ii}/w_i + w_i,$$

(20) $$\delta_{ij} = \gamma_{ij}/w_i + w_j,$$

where ε and δ denote Marshallian and Hicksian elasticities respectively. The expenditure elasticities can be obtained from the estimated coefficients as well:

(21) $$\eta_i = 1 + \beta_i/w_i.$$

Seasonality in a more appropriate manner would be incorporated into the model by interacting each variable in the model with seasonal dummies[5]. In terms of Colombia, the model specification can be expressed:

(22) $$w_{usMcol} = \alpha_{us} + \gamma_{US,uscol} \ln P_{uscol} + \gamma_{US,candcol} \ln P_{candcol} + \gamma_{US,ROWcol} \ln P_{ROWcol} + \beta_{US,usMcol} \ln(X_{col}/P),$$

(23) $$w_{canMcol} = \alpha_{can} + \gamma_{CAN_{uscol}} \ln P_{uscol} + \gamma_{CAN_{candcol}} \ln P_{candcol} + \gamma_{CAN_{ROWcol}} \ln P_{ROWcol} + \beta_{CAN_{canMcol}} \ln(X_{col}/P),$$

(24) $$w_{ROWMcol} = \alpha_{ROW} + \gamma_{ROW_{uscol}} \ln P_{uscol} + \gamma_{ROW_{candcol}} \ln P_{candcol} + \gamma_{ROW_{ROWcol}} \ln P_{ROWcol} + \beta_{ROW_{ROWMcol}} \ln(X_{col}/P).$$

Where w_{usMcol} is the United States' budget share of expenditure of Colombian wheat imports, $w_{canMcol}$ is the Canadian budget share of expenditure of Colombian wheat

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* Green and Alston show that $d\ln P/d\ln P_j = w_j + \sum_k w_k \ln(P_k)\{d\ln(w)/d\ln(P_j)\}$. Since $\sum_k w_k \ln(P_k)\{d\ln(w)/d\ln(P_j)\}$ is small (less than 0.05 in absolute value) Chalfant assumes this tem equal to zero hence $d\ln P/d\ln P_j = w_j$.

5 $w_i = \alpha_i + \sum_j \gamma_{ij} \ln P_j + \beta_i \ln\{X/P\} + Q_1 + Q_2 + Q_3 + Q_4$ Where Q_1, Q_2, Q_3, and Q_4 are seasonal dummy variables.

imports, $w_{ROWMcol}$ is the rest-of-the-world budget share of expenditure of Colombian wheat imports, P_{uscol} is the price of United States imported wheat in Colombia, $P_{candcol}$ is the price of Canadian imported wheat in Colombia, P_{ROWcol} is the price of rest-of-the-world imported wheat in Colombia, X_{col} is the total Colombia's expenditure on imported wheat, and P is the price index. From equation (15) the Stone Price Index could be represented by:

(25) $$\ln P = w_{usMcol} \ln P_{uscol} + w_{canMdcol} \ln P_{candcol} + w_{ROWMcol} \ln P_{ROWcol}$$

However, in the AIDS *P,* which is the Stone's Price Index implies the sum of lagged share minus weighted log prices. The lagged budget shares are used as weights in constructing Stone's Price Index to avoid simultaneity since the budget shares are also the dependent variables.

Data Estimation and Procedure

The wheat import demand system to be estimated is on a per capita basis and includes wheat imports from the United States and Canada. The study uses monthly data from 1980 to 1999 provided by United States Department of Agriculture, Economic Research Service (USDA, 2000). Quantity, price and price index data were obtained from the United States Department of Agriculture. The United States has 57 percent of the budget share of expenditure on the average, while Canada accounted for 34 percent of the budget share of expenditure of the total Colombian wheat imports during the 1980-1999 period (USDA, 2000).

The systems of equations were estimated with Zellner's Seemingly Unrelated Regression (SUR). Both homogeneity and symmetry restrictions were imposed in the estimation process. The restrictions were not tested individually since the equations were estimated as a system. Instead, overall hypotheses regarding the restrictions were tested using an F-test. The test statistic is defined as follows:

$\hat{g} = (R\beta - r)^{\prime}(R[X^{\prime}(\sum^{-1} \otimes I)X]^{-1} R^{\prime})^{-1}(R\beta - r) \xrightarrow{d} F_{(J,TM-K)}$, where $\hat{g}$ is the test statistic, R is a matrix of restrictions of dimensions J (number of linear restrictions) by K (number of parameters in the system), β is the unrestricted SUR estimate, r is a vector of restriction constants, X is the design matrix, $\sum$ is the cross equation covariance matrix, $\otimes$ is a symbol for Kronecker product, and I is an identity matrix of dimension equaling the number of observations. The elasticity was formulated by different form when Stone's Price Index was defined with lagged budget shares. Since these elasticities are functions of estimated parameters, they can be tested by hypothesis.

The starting values for the coefficients of the models were obtained through the use of Ordinary Least Squares (OLS) on each estimated expenditure share equation. Given that the N expenditure shares must sum to one in a demand system $\sum w_i = 1$, only N-1 independent expenditure share equations can be estimated; hence one equation was dropped. The adding-up, homogeneity, and symmetry conditions were imposed, implying the following restrictions: $\sum \alpha_i = 1$, $\sum_i \gamma_{ij} = 0$, $\sum \beta_i = 0$, $\sum_j \gamma_{ij} = 0$, and $\gamma_{ij} = \gamma_{ji}$. However, because of high degree of positive serial correlation, the demand systems had to be estimated using first differences (Lafontaine and White, 1986).

LaFrance (1991) indicated that conditional least squares estimators applied to conditional demand systems are not consistent or efficient because group expenditure is not exogenous, except for some special cases. In addition, standard instrumental variable methods do not yield consistent estimates unless the conditional demands are linear in expenditures. These findings are important for empirical applications of the AIDS model because the expenditure is nonlinear with respect to quantity demanded in the AIDS framework. Hence, he suggested using Anderson's iterative instrumental variable method. Even though the estimation procedure suggested by LaFrance provides efficient estimates, it is computationally complex and difficult. The AIDS model might have lost one of its vital properties, estimation simplicity. Therefore, Edgerton (1993) proved that an alternative stochastic specification allows budget shares to be linear in logarithm of group expenditure and that the standard instrumental variable methods give consistent estimates.

Among the assumptions of the classical linear regression model is that the residuals are mutually independent. The use of time series data may result in high correlation between the successive residuals, a situation known as serial correlation or autocorrelation. In this study, the Durbin Watson *d*-statistic is used to test for the presence of autocorrelation. The statistic is usually given by:

(24)
$$d = \frac{\sum_{t=2}^{n} \left(u_t - u_{t-1}\right)^2}{\sum_{t=1}^{n} u_t^2}.$$

Where u_t is the residual resulting from OLS regression. The range of d is from zero to four, d is less than two for positive autocorrelation; d is greater than two for negative autocorrelation; and d is about zero for zero autocorrelation. The program that was used in the analysis provides Durbin-Watson d-statistic among other statistical measures of an Ordinary Least Squares regression.

The Durbin-Watson Tables were used to test the hypothesis of zero autocorrelation. These tables provide d_u and d_L as the upper and the lower bound respectively for the significance of the d statistic. The decision criteria for positive autocorrelation are: if d is less than d_u, reject the hypothesis of zero autocorrelation in favor of the hypothesis; and if $d_L < d < d_u$, the test is inconclusive (Johnson, Marvin and Buse, 1987). The decision criteria for negative autocorrelation are if $d > (4 - d_L)$, reject the hypothesis of zero autocorrelation in favor of the hypothesis of negative autocorrelation as the $d_L < (4 - d_u)$, do not reject the null hypothesis and if $(4 - d_L) > (4 - d_u)$, the test is inconclusive. For models whose Durbin Watson d-statistics showed evidence of autocorrelation, the Cochran iterative method was used as a corrective measure for first order autocorrelation.

Colombia Wheat Import Market Estimation Results

Parameter estimates for Colombian wheat imports from the United States, Canada, and the rest-of-the-world with seasonality effect are presented in Table 1.3 and without seasonality in Table 1.4. The system R-squared values for all three regressions are within a reasonable range. The results presented in Table 1.5 show that all the expenditure elasticity estimates are statistically different from zero at $\alpha = 0.05$ level. The expenditure elasticities are useful when the analyst is interested in the effect of a change in the consumption volume of the commodity group on a budget share. Including seasonal dummy variables in the AIDS model indicates the influence of seasonality on Colombian import demand for wheat. Several seasonal patterns become evident from the parameter estimates by Table 1.3. First, a general positive seasonal trend exits in the first and second quarters as Colombian wheat stocks diminish prior to harvest. In addition, the United States in particular, has a strong advantage in both the second and third quarters in comparison to other wheat exporting countries. Second, Canada has negative seasonality for all the three quarters indicating less substantial seasonal effect for Canada. However, the seasonal impact in the second quarter is almost the same across the board for all wheat exporters in general. Third, in the fourth quarter, all three regressions indicate negative seasonal impact suggesting that wheat imports by Colombia in the fourth quarter are weak.

Marshallian and Hicksian wheat import demand elasticities for Colombia wheat are presented in Table 1.5. Marshallian uncompensated demand elasticities refer to the percentage change in quantity demanded for a product due to 1 percent change in price when demand is expressed as function of prices and income (Deaton and Muellbauer, pp.25 1980). Hicksian uncompensated demand elasticities are derived as the percent change in quantity demanded due to a 1 percent change in the price of a product when the demand is expressed as a function of prices and utility is held constant (Deaton and Muellbauer, pp.28 1980). All the own-price elasticities exhibit the correct sign and are statistically significant.

The Hicksian uncompensated demand elasticities reflect the tastes and preferences of the wheat import markets' consumption habits. Therefore, a consumer's utility function remains unchanged over a short period of time as a result of price and income changes. Furthermore, Hicksian demand results give a long-term view of how changes in price affect the quantity demanded by the import country in respect to the amount of utility the consumer receives from the particular good. The signs of the Hicksian elasticities are expected to be symmetric throughout each elasticity matrix and significant. In the following discussion of estimation results, only the Marshallian demand elasticities are discussed, while the Hicksian demand elasticities are presented for reference.

The Marshallian cross-price elasticities indicate the type of relationship among exporters in the case of the United States, Canada, and the rest-of-the-world. A significant positive cross-price elasticity indicates a competitive relationship between the United States and Canada, while a significant negative cross-price elasticity reveals a complementary relationship[6] between the two main wheat exporters.

The Colombia wheat import demand for the United States, Canada and rest-of-the-world is elastic with respect to own-price. All expenditure elasticities indicate that wheat import demand is a normal good. The values of expenditure elasticities are consistent with the existing economic theory and perhaps the most interesting result is how small these elasticities are. Hence, the United States, Canada and rest-of-the-world are in a favorable exporting position in wheat because they all have positive expenditure elasticities. This implies that as Colombia's income level increases, the wheat exporting countries such as the United States and Canada will also increase their wheat exports to Colombia. The cross-price elasticities are also positive and significant reflecting a competitive relationship.

[6] Complementary relationships can be expected due to the importer behavior of blending different types of wheat for milling of wheat flour. For example, as blending either wheat or flour of lower quality with high quality wheat to ensure consumable quality of final product.

In the Colombia wheat market, export competition is between the United States and Canada. Wheat from Canada provides the greatest competition for the United States because it has positive significant cross-price elasticity for the United States. The United States provides the most significant competition for Canada and rest-of-the-world with cross-price elasticity of 0.0317 and 0.2296 respectively.

The results of this estimation broadly coincide with previous studies where expenditure elasticities ranged from 0.981 to 1.438, and own price elasticities from 0.640 to 2.364 in Algeria, Egypt, and Jordan from previous studies such as Fritz, (1997). The Fritz studies were based on 1970 through 1993 average data in Algeria, Egypt, and Jordan respectively and also employed an RSDAAIDS model. Therefore, it appears that wheat import demand in Colombia in the past decade may, in part, be comparable to that in Algeria, Egypt, and Jordan during 1990s.

Results from this research study have some important policy implications for the United States wheat industry and policy makers. One is that import demand for United States wheat has declined through the 1990s. Consumption needs in Colombia are increasing as the gross domestic product increases (Figure 1.1). Hence, Colombia's wheat import demand is growing rapidly. Thus, there is need to assist Colombia markets achieve economic development and to generate positive political environment that may lead to the development and maintenance of a successful relationship for international trade. This is because markets with price elastic demands are more sensitive to changes in the price of imported wheat and competition. Previous studies such as Dahl and Wilson (2000) and Wilson and Carter (1997) have suggested that policy makers should encourage producers to improve the quality of wheat imports. Furthermore, quality specifications in the wheat markets play an important role in the decision to import (USDA, 1996a). United States wheat farmers may benefit from producing high quality wheat demanded in Colombia's wheat import markets.

Summary and Conclusions

The results from the AIDS models for Colombia's wheat imports provide valuable information about wheat trade and competition among exporters. First, an exporter was considered to have a favorable trading position when expenditure elasticity is elastic. Therefore, according to this criterion, United States' wheat is very competitive in Colombian wheat imports market. Second, the strength of competition between exporters is measured by the magnitude of the cross-price elasticity. The United States provides the most significant competition for Canada and rest-of-the-world.

However, there are some limitations with the scope of this study that give important implications for further research. The first limitation is the exclusion of domestic production in each import demand AIDS model. Theory suggests that domestic production affects the import decision of a particular market to import any good. Hence, further research to determine the impact of domestic wheat production would be useful to the United States. Another limitation is the use of expenditure for each import demand system. Colombia's total income may be a better explanation of expenditure used for importing goods. Finally, it would be interesting to look at the relationship between United States wheat market share and own-price import demand elasticity in the Colombian wheat import market.

Table 1. 1: Colombia Economic Statistics, 1996 – 1999

	1996	1997	1998	1999
Population (millions)	39.4	40.1	40.7	41.1
GDP (US$ billions)*	86.4	95.2	100	92.6
GDP growth rate (%)	2.1	3.1	0.2	1.6
GDP per capita (US$)	2,264	2,279	2,256	2,261
Exchange rate (pesos/US$)	1,037	1,140	1,536	1,782
Inflation rate (%)*	20.2	18.5	18.5	30.0

* International Monetary Fund
Source: FAO

Table 1. 2: Colombia: Wheat Supply and Disposition, 1997-2000

July-June Marketing Year	1997-1998	1998-1999	1999-2000f
Harvested Area (000 ha)	19	13	13
Yield (t/ha)	1.58	1.92	1.92
	…………………*thousand tonnes*………..…………		
Carry-in Stock	112	102	127
Production	30	25	25
Import	1,048	1,100	1,000
Total Supply	**1,190**	**1,227**	**1,152**
Feed Use	20	20	20
Food, Seed, Industrial Use	1,068	1,080	1,005
Total Domestic Use	**1,088**	**1,100**	**1,025**
Carry-out stocks	102	127	127

f: forecast, February 2000
Source: FEDEMOL (Colombian Grain Mill Federation)
Source: USDA

Table 1. 3: Parameter Estimates for Colombian Wheat Imports Using an Almost Ideal Demand System Models with Seasonality, 1980-1999

	Dependent Variables (The budget share of per capita wheat import of:)		
Independent Variables	United States-Colombia	Canada-Colombia	ROW-Colombia
Prices of:			
United States-Colombia	0.0082**	-0.0176**	0.0086**
	(0.0513)	(0.0624)	(0.0381)
Canada-Colombia	-0.1823**	-0.4621**	-0.2739**
	(0.1540)	(0.1874)	(0.1130)
ROW-Colombia	0.0780**	-0.0942*	0.0115**
	(0.0906)	(0.1104)	(0.0657)
Expenditure[a]	-0.1072*	-0.0523**	0.1593**
	(0.0431)	(0.0525)	(0.0321)
Seasonal Dummies :			
Quarter 2	0.0481*	-0.0573**	0.0126**
	(0.0424)	(0.0516)	(0.0296)
Quarter 3	0.1522**	-0.1108**	-0.0378**
	(0.0424)	(0.0531)	(0.0010)
Quarter 4	-0.04788*	-0.0528*	-0.0013*
	(0.0444)	(0.0541)	(0.0306)
R^2	0.901	0.909	0.900

Note: The numbers in parenthesis are standard errors.
Single (*) and double asterisks (**) denote significance at the 15% and 10% level, respectively.
[a] Expenditure denotes per capital expenditure on total wheat imported to Colombia.

Table 1. 4: Parameter Estimates for Colombian Wheat Imports Using an Almost Ideal Demand System Model without Seasonality, 1980-1999

	Dependent Variables (The budget share of per capita wheat import of:)		
Independent Variables	United States-Colombia	Canada-Colombia	ROW-Colombia
Prices of:			
United States-Colombia	0.0242**	-0.0312*	0.9983*
	(0.0583)	(0.0661)	(0.0378)
Canada-Colombia	-0.0241**	-0.4964**	-0.0255**
	(0.0169)	(0.0193)	(0.1101)
ROW-Colombia	-0.1277**	-0.1243**	-0.0034**
	(0.0973)	(0.0110)	(0.0632)
Expenditure[a]	-0.10546**	-0.0994**	0.1579**
	(0.0486)	(0.0501)	(0.0352)
R^2	0.845	0.893	0.814

Note: The numbers in parenthesis are standard errors.

Single (*) and double asterisks (**) denote significance at the 15% and 10% level, respectively.

[a] Expenditure denotes per capita expenditure on total wheat imported to Colombia

Table 1. 5: Marshallian and Hicksian Demand Elasticities for Colombian Wheat Imports Estimated Using AIDS Model, 1980-1999

	Dependent Variables (The budget share of per capita wheat import of:)		
Independent Variables	United States-Colombia	Canada-Colombia	ROW-Colombia
MARSHALLIAN:			
Prices of:			
United States-Colombia	-1.1608** (0.0021)	0.0317* (0.01036)	0.2296* (0.0231)
Canada-Colombia	0.0638** (0.0501)	-1.04867* (0.0152)	-0.3068* (0.0821)
ROW-Colombia	0.3277* (0.0101)	-2.1904* (0.0731)	-1.2722* (0.1027)
Expenditure	0.8150** (0.1701)	0.6686* (0.0451)	0.0563* (0.0091)
HICKSIAN:			
United States-Colombia	-0.6150* (0.0113)	0.3577* (0.0891)	0.2541* (0.1409)
Canada-Colombia	0.4921* (0.0090)	-0.7011* (0.1101)	-0.2808* (0.0917)
ROW-Colombia	0.8977* (0.0130)	0.3149* (0.0911)	-1.0843* (0.0137)

Note: The numbers in parenthesis are standard errors.
Single (*) and double asterisks (**) denote significance at the 15% and 10% level, respectively.

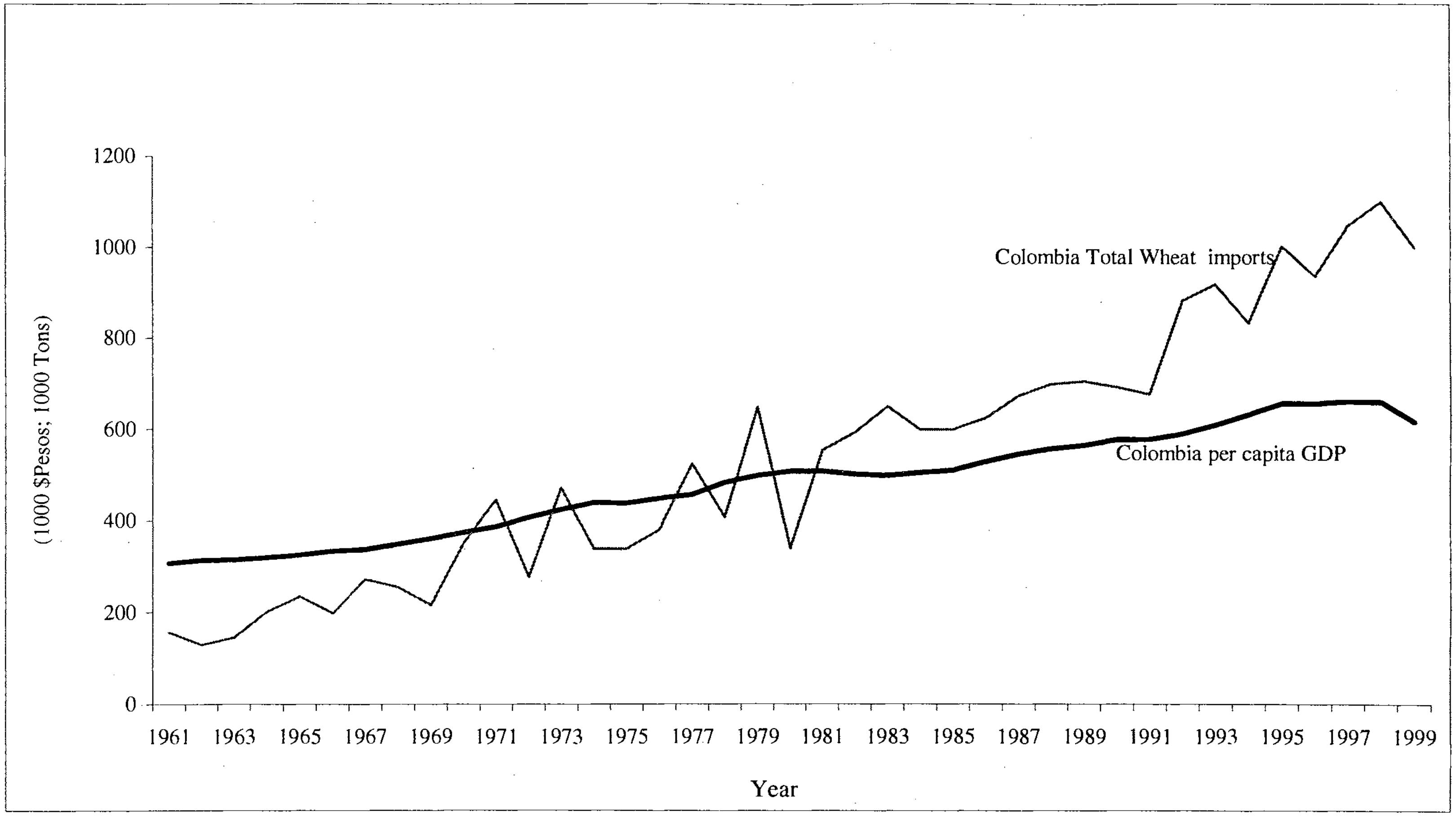

Figure 1. 1: Colombia Total Wheat Imports and GDP Per Capita, 1961-1999.

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CHAPTER

II.

FORECAST EVALUATION AND MODELING OF UNITED STATES TOTAL WHEAT TRADE IN COLOMBIA: AN ECONOMIC PERSPECTIVE*

Introduction

An old saying states that a study of economics usually reveals that the best time to buy is last year. Therefore, forecasts are of great importance and widely used in agricultural economics and trade. Quite simply, sound forecasts lead to good decisions. The importance of forecast evaluation follows immediately --- forecast users naturally have a keen interest in monitoring and improving forecast performance.

Wheat as a major agricultural export commodity from the United States has accounted for more than 20 percent of the United States total bulk of agricultural exports during the decade of the 1990s (USDA, 1999). However, factors affecting the United States wheat prices are changing due to changing farm policies such as changes in price subsidies and economic dynamism. Furthermore, policy makers,

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economists, and farmers have periodically raised concerns over the price and market share competitiveness of the grain trade, particularly for wheat.

Colombia, a Latin-American country, has emerged over the past six years as a stable growth market for the United States exports of agricultural products, in particular grain exports, and it continues to beckon with opportunity as interested agricultural exporters set forth to explore trade liberalization in 1991 (USDA, 1996a). Colombian trade data show that the U.S. market share of Colombia's total agricultural imports has risen from 29 percent of total import value in 1991 to 42 percent in 1995 and to 45 percent in 1996 (USDA, 1998).

Colombia is currently experiencing some developments in the domestic wheat sector and trade policy negotiations which seem certain to affect the United States competitive position in this market in both the short and long run (USDA, 1999). Disappearing Colombian wheat production and increasing experience with the free market system by the Colombian government could eliminate the price band system which is a mechanism for the stabilization of domestic prices by fixing a reference "floor" price and a reference "ceiling" price, between which it's hoped to maintain the import cost of a certain commodity. Stabilization is reached increasing the general ad-valorem tariff when the international price falls below the floor level, and reducing such tariff up to zero, when the price increases over the ceiling (Altimir, 1995; Besley and Kanbur, 1990; and Valdés, 1995). Although growth is expected in Colombia market, the United States' market share is being challenged by Canada and could face increased competition from Argentina, which will likely receive duty preferences in the years to come (USDA, 1999).

Prior to 1992, the Agricultural Marketing Agency of the Ministry of Agriculture of Colombia (AMAMA) was the exclusive importer of wheat and had restricted imports. After 1992, importation was turned over to the private sector and the AMAMA was officially eliminated in 1997. Import volumes and consumption have risen dramatically as a result of this market opening and liberalization of the government program. As a result, Colombian production has declined drastically, and as Colombian millers become more attuned to directly importing wheat, increased imports are anticipated in the coming years (USDA, 1999).

Wheat plays important roles in linkages with the agricultural sector among various crops and between crops and livestock. Consequently, events that affect the market conditions that create the supply and demand for wheat ---and its subsequent price is carefully watched throughout much of the agricultural sector. Forecasting of prices and quantities of grain involves full understanding of the forces or factors that cause both price and quantity to change (USDA, 1999).

The United States Department of Agriculture grain supply estimates include the actual volume produced and the predicted amount expected to come on the market in the near future and based on the world grain production at large (USDA, 2000). However, since wheat is not an extremely perishable product, buyers and sellers investigate probable future supply and probable future price before they decide upon the price at which they will buy or sell. Therefore, on the side of producers, the difficulty of obtaining market information is a serious problem. Hence, the United States Department of Agriculture has taken various steps to identify and correct this problem, but data are not available quickly enough for necessary analysis.

Furthermore, historical statistical information about what has actually taken place is subject to some degree of error. However, some of the supply series, even if they are not precise, are sufficient for the purpose of explaining trade flows and form a relatively good basis upon which to forecast total wheat exports and price changes (Kenyon, Jones and McGuirk, 1993).

Another problem faced is determining the source of prices for analysis. Theoretically, everything else being equal, the price must be consistent and no interfering conditions should exist that would result in the prices in the central markets of the world differing by more than the cost of transportation (Shalaby, Yanagida and Hassler, 1991).

The main objective of this study is to forecast the United States' total wheat exports to Colombia. The specific objective is to explore the possibility of the autoregressive integrated-moving average (ARIMA) process as a viable model option for predicting and projecting United States' wheat exports to Colombia. Once the model has been identified, all the parameters have been estimated, and the adequacy of the model has been determined, forecasts can be checked for reliability.

Report on Colombian Wheat Consumption from the United States Department of Agriculture

Colombia's wheat production continues to fall, with output in 1998-1999, not expected to exceed 25,000 tons. Wheat millers, through corpotrigo (Corporation for the Modernization Diversification of Wheat Production), have actively encouraged growers to switch to other crop alternatives. This development has resulted from the

Colombian milling industry's reluctance to purchase low-quality soft wheat produced by the country's farmers (USDA, 2000).

Colombian wheat consumption is estimated to record only a one percent increase in 1998-1999 due to a slowdown in the general economy. A modest increase of about 2 percent is forecast for 1999-2000 in response to a slight improvement in the overall Colombian economy that should prompt an increase in demand for wheat products. Colombia's per capita annual wheat consumption is estimated at 30 kilograms for year 2000. In comparison, annual per capita consumption in the United States is 68 kilograms. Wheat flour prices in Colombia at present average 32,000 pesos per 50 kilograms ($410 per ton), 23 percent above a year ago (USDA, 1997). Figure 2.1 shows that per capita consumption grew with wheat imports to Colombia for the time period 1961-1999. The increase in the price of wheat flour has exceeded the general rate of inflation, making wheat products a more costly food alternative for Colombian consumers which has created a market opportunity for bulk wheat exporting countries such as the United States and Canada. About 75 percent of wheat consumed in Colombia is used for producing flour for bread production, 15 percent is used for cracker production, and the remainder is used for pasta. Colombia's total annual wheat milling capacity is estimated at 1.7 million tons (USDA, 2000).

The Colombian Total Wheat Import and Trade Policy

Colombia's wheat imports during marketing year 1998-1999 are estimated at 970,000 tons, up 1 percent over a year earlier. This import volume is expected to consist of approximately 870,000 tons of hard wheat and 100,000 tons of soft wheat.

However, in recent years Canadian wheat producers have increased their market share at the expense of the United States. In the early 1990's, the United States was supplying about two-thirds of Colombia's import needs (USDA, Grain Report 2000).

The United States' share of Colombia's wheat imports fell from 52 percent in 1991 to 32 percent in 1996-1997, but increased to almost 40 percent in 1997-1998. The United States is expected to account for as much as 50 percent of all imports by 1998-1999. United States wheat prices have become more competitive relative to those of Canada.

Canada reportedly is prioritizing its wheat exports for the 2000-2001 season to Asian markets and is expected to reduce its total sales volume to South America by 20 percent (USDA, 2000).

The following section outlines some of the duties applicable to wheat commodities in recent years by the Government of Colombia:

Import Licensing:

Wheat millers must obtain an import license in order to import wheat. This import license is issued by the Colombian Institute of Trade (Instituto Colombiano de Comercio Exterior---INCOMEX), an agency of the Ministry of Foreign Trade. INCOMEX only issues an import license after the Ministry of Agriculture provides its approval. Agriculture's approval is contingent upon miller compliance with the government of Colombia's (GOC) absorption agreements for domestic crops. Approval and issuance of wheat import licenses have become fairly routine because of the limited amount of wheat that is now being produced in Colombia (USDA, 2000).

Wheat Duty:

Colombia committed under the Uruguay Round to a tariff rate quota for wheat of 692,118 tons with a duty rate of 124 percent. INCOMEX is responsible for administering Colombia's tariff rate quota established under the Uruguay Round. In practice, the tariff quota rate is not utilized since the actual duty applied to wheat imports is below the tariff rate quota. The common external duty rate for wheat in Andean Community (AC) is 15 percent. Wheat imports also are subjected to the application of the AC's price band and reference price systems that resulted in a variable surcharge applied to wheat (USDA, 2000).

The United States views these systems employed by Colombia to be inconsistent with Colombia's World Trade Organization obligations. The variable surcharge calculation for wheat is based upon the adjusted floor, ceiling, and reference price levels determined by the Andean Board of Directors. Under this system, import duties are levied on calculated reference prices and not on actual invoice prices. The Andean Community revises annual ceiling and floor price in April. Reference prices are adjusted by the Andean Community every two weeks. The highest total effect duty rate for wheat over the past 12 months occurred in October 1998 when it reached 70 percent of the reference price[†] (USDA, 2000).

[†] Reference price is the world market price, which has noted in the past, frequently overstates the actual prices at which wheat is traded on world markets because of the promotion policies and trade restrictions of some major exporters and importers.

Credit:

The GOC established a requirement in 1997 that all foreign debt contracted for a period of more than 180 days be subject to a mandatory Central Bank reserve requirement equal to 25 percent of the loan value. The deposit was required to remain in a non-interest bearing account in the Central Bank for a period of 12 months. The deposit amount and the time period were reduced in September 1998 to 10 percent and 6 months, respectively. This has resulted in a reduction in the cost of borrowing under United States Department of Agriculture's Export Credit Guarantee Programs (GSM) and, therefore, has prompted a recovery in their utilization. Wheat, corn and sorghum are included in the recently authorized GSM-103 program for Colombia[1]. Import purchases of both wheat and corn are being made under the GSM-103 program (USDA, 2000).

Andean Community and Mercosur Merger:

Colombia and the Andean Community are hoping to sign a merger agreement during 1999 with the Mercosur trade bloc---Argentina, Brazil, Paraguay and Uruguay that will become effective January 1, 2000. The GOC hopes that the elimination of duties on agricultural products imported from Mercosur countries will be phased out in over an extended period of 7 to 8 years. The local wheat milling industry is urging the GOC to reduce the common external tariff on bulk wheat from 15 percent to 10 percent while at the same time modifying Colombia's band system that would

[1] Export Credit Guarantee Program (GSM-102), begun in 1982, is the largest U.S. agricultural export promotion program. It guarantees repayment of private, short-term credit for up to 3 years. The 1996 Farm Act continues the

significantly reduce variable surcharges assessed on wheat imports. Currently, the total effective duty against the United States wheat imported into Colombia is about 50 percent: a 15 percent applied duty rate and a 35 percent variable duty surcharge (USDA, 2000).

Model Considerations

Agricultural economists have proposed various models for analyzing price formation in the world market through a forecasting framework. In general, the literature on forecasting offers two main approaches. These procedures are called causal forecasting and econometric forecasting models. First, causal forecasting model uses historical data to estimate the relationship between the variable to be predicted - that is, the dependent variable or response variable - and other variables such as independent variables or explanatory variables. It is based on a known relationship between the factor to be forecasted and other external or internal factors. Causal forecasting appears in number of different forms, such as:

(i) Regression: Mathematical equation relates a dependent variable to one or more independent variables that are believed to influence the dependent variable.

(ii) Input-Output Models: Describes the flows from one sector of the economy to another, and so predicts the inputs required to produce outputs in another sector.

(iii) Simulation Modeling: The construction of models and the study of their behavior in comparison with the performance of real systems is termed simulation. Simulation models can provide valuable information on probable changes to a target

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authorization for GSM-102, mandates annual program funding levels for GSM-102 and GSM-103, and allows variable or variables based upon a changing scenario of external effects or impacts (Evans, 1973).

Second, the econometric forecasting model is primarily intended to provide a superior mechanism for generating forecasts of an economic trade system based on existing, or more precisely, statistically proven trade relationships. These statistically-based models are designed to incorporate a variety of economic relationships and, while particularly well suited for long-term forecasts, they often become difficult to specify and overly complicated, unwieldy, and cumbersome when inappropriately applied to assess short-term impacts or rapid and dynamic changes in an economy, particularly when historical precedents of such effects do not exist (Armstrong, 1985 and Wallis, 1986).

Furthermore, the econometric forecast model, in turn, can use the information on trade interactions and relationships obtained directly from the input-output modeling process and provide a better vehicle for generating long-term forecasts of the economy based on various growth scenarios of key trade sectors and their relationships to other sectors (Pindyck and Rubinfeld, 1981).

International markets for agricultural commodities frequently experience sharp fluctuations. The forecasting of commodity markets is full of uncertainty simply because many important variables such as weather conditions and exchange rates are often difficult to predict (Labys,1999). Voon extended the model by incorporating two, rather than one, independent variables in the distributed-lag market share model and applied a multivariate market share function in a Multinomial Logit (MNL)

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flexibility in how much is made available for each program (USDA, 1999).

market share model developed by Cooper and Nakanishi (1988). The model has a clear advantage over the conventional distributed-lag market share model and the mathematical formulation does necessarily guarantee that predicated market share equation shares sum to unity and can never be negative, regardless of the values of the explanatory variables.

Samarendu, Meyers and Danell (1999) examined price relationships in the international wheat market for the years 1981-1993 using a cointegration and error correction approach. Price series are found to be first difference stationary and cointegrated. The results provide evidence that the United States, Australia, the European Union and Argentina react to Canadian pricing decisions. Additional findings indicate that Canada does not respond to price changes other than Australia's. However, these studies failed to examine the price series for nonstationarity. As a result, co-integration could be misspecified because other important economic variables such as gross domestic product, exchange rates, and others were not included in the model.

Goodwin and Schroeder (1991) used a vector autoregression model to evaluate dynamic relationships among international wheat prices. The effects of freight rates and exchange rates were also considered. Forecast error variance decompositions and impulse response functions were used to investigate price dynamics in six important international wheat markets. The results suggested significant dynamic relationships among prices in different international wheat markets and between the price on one hand and exchange rates and transportation costs on the other hand. However, instead of using price ratios, their model presumed exchange rates. It is often suggested that variables such as gross domestic product and price ratios could be used instead of exchange rates because they can influence trade flows and price expectation.

Keane and Runkle (1989) explained that forecasters should correctly use any relevant information they know in making their predictions. Their results showed that forecast rationality could be tested by determining whether the forecasters' prediction errors are predictable. Furthermore, after addressing the data and methods to be used to test for rationality, the study presented tests of the price-forecast rationality of individual professional forecasters. Unlike results of previous studies, the test results showed that those forecasters' price predictions appear to be rational. Nevertheless, this study does not take into account that the joint tests of specification and forecast rationality of variables are often essential, since market and trade flows are not static. Hence, a multivariate forecast should be considered in order to show a strong market relationship. Distributed-lag regression models are frequently used in the literature for formulating market share equation (Capel and Rigaux, 1974; Tellis, 1989). In those models, market share was commonly specified as function of lagged share and one explanatory variable (i.e. relative price). Therefore, according to economic theory, the inclusion of this key variable could improve the predictive performance of the model.

Difference in stationary and trend models of the same time series may imply very different predictions (Diebold and Senhadji, 1996). Deciding which model to use is therefore tremendously important for applied forecasters. Rather than employing one or the other model by default, one may use a unit root test as a diagnostic tool to guide the decision. In fact, one of the motivations for unit root tests was precisely to help determine whether to use forecasting models in differences or levels in particular applications (Dickey, Bell, and Miller, 1986).

Much of the recent econometric unit root literature has focused on the inability of the unit root tests to distinguish in finite samples the unit root null from nearby stationary alternatives (Christiano and Eichenbaum, 1990; Rudebusch, 1993). But low power against nearby alternatives, which are typically the relevant alternative in econometrics, is not necessarily a concern for forecasting. It has long been asserted, for example, that the accuracy of forecasts may be improved by employing a model in differences rather than a model in levels, if the root of the process is close to but less than unity (Box and Jenkins, 1976, p.192). Ultimately, the question of interest for forecasting is not whether unit root pretests the selection of the true model, but whether it selects the model that produces superior forecasts. Surprisingly little is known about the efficiency of unit root tests for this purpose.

Stationarity and Non-stationarity of Time Series:

A time series sequence (y_t) is stationary if the mean of the series is finite and independent of time. All periods of the variable have the same finite mean, $E(y_t) = E(y_{t-s}) = \mu_x$. The variance of the series is finite and time independent. That is; $Var(y_t) = Var(y_{t-s}) = \sigma_y^2$ or $E(y_t^2) = E(y_{t-s}^2) = \sigma_y^2$.

All autocovariances are finite and time independent,

$Cov(y_t, y_{t-s}) = Cov(y_{t-j}, y_{t-j-s}) = \gamma_s$ or $E(y_t, y_{t-s}) = E(y_{t-j}, y_{t-j-s}) = \gamma_s$ where

$\mu_y, \sigma_y^2, \gamma_s$ are all constant and stationary. If the three conditions hold, this series sequences shows weak stationarity. If the probability distribution $\mathbf{P}(y_1, y_2, ..., y_t)$ is also stationary, then the time series process is strictly stationary. However, if the probability distribution of a time series process changes overtime, then it is a non-stationary time series (Granger, 1981).

Most times series of economic variable exhibits non-stationary in level (variable before differencing). Such time series are subjected to detrending procedures to make them stationary before proceeding with further analysis. If stationarity is achieved after fitting a time trend, the variable is said to be trending stationary. The trend stationary process arises because of the effect of a deterministic trend. The second approach is to take the first difference [†] of the series of interest and use the first difference as the detrend stationary. If stationarity is achieved after differencing, the variable is said to be difference stationary. A difference stationary process is a random walk, or it has a stochastic trend. An advantage of the second approach is that if the series are in log levels, the first differences are approximately the percentage change over the previous period (Granger, 1981; Nelson and Plosser, 1982).

[†] Consider a pure random walk model $y_t = y_{t-1} + \varepsilon_t$, differencing is often achieved by taking the first difference $\Delta y_t = y_{t-1} - y_{t-2} - \varepsilon_t$. Clearly, the sequence is stationary since the mean and variance are constant and the covariance between Δy_t and Δy_{t-s} depends solely on: $E(\Delta y_t) = E(y_t) = \mu_x = 0$. The variance is $Var(\Delta y_t) = E(\Delta y_t)^2 = E(\varepsilon_t^2) = \sigma_y^2$ and covariance is $Cov(\Delta y_t, \Delta y_{t-s}) = E[(\Delta y_t, \Delta y_{t-s})] = E(\varepsilon_t, \varepsilon_{t-s}) = 0$.

Unit Root and Stationarity:

The econometric literature on unit root took off after the publications of the paper by Nelson and Plosser (1982) that argued that most economic time series have unit roots and that is important for the analysis of economic polices. That a difference stationary series is said to be integrated and is denoted as I(d) where d is the order of integration. The order of integration is the number of unit roots contained in the series, or the number of differencing operations it takes to make the series stationary. For the random walk above, there is one unit root, so it is an I(1) series. Standard inference procedures do not apply to regressions which contain an integrated dependent variable or integrated regressors. Therefore, it is important to check whether a series is stationary or not before using it in a regression. The formal method to test the stationarity of a series is the unit root test (Perron, 1992).

Considerations in Forecasting Model Selection:

In selecting a forecasting model, a myriad of factors must be considered such as the purpose of the forecast, availability and accuracy of data, the forecasting time horizon, ease of model application, the cost involved, and most importantly, the accuracy of the forecasting technique. Hence, a discussion of all of these considerations is well beyond the scope of this paper, however, Makridakis and Wheelwright (1979) provide an excellent and thorough discussion of all of these issues. From a pragmatic standpoint, ease of model use and model accuracy would be two of the most prominent concerns to the forecaster and will thus be the focus of attention.

Anandalingan and Chen (1989) assert that model accuracy is the most important factor to be considered in the selection of a forecasting model. Holding to the notion that more rigorous models should provide greater accuracy, researchers have devised increasingly complex forecasting models. Seemingly, the result is a compromise between ease of model use and model accuracy. However, findings from recent studies indicate that no unique model, complex or otherwise, is most accurate in all situations and that there is significant evidence to suggest that simple may be better (Dalrymple,1987; Moriarty,1985; Tyebjee,1987; and Wright et al. 1986).

Time Series versus Causal Models:

One area of debate concerns the superiority of time series versus causal forecasting models. Time series models operate on the assumption that the behavior of past data is indicative of the future. Using this approach, past data values are extrapolated into the future. Causal models, on the other hand, attempt to identify and isolate those variables (i.e. independent variables) which influence or are related to the variable that is being forecasted (i.e. dependent variable). Once identified, values of the independent variables are used to forecast the behavior of the dependent variable into the future (Gaither, 1990).

Makridakis (1986) contends that causal forecasting method is inherently more complex and difficult to use. Newbold and Granger (1974) concur, adding that causal forecast requires information above and beyond the variable of interest, information that may not be available. This requirement is especially onerous in the case of the small business forecaster operating with limited resources such as time, expertise, etc.

Fortunately, studies by Cooper (1972), Nelson (1972), Reid (1975), and Schmidt (1979) suggest that the easier to use time series method generally yields more accurate results than does causal forecast method. Furthermore, studies by Carbone et al. (1983), Groff (1973), Makridakis and Hibon (1979), and Makridakis et al. (1982) comparing simple time series models with more complex time series methods found no reason to conclude that the complex time series methods are any more accurate than simple ones.

Box-Jenkins Models:

Box and Jenkins (1976) developed a practical procedure for an entire family of models, the autoregressive integrated moving-average (ARIMA) models. The ARIMA models are applicable only to a stationary data series, where the mean, the variance, and the autocorrelation function remain constant through time. ARIMA models are appropriate for series with strong trend characteristics, random walk series, and seasonal and nonseasonal time series.

Cleary and Levenbach (1982), Anderson (1976), and Pankratz (1983) point out that the Box-Jenkins approach is a powerful and flexible method for short term forecasting because ARIMA models place more emphasis on the recent past and where structural shifts occur gradually, rather than suddenly. This makes the ARIMA models especially valuable when dealing with economic time series data. This emphasis on the recent past makes long-term forecasts less reliable due to accumulation of error terms. The process of selecting the model is a process of evaluation, adaptation, and trial and error. When a phenomenon is completely understood it is possible to describe it exactly in a mathematical expression. Nevertheless, in economics incomplete theoretical knowledge is used to indicate a suitable class of mathematical functions which can then be fitted empirically.

In the first stage of selecting a model we need to identify a rough class of models, followed by identification of their subclasses. This tentative model is then fitted to the data and estimated for its parameters. The rough estimates obtained during this identification stage are used as starting values for estimating the parameters. Finally, diagnostic checks are used to discover any lack of fit. If no inadequacy is indicated the estimated model will be used for forecasting. However, if any inadequacy is found, the iterative cycle of identification, estimation, and diagnostic checking is repeated until a suitable model is found (Diebold, 1998).

Time Series Model Building

The value of the prediction of a time series is determined by the nature of the stochastic model which describes that series. The principle of parsimony which is widely used by forecasters states that the model should adequately represent the data using as few parameters as possible. The main effort is directed to obtaining a suitable stochastic model for forecasting future value of the series. Stochastic model is a forecasting model representing the behavior of a phenomenon in a probabilistic fashion. Stochastic model cannot be predicted based solely upon their historical behavior (Granger and Newbold, 1986). The stochastic models can be interpreted as descriptions of physical phenomena possessing the right general character, but do not represent exact physical reality and are not fitted to data empirically. This section is a brief review of the class of time series models, widely known as Box-Jenkins model (Box and Jenkins, 1976; Box et al., 1994).

The theoretical underpinnings described in Box and Jenkins (1976) are quite sophisticated, but it is possible for the nonspecialist to get an understanding of the essence of the methodology. Although C. J. Clark adapted this original procedure of Box and Jenkins for seasonal forecasting (Harrison and Scott, 1971), Harrison suggests that there are better methods for both seasonal and non-seasonal forecasting than the early versions of the Box-Jenkins procedure. Box-Jenkins (1976) effectively compiled relevant information in a comprehensive manner required to understand and use univariate time series ARIMA models.

The basis of this approach is summarized in Figure 2.2 and consists of three phases:

- Phase I: Identification
- Phase II: Estimation and Testing
- Phase III: Application (Gershenfeld and Weigend, 1994).

The main stages in setting up a Box-Jenkins forecasting model are as follows:

- Model Identification: Examine the data set to see which model in the class of ARIMA processes appears to be the most appropriate.
- Estimation: Estimate the parameters of the chosen model by least squares.
- Diagnostic Checking: Examine the estimated residuals from the fitted model to see if it is adequate.
- Consider Alternative Methods if Necessary: If the first model appears to be inadequate for some reason, then other ARIMA models may be studied by

repeating the above procedure until a "satisfactory" model is found (Harrison and Scott, 1971).

Suppose that n consecutive observations $y_1, y_2, y_3, \ldots$, from a series are available and we wish to determine a suitable model. We denote the value of a time series at equispaced time t, $t-1$, $t-2, \ldots$ by y_t, $y_{t-1}, \ldots$. Let B denote the backward shift operator so that

(1) $$By_t = y_{t-1} \quad \text{and} \quad (1-B)y_t = y_t - y_{t-1} = \nabla y_t$$

A useful model to represent a non-stationary time series of the type that occurs in many trade models and applications is the autoregressive integrated moving average model ARIMA (p, d, q) model:

(2) $$\phi_p(B)\nabla^d y_t = \theta_q(B)a_t \quad \text{or} \quad \phi_p(B)\nabla^d y_t = C + \theta_q(B)a_t$$

The polynomial $\phi_p(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$ is the p- order autoregressive AR operator and the polynomial $\theta_q(B) = 1 - \theta_1 B - \ldots - \theta_q B^q$ is the q-order moving average MA operator.

The reason for introducing both a finite autoregressive operator $\phi_p(B)$ and a finite moving average operator $\theta_q(B)$ is that a finite moving average is equivalent to an infinite autoregressive series, and vice versa, so that including both types of terms makes for parsimony. The difference operator ∇^d with d-order differencing operator introduces factor termed as homogeneous non-stationarity. The a_t, a_{t-1}, a_{t-2}, etc. a sequence of random shocks which are random variables identically, independently, and approximately normally distributed (Granger, 1989).

Suppose the model for single time series has been tentatively identified as of some specific form within the family of $\phi(B)\nabla^d y_t = \theta(B)a_t$. Then, for a sequence of observations y_t and for given $\phi(B)$ and $\theta(B)$, we can compute

(3) $$a_t = \frac{\phi(B)}{\theta(B)}(1-B)^d y_t \qquad t = 1, 2..., n.$$

Then the log likelihood for specific $\phi(B)$ and $\theta(B)$ is closely approximated by a linear function of the sum of the squares of the residual:

(4) $$S(\phi,\theta) = \sum_{t=1}^{n} a_t^2$$

In practice the a_t resulting from a trial choice of the ϕ 's and θ 's are conveniently calculated recursively and approximate maximum likelihood estimates are obtained by minimizing $S(\phi,\theta)$ (Liu and Hudak, 1992).

Two procedures for checking the tentative fitted model are:

- Examination of residual a_t s
- Overfitting

In this approach, if the model is adequate and the number of fitted observations is not too small, then the estimated values $(\hat{\phi},\hat{\theta})$ obtained from the fitted model will be sufficiently close to the values (ϕ,θ) and that the residuals, $a_t(\hat{\phi},\hat{\theta})$ will be uncorrelated deviations. When there is a particular elaboration of tentatively identified model to be checked, a more sensitive check procedure is provided by comparing the fits of the more elaborate and the less elaborate model (i.e. overfitting).

Furthermore, a considerable widening of the range of useful application of the model is achieved if the possibility of transformation is allowed. Thus $y_t^{(\lambda)}$ is substituted for y_t where $y_t^{(\lambda)}$ is some non-linear transformation of parameters λ. A suitable transformation may be suggested by the physical situation or in some cases be estimated from data. For example, if y_t were increasing at a rapid rate and percentage fluctuation showed stability rather than the absolute fluctuation, it would be sensible to analyze the logarithm of y_t (Box and Cox, 1964).

Forecasting Method

Suppose a model of the form $\phi_p(B)\nabla^d y_t = C + \theta_q(B)a_t$ has been fitted. This may be used to make a minimum mean square error forecast $\hat{y}_t(l)$ of some future value $y_{t+l}\,(l \geq 1)$, that has the origin t and lead time l. It is a linear function of current and previous observations $y_t, y_{t-1}, \ldots$ and can also be written as a linear function of current and previous shocks $a_t, a_{t-1}, \ldots$. In practice the forecasts are most easily calculated directly from the fitted stochastic difference equation model.

(5) $$\phi(B) = \theta(B)(1-B)^d = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_{p+d} B^{p+d}$$

We can use the fitted model to express the observation to be forecast in terms of previous y s and a s as follows:

(6) $$y_{t+1} = \phi_1 y_{t+l-1} + \ldots + \phi_{p+d}\, y_{t+1-p-d} - \theta_1 a_{t+l-1} - \ldots - \theta_q a_{t+l-q}$$

where B is the backward shift operator, d is the degree of differencing involved, p is the order of the autoregressive process and q is the order of the moving average process.

The forecast at origin t for lead time l is found by taking conditional expectations at time t on both sides of equation. The $y_{t-j}(j = 0, 1, 2, \ldots,)$, which have already happened at origin t, are left unchanged. The $y_{t+j}(j = 1, 2, \ldots)$, which have not yet happened, are replaced by their forecasts $\hat{y}_t(l)$ at origin t. The $a_{t-j}(j = 0, 1, 2, \ldots)$, which have happened, are available from $y_{t-j} - \hat{y}_{t-j}$. The $a_{t+j}(j = 1, 2, \ldots)$ which have not happened, are replaced by zero. This provides forecast $\hat{y}_t(l)$ entirely in terms of previous forecasts and known values of the series (Box and Jenkins, 1976).

In practice, we do not have the exact value of the model parameters, but only estimates which we substitute instead. Experience shows that the forecast is rather robust to moderate changes in the parameter value and that the approximation is very good whenever the number of observations used to estimate the coefficients is reasonably large. Forecasts of this kind so far discussed might be called autoforecasts since they used their own past to predict the future. For example, a series of past values of quantity of wheat exported by the United States to Colombia might be used to identify, fit and check a time series ARIMA model in the manner described above and use it to forecast future quantities of United States wheat exports.

Using this approach, only the United States wheat exports to Colombia and the past values of United States wheat exports to Colombia would be used to forecast future values. The autoforecast model does not entirely ignore the effect of the other variables on United States wheat exports to Colombia because they are partially taken into account by the past values of the United States wheat exports themselves. Nevertheless, a better result frequently can be obtained by a transfer function model that takes explicit account of other concomitant variables such as prices, exchange rates, production level and others.

Another method used is based upon the assumption that the forecast errors of the autoforecasts may be correlated with past and present values of the concomitant variables. In this case, the forecast errors contain information that was not fully extracted by the autoforecast model and improved forecasts should be possible if some function of the correlated variables is added to the autoforecast model. Adding these new variates creates a multivariate time series model known as transfer function model in which variables are considered in terms of inputs and outputs.

Transfer Function Models

Transfer function models incorporate concomitant variables via linear dynamic model expressed as linear difference equations of the same general form as the stochastic models previously discussed. Figure 2.3 shows succinctly what the transfer function model deals with. This is an output time series which is presumed to be influenced by (1) an input time series and (2) other inputs collectively grouped and called “noise” which result in dynamic system. In order words, the input series exerts its influence on the output series via a transfer function

Figure 2.4 illustrates the basic approach of a transfer function model and consists of the following stages:

- Identification of the Model Form.
- Estimation of the Parameters of the Transfer Function Model.
- Diagnostic Testing of the Transfer Function Model.
- Using the Transfer Function Model for Forecasting.

Suppose that values are available on predictor variables $x_{1t}, x_{2t}, ...,$ (e.g. price, exchange rates) and an output variable y_t (total quantity of wheat exported by the United States). Then the dynamic characteristics of such systems can often be approximated parsimoniously by linear difference equations of the form:

(7) $$\phi(B)y_t = \theta(B)x_t \quad \text{or} \quad y_t = \frac{\theta(B)}{\phi(B)}x_t$$

where $\theta(B) = (\theta_0 - \theta_1 B - ... - \theta_p B^p)B^p$ and $\phi(B) = \phi_0 - \phi_1 B - ... - \phi_q B^q$.

If there are several inputs and we allow for a general ARIMA model, we can write

(8) $$y_t = \sum_{i=1}^{k} \frac{\theta_i(B)}{\phi_i(B)}x_{it} + \frac{\theta(B)}{\phi(B)}\alpha_t$$

where α_t are independent and identically distributed normal series which are not necessarily the same as shock series, a_t of the univariate model. In general $\theta_i(B) \neq \theta(B)$ and $\phi_i(B) \neq \phi\ (B)$. Methods for identifying, fitting, and checking models of this kind closely parallel to those of the univariate models are fully described in Box and Jenkins (1976).

Data Estimation and Procedure of the United States Total Wheat Trade in Colombia

Monthly quantity data in unit metric tons of Colombian wheat imports from the United States are used for this study (USDA, 2000). However, value data are not available on a monthly basis. This limitation of data makes forecasting of the United States wheat exports to Colombia complicated. This results in the necessity of using another price series of wheat value as a proxy. One could use the U.S. price of wheat for example. On annual basis, on the other hand, the data are more abundant. Other variables such as Colombian gross domestic product (GDP), and population are available for at least thirty years on an annual basis. Exchange rates data are also available on monthly basis. At the same time, imports of wheat in values and quantities are also provided by the United States Department of Agriculture (USDA, 2000).

The United States total wheat exports to Colombia obtained from the United States Department of Agriculture is shown in Figure 2.5. Stationarity of the United States wheat exports to Colombia data was determined by unit-root tests using Augmented Dickey-Fuller procedure (1981). The ADF test consists of running a regression of the first difference of the series against the series lagged once, lagged difference terms and optionally a constant (and a time trend). The first stage in testing for stationarity of a time series is to determine the order of integration of individual time series that is, to determine how many times a variable require to induce stationarity (Granger and Engle, 1987). The ADF test results are presented in Table 2.0a and Table 2.0b. In this case, the null hypothesis of the root is rejected at about 10 percent level for the data. Table 2.0b shows that the United States wheat exports to Colombia data are stationary after the first differencing.

The series shows cyclical behavior and the cycle repeats at lag 1 of 12 months, which is typical for the monthly observed data. However, a disproportionate amount of United States total wheat exports to Colombia occurred in a relatively short period within the third quarters of every year. This circumstance does not appear to jeopardize the stability of the variance. Thus, the transformation of the original data in marginal cases is not advisable because the back transformation can introduce a bias into the analysis (Salas et al., 1980).

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the United States total wheat exports to Colombia series are plotted in Figure 2.6. The character of these plots indicates that the series is non-stationary and therefore in need of differencing. The ACF for the series shows significant cyclical peaks at lags 12, 24, and 36.[2a] As it will be shown later it is enough to include in the

[2a] The Autocorrelation Function (ACF) is used in the identification stage of time series (Box-Jenkins) analysis. It is a graph that plots the estimated *k*th-order autocorrelation coefficient as a function of *k*. Autocorrelation plots (*Box and Jenkins, pp. 28-32, 1976*) are a commonly-used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero. In addition, autocorrelation plots are used in the model identification stage for Box-Jenkins autoregressive, moving average time series models. If seasonality is present, it must be incorporated into the time series model. The run sequence plot is a recommended first step for analyzing any time series.

The Partial Autocorrelation Function (PACF) is also used in the identification stage of time series (Box-Jenkins) analysis. It is a plot of the estimated *p*th coefficient, assuming an AR(p) model, against p. Partial autocorrelation plots (*Box and Jenkins, pp. 64-65, 1976*) are a commonly used tool for model identification in Box-Jenkins models. The partial autocorrelation at lag k is the autocorrelation between X_t and X_{t-k} that is not accounted for by model only 24-month seasonality[2b]. These peaks do not die out quickly, meaning that the series has a seasonal non-stationarity trend which is typical for monthly data. The significant autocorrelations at half-seasonal lags can be due to strong seasonal variations and they often become insignificant after seasonal differencing when seasonal AR and MA coefficients are estimated (Pankratz, 1988).

The autocorrelations at lags 3, 5, and 7 have also respective low t-values of 0.112, 0.219 and 0.198. This kind of autocorrelation structure is ambiguous and such patterns are sometimes formed only because of sampling errors. A safe procedure in such circumstance is to ignore this altogether and perform the identification of the first tentative model by considering only the remaining patterns. The remaining pattern in this case is only the significant spikes at lags 12, 24, ... for which a seasonal ARIMA may be sufficient. The autoregressive order $p = 1$ was obtained by using MINIC and PROC STATESPACE procedures in SAS package program for the first difference stationary data of the United States wheat exports to Colombia. Hence, pursing these indications, the following ARIMA models can be considered as

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lags 1 through k-1. Specifically, partial autocorrelations are useful in identifying the order of an autoregressive model. The partial autocorrelation of an AR(p) process is zero at lag p+1 and greater. If the sample autocorrelation plot indicates that an AR model may be appropriate, then the sample partial autocorrelation plot is examined to help identify the order. We look for the point on the plot where the partial autocorrelations essentially become zero. Placing a 95% confidence interval for statistical significance is helpful for this purpose.

[2b] Although seasonality can sometimes be indicated with this plot, seasonality is shown more clearly by the seasonal subseries plot or the box plot. The seasonal subseries plot does an excellent job of showing both the seasonal differences and also the within-group patterns. The box plot shows the seasonal difference quite well, but it does not show within group patterns. However, for large data sets, the box plot is usually easier to read than the seasonal subseries plot. Both the seasonal subseries plot and the box plot assume that the seasonal periods are known. In most cases, the analyst will in fact know this. For example, for monthly data, the period is 12 since there are 12 months in a year. However, if the period is not known, the autocorrelation plot can help. If there is significant seasonality, the autocorrelation plot should show spikes at lags equal to the period. For example, for monthly data, if there is a seasonality effect, we would expect to see significant peaks at lag 12, 24, 36, and so on (although the intensity may decrease the further out we go) *Box and Jenkins, 1976*.

possible choices (i) ARIMA (1,1,1); (ii) ARIMA(1, 1, 1)(0, 1, 1)$_{12}$; (iii) ARIMA(1, 1, 1)(1, 1, 1)$_{12}$ and (iv) ARIMA (1, 1, 2)(1, 1, 1)$_{12}$.[3]

These ARIMA models are then estimated and checked for adequacy using SAS and Eviews packages (Shumway, 1988) as follows: The estimation results from SAS and Eviews are contained in Table 2.1. Models I , II and IV have high Akaike Information Criteria and (AIC) and Schwartz Bayesian Criteria (SBC).[4] It is clear that the variance, AIC and SBC for these models do not vary significantly. In addition, the sum of AIC and SBC are higher than that of Model III. The ACF and PACF for Model III are shown in Figure 2.7, which is clear from any significant peaks at lower lags. A higher correlation at lag 12 may be due to the seasonal nature of the data. Although the data are seasonally differenced, seasonal effects are not always cleared completely and therefore such correlations at higher lags can be safely neglected. Model III is then checked for the consistency of its inherent behavior. Such a check is carried out by deleting some of the data points and the same model is again estimated from the reduced set (Pankratz, 1988).

The number of points to be deleted depends upon the total number points in the series. In this study, the last 16 months are dropped and the first 65 months are used. The selected ARIMA(1, 1, 1)(1, 1, 1)$_{12}$ is again estimated from this subset of data. The comparison of the parameters for the full and reduced data sets is shown in

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[3] Multiplicative models are written in form ARIMA(p,d,q)(P,D,Q), where
p and q = the seasonal ARIMA differences
d = number of nonseasonal differences
P =number of multiplicative autoregressive coefficients
D = number of seasonal differences
Q = number of multiplicative moving average coefficients and
S = seasonal period.

[4] The two most commonly used model selection criteria are the Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC). Ideally, the AIC and SBC will be as small as possible in selecting the most appropriate

Table 2.2. The estimated parameters are almost the same, which indicates that the long-term behaviors of the United States total wheat exports to Colombia for the selected ARIMA model was consistent with the selected model ARIMA(1, 1, 1)(1, 1, 1)$_{12}$ and the forecast is shown in Figure 2.8. The residual plot, actual and fitted ARIMA(1, 1, 1)(1, 1, 1)$_{12}$ is shown in Figure 2.9. The actual and the fitted series do match reasonably, which also strengthen the appropriateness of ARIMA(1, 1, 1)(1, 1, 1)$_{12}$ in modeling the United States wheat exports to Colombia data sets.

(9) $$Q_t^{US} = 34.08 + u_t$$

(10) $$(1-0.22L)(1-0.94L^4)u_t = (1-0.71L)(1+0.99L^4)\varepsilon_t$$

(11) $$Q_t^{US} = 0.025 + 0.22Q_{t-1}^{US} + 0.94Q_{t-4}^{US} + 0.21Q_{t-5}^{US} + \varepsilon_t - 0.71\varepsilon_{t-1} + 0.99\varepsilon_{t-4} - 0.70\varepsilon_{t-5}$$

A particular kind of multivariate modeling uses regression analysis that usually consists of fitting a linear regression (Draper and Smith, 1964):

(12) $$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_k X_{kt} + \varepsilon_t$$

Where $X_{1t}, X_{2t}, \ldots, X_{kt}$ are assumed measures without error, $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ are fixed parameters, and ε_t is the random variable that is normally distributed around zero and has a variance of σ_t^2. For the purpose of modeling the United States wheat exports to Colombia, a univariate model may be totally invalid and also misleading. Problems arise because of (1) autocorrelated data, (2) dependence between input (predictor) variables, (3) dynamic relations between input and output variables, and (4) parsimonious use of variables. Hence, ordinary least squares used in regression analysis is only appropriate for uncorrelated data. Ordinary regression analysis does

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model. AIC = Tln(residual sum of squares) + 2n; SBC = Tln(residual sum of squares) + $n$ln(T) (Judge. et al., 1988).

not account for system inertia which occurs in wheat exports. A change in level of an input may not be transmitted immediately to the output but gradually takes effect. Dynamic models allow for this behavior. Therefore, the fewest number of parameters are used to provide an adequate transfer function model (parsimony).

For this study, exchange rates (*USCOEx*) and wheat price (*USPR*) are incorporated into the model. Considerable effort was necessary in the model building to select useful independent variables and develop the basic model structure. A key step was discovering that all the time series of all the variables could be modeled as transfer function model with ARIMA $(1, 1, 1)(1, 1, 1)_{12}$

$$Q_t^{US} = -42.92 + u_t \tag{13}$$

$$(1-0.18L)(1-0.93L^4)u_t = (1-0.88L)(1+0.70L^4)\varepsilon_t \tag{14}$$

$$\begin{aligned} Q_t^{US} = {} & 0.014 - 0.008USPR + 0.011USCOEx + 0.18Q_{t-1}^{US} + 0.93Q_{t-4}^{US} + \\ & + 0.17Q_{t-5}^{US} + \varepsilon_t - 0.88\varepsilon_{t-1} + 0.70\varepsilon_{t-4} - 0.62\varepsilon_{t-5} \end{aligned} \tag{15}$$

The residual plot, actual and fitted, for the transfer function model is shown in Figure 2.11. The actual and the fitted series do match reasonably well, which also strengthens it's appropriateness in modeling the United States wheat exports to Colombian data sets. The signs of the *USCOEx* and *USPR* are in accordance with the existing economic theory. However, nothing can be said about their magntitudes. The forecasting capability of the selected univariate ARIMA$(1, 1, 1)(1, 1, 1)_{12}$ are then compared with the forecast values form the transfer function model. Table 2.3 and 2.4 show a comparison of observed and forecast values for the selected univariate model, the forecasting capability of the selected ARIMA$(1, 1, 1)(1, 1, 1)_{12}$ and the transfer function model.

Forecasting Accuracy

The transfer function which uses observations for the United States' total wheat exports data as a function of exchange rates and wheat price as the process inputs gives more accurate forecasts than the univariate model. However, to the extent that the process output which is the forecast values of the United States' total wheat exports is a function of process inputs, the process output actually does incorporate information about the inputs when these inputs are explicitly shown in the model. The resulting information is indirectly incorporated in the univariate model forecast. Figures 2.8 and 2.10 show the forecasts of the United States' total wheat exports to Colombia for the univariate model and transfer function model, respectively.

The forecasting accuracy of the two models may be compared quantitatively using the values of the estimated standard deviation of the residuals $\hat{\sigma}_a$. The values $\hat{\sigma}_a$ of the transfer function were about 33.6 percent less than $\hat{\sigma}_a$ of the univariate model. The amount of information is proportional to the inverse of the variance. Thus, the percentage improvement supplied by the transfer function is $(0.04^2/0.03^2 - 1)100 = 33.62\%$.

Another criterion for comparing the forecasts which is an estimate of the variance of the one-step ahead of forecast is the mean square error (MSE). A model with a small MSE gives more accurate forecasts than a model with large MSE (Enders, 1995 pp. 206). The MSE is defined as the average square of residuals of the forecasts where the residual is the difference between forecasted and the observed values:

(16)
$$\text{MSE} = \frac{1}{n}\sum_{i=t_0}^{t_0+n}\left(Y_i - \hat{Y}_i\right)^2$$

The MSE is computed over a period of $n+1$ forecasts, running from month t_0 to month $t_0 + n$. To compare the forecasting accuracy of the models, the models were developed using data through month 79 and the fitted model was used to forecast the United States' total wheat exports to Colombia from month 64 to month 79. However, the first 63 observations are used also to develop the model: that is the accuracy should be the prediction of the unknown, not the fitting of the model. Since data that are used to develop a model might not necessarily be used to check its accuracy. The $\sqrt{MSE}$ values for the forecasts from months 64 to 79 for univariate and transfer function forecasting models of the United States' total wheat exports to Colombia are 0.04 and 0.03 respectively. The corresponding MSE values indicate that the transfer function model forecasts more accurately than the univariate model.

In addition, another criterion which has been advocated by Theil (1966), is to calculate the root mean square error of the predicted change, denoted *U*:

(17)
$$U = \sqrt{\frac{\frac{1}{n}\sum\left(\Delta\hat{Y}_i - \Delta Y_i\right)^2}{\frac{1}{n}\sum(\Delta Y_i)^2}}$$

This statistic has the advantage of possessing two natural calibration points. First, it is equal to 0 if the forecasts are perfectly accurate, and second, it is automatically equal to 1 for the naïve prediction of no change. If (ΔY_i) is equal to 0 for each forecast, the numerator is equal to $\frac{1}{n}\sum\left(\Delta\hat{Y}_i-\Delta Y_i\right)^2$, which is the same as the denominator. Since a forecasting model ought at a very minimum to be able to beat the forecast of no change, U ought to lie between 0 and 1, its closeness to 0 being an indicator of its relative success. For this study, the Theil value (U) for the transfer function is lower than that of univariate model ARIMA$(1,1,1)(1,1,1)_{12}$ indicates it forecasts accuracy over the univariate model.

Finally, it was established that United States' total wheat exports to Colombia can be modeled as transfer function ARIMA$(1,1,1)(1,1,1)_{12}$ process. The correlation coefficient value 0.75 allows to use such a model for practical applications forecasting of monthly United States total wheat exports to Colombia.

Summary and Conclusions

The results from this study provide valuable information about forecast evaluation and modeling of the United States' wheat trade in Colombia. First, the United States total wheat exports to Colombia is first differencing stationary by unit-root tests using Augmented Dickey-Fuller procedure (1981). The transfer function which uses observations for the United States' total wheat exports data as a function of exchange rates and wheat price gives more accurate forecasts than the univariate model with amount of information improvement supplied about 33.62%.

Second, several criteria were used to determine the accuracy of the transfer function model over the univariate model. The mean square error (MSE) values indicate that the transfer function model forecasts more accurately than the univariate model. The Theil value (*U*) for the transfer function is lower than that of univariate model showing the superiority of the transfer function model. Finally, it was established that United States' total wheat exports to Colombia can be modeled as transfer function ARIMA$(1,1,1)(1,1,1)_{12}$ process. The correlation coefficient value 0.75 allows use of such a model for practical applications; that is forecasting of monthly United States total wheat exports to Colombia.

Table 2.0 a: Augmented Dickey-Fuller (ADF) Unit Root Test for the United States Wheat Exports to Colombia Monthly Data (1993-1999)

ADF Test Statistic	-4.183450	1% Critical Value*	-2.5922
		5% Critical Value	-1.9443
		10% Critical Value	-1.6179

*MacKinnon critical values for rejection of hypothesis of a unit root.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UR01)
Method: Least Squares
Date: 11/05/01 Time: 16:17
Sample(adjusted): 1993:02 1999:08
Included observations: 79 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
UR01(-1)	-0.383563	0.091686	-4.183450	0.0001

R-squared	0.183019	Mean dependent var	0.543734
Adjusted R-squared	0.183019	S.D. dependent var	32.07151
S.E. of regression	28.98848	Akaike info criterion	9.584251
Sum squared resid	65545.87	Schwarz criterion	9.614244
Log likelihood	-377.5779	Durbin-Watson stat	2.619663

Table 2.0 b: Augmented Dickey-Fuller (ADF) Unit Root Test for the United States Wheat Exports to Colombia after First Differencing Monthly Data (1993-1999)

ADF Test Statistic	-18.03876	1% Critical Value*	-4.0787
		5% Critical Value	-3.4673
		10% Critical Value	-3.1601

*MacKinnon critical values for rejection of hypothesis of a unit root.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(Qus,1,1)
Method: Least Squares
Sample (adjusted): 1993:03 1999:08
Included observations: 78 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(Qus(-1))	-1.633186	0.090538	-18.03876	0.0000
C	0.585810	5.925683	0.098860	0.9215
@TREND(1993:01)	0.003441	0.127881	0.026906	0.9786

R-squared	0.812705	Mean dependent var	0.600474
Adjusted R-squared	0.807711	S.D. dependent var	57.98599
S.E. of regression	25.42732	Akaike info criterion	9.347228
Sum squared resid	48491.13	Schwarz criterion	9.437870
Log likelihood	-361.5419	F-statistic	162.7192
Durbin-Watson stat	2.578019	Prob(F-statistic)	0.000000

Table 2. 1: Estimation Results of I-1V ARIMA Models

Model I: ARIMA(1,1,1)

Parameter	AR(1)	MA(1)
Parameter value	-0.2863	0.9720
Standard error	0.1191	0.0132
t-value	2.4043	7.3866
Variance	31.2164	
Akaike Information Criteria (AIC)	7.4499	
Schwarzt Bayesian Criteria (SBC)	7.5707	
Sum of AIC and SBC	15.0206	
R-squared	0.76931	

Model II: ARIMA$(1, 1, 1)(0, 1, 1)_{12}$

Parameter	AR(1)	MA(1)	SAR(0)	SMA(1)
Parameter value	0.5896	0.0015		0.8741
Standard error	0.1109	0.0967		0.0253
t-value	5.315	0.0151		0.0253
Variance	31.2164			
Akaike Information Criteria (AIC)	7.0043			
Schwartz Bayesian Criteria (SBC)	7.1553			
Sum of AIC and SBC	14.1596			
R-squared	0.8560			

Model III: ARIMA$(1, 1, 1)(1, 1, 1)_{12}$

Parameter	AR(1)	MA(1)	SAR(1)	SMA(1)
Parameter value	0.2174	0.7071	0.9364	-0.9849
Standard error	0.1362	0.0691	0.0144	0.1185
t-value	1.5958	0.6912	4.8787	0.1185
Variance	31.707			
Akaike Information Criteria (AIC)	5.7631			
Schwartz Bayesian Criteria (SBC)	5.9222			
Sum of AIC and SBC	11.6853			
R-squared	0.9599			

Model IV: ARIMA(1, 1, 2)(0, 1, 1)$_{12}$

Parameter	AR(1)	MA(2)	SAR(1)	SM(1)
Parameter value	0.6410	0.6620	0.9554	-0.9849
Standard error	0.1500	0.0283	0.0088	0.0964
t-value	2.2820	-3.4306	6.7867	8.9895
Variance	31.1615			
Akaike Information Criteria (AIC)	5.2858			
Schwartz Bayesian Criteria (SBC)	5.4849			
Sum of AIC and SBC	10.8707			
R-squared	0.9741			

Table 2. 2: Comparison of Selected Model III: ARIMA(1, 1, 1)(1, 1, 1)$_{12}$ from Reduced Data of 63 Months

Model III: ARIMA(1, 1, 1)(1, 1,1)$_{12}$

Parameter	AR(1)	MA(1)	SAR(1)	SMA(1)
Parameter value	0.2174	0.7071	0.9364	-0.9849
Standard error	0.1362	0.0691	0.0144	0.1185
t-value	1.5958	0.6912	4.8787	0.1185
Variance	31.707			
Akaike Information Criteria (AIC)	5.7631			
Schwartz Bayesian Criteria (SBC)	5.9222			
Sum of AIC and SBC	11.6853			
R-squared	0.9599			
Theil Value (*U*)				

Model III: ARIMA(1, 1, 1)(1, 1, 1)$_{12}$ from Reduced Data of 63 Months

Parameter	AR(1)	MA(2)	SAR(1)	SMA(1)
Parameter value	1.0102	0.6881	0.9312	-0.9880
Standard error	0.0080	0.0324	0.0151	0.1137
t-value	2.2820	-3.4306	6.7867	8.9895
Variance	31.7068			
Akaike Information Criteria (AIC)	5.8289			
Schwartz Bayesian Criteria (SBC)	5.9945			
Sum of AIC and SBC	11.8234			
R-squared	0.9558			
Theil Value (*U*)	0.0542			

Transfer Function Model: ARIMA(1, 1, 1)(1, 1, 1)$_{12}$

Parameter	USPR	USCOEX	AR(1)	MA(2)	SAR(1)	SMA(1)
Parameter value	-0.0079	0.0111	0.1780	0.8793	0.9266	-0.7030
Standard error	0.0080	0.0067	0.1420	0.0726	0.0220	0.0686
t-value	0.9897	1.6933	1.2533	2.1105	2.0970	1.2460
Variance	31.1615					
Akaike Information Criteria (AIC)	5.5690					
Schwartz Bayesian Criteria (SBC)	5.2107					
Sum of AIC and SBC	10.7797					
R-squared	0.9672					
Theil Value (*U*)	0.0450					

Table 2. 3: Observed and Forecast Values of the United States Total Wheat Exports to Colombia Using Univariate ARIMA(1 ,1, 1)(1,1,1)$_{12}$ Model 1980-2000.

Month no.	Observed value	Forecast value	95% Confidence bounds Lower	Upper	Forecast error
64	73.00	70.25	10.70	20.60	2.75
65	11.00	10.81	9.11	17.89	0.19
66	28.00	28.46	11.21	16.82	-0.46
67	49.00	52.06	19.09	23.66	-3.06
68	45.00	34.77	6.90	21.75	10.23
69	35.00	26.41	26.42	9.02	8.59
70	20.00	18.27	17.03	22.98	1.73
71	60.00	45.09	15.83	12.11	14.91
72	30.00	23.81	6.74	19.10	6.19
73	18.00	18.06	10.93	17.45	-0.06
74	36.00	37.08	23.07	20.63	-1.08
75	23.11	25.16	12.92	11.87	-2.05
76	72.00	69.27	8.39	15.01	2.73
77	12.00	11.79	11.47	19.02	0.21
78	26.00	27.93	10.05	23.36	-1.93
79	63.00	58.95	14.02	11.25	4.05

Root mean squared error is 0.04. Maximum observed is 14.91.

Table 2. 4: Observed and Forecast Values of the United States Total Wheat Exports to Colombia Using Exogenous Transfer Function ARIMA Model 1980-2000.

Month no.	Observed value	Forecast value	95% Confidence bounds Lower	Upper	Forecast error
64	73.00	69.55	13.52	23.49	3.45
65	11.00	12.13	12.32	9.41	-1.13
66	28.00	31.24	8.91	11.73	-3.24
67	49.00	51.61	19.09	16.91	-2.61
68	45.00	37.35	10.02	19.85	7.65
69	35.00	28.96	12.84	11.41	6.04
70	20.00	21.26	14.19	8.92	-1.26
71	60.00	47.21	15.39	11.47	12.79
72	30.00	26.01	11.91	19.10	3.99
73	18.00	21.32	15.82	26.30	-3.32
74	36.00	39.10	7.26	15.25	-3.10
75	23.11	27.53	8.37	23.94	-4.42
76	72.00	69.98	11.28	8.15	2.02
77	12.00	14.55	7.59	16.54	-2.55
78	26.00	33.23	12.53	9.64	-7.23
79	63.00	62.10	8.62	15.05	0.90

Root mean squared error is 0.03. Maximum observed is 12.79.

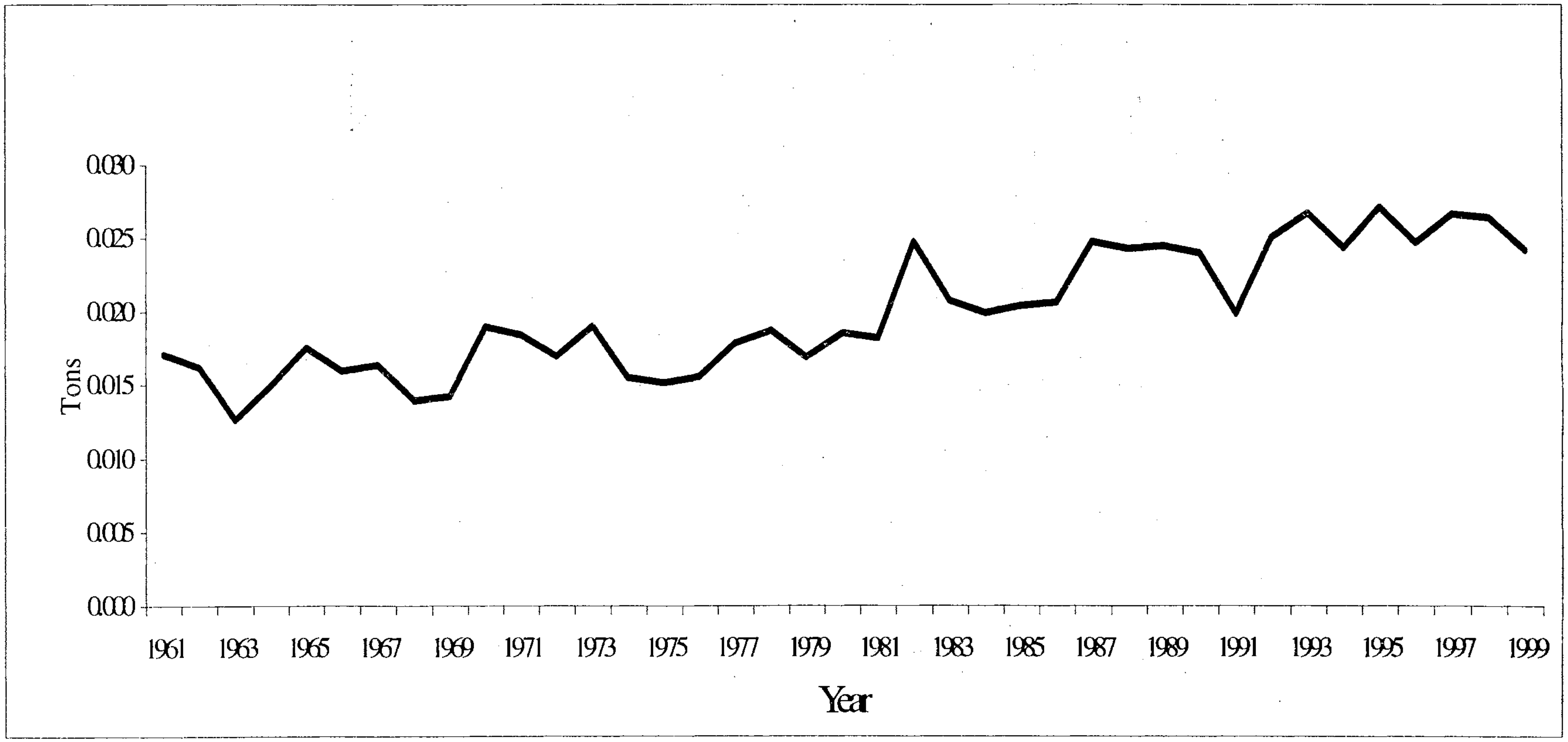


Figure 2. 1: Per Capita Consumption of Wheat in Colombia. Period 1961-2000

Source: USDA-ERS 2000

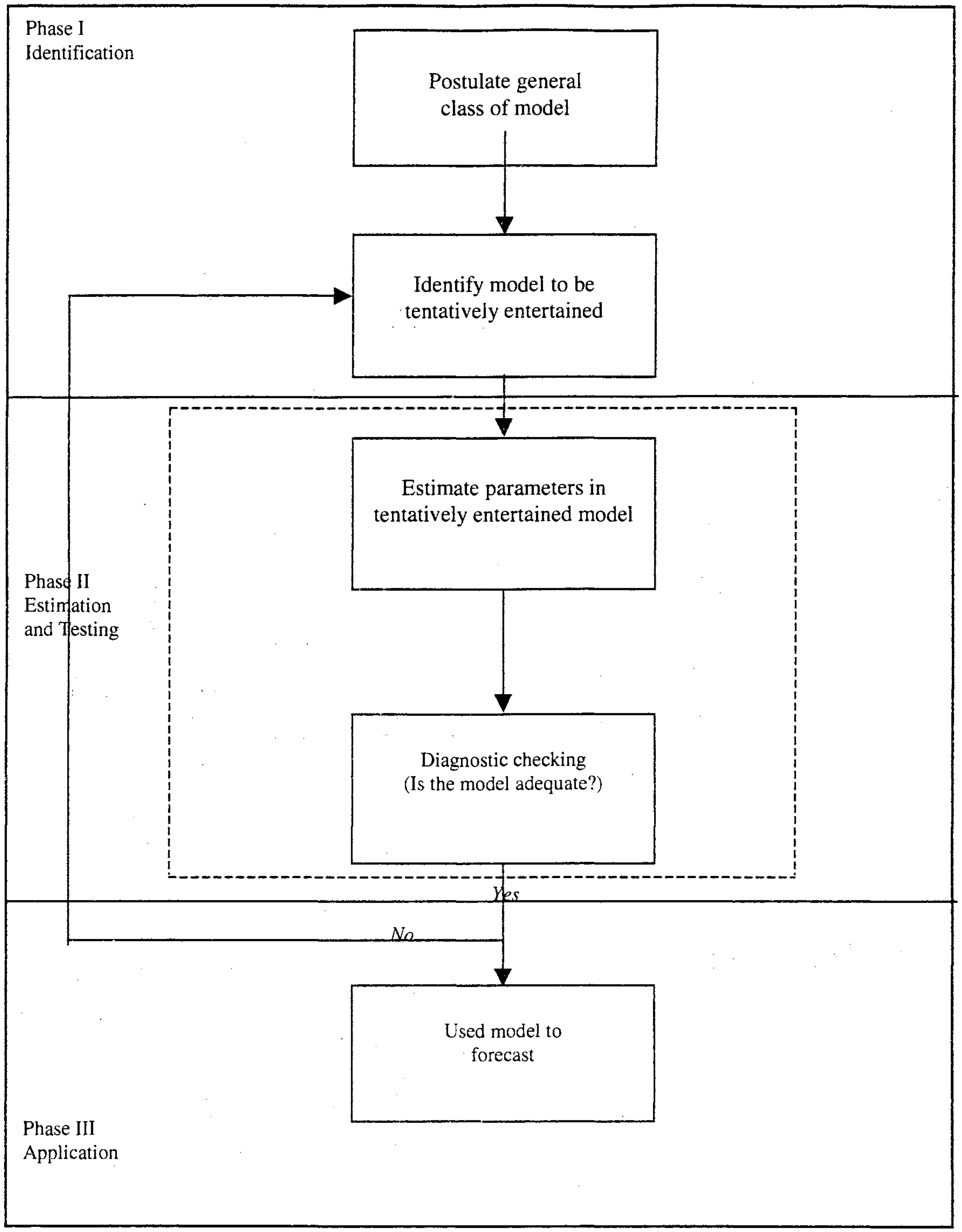


Figure 2. 2: Schematic Representation of the Box-Jenkins Approach

Source: Spypros Makridakis, Steven C. Wheelwright, and Victor E. McGee. 1983. Forecasting: Methods and Application Page 414, second edition, John Wiley and Sons, Inc.

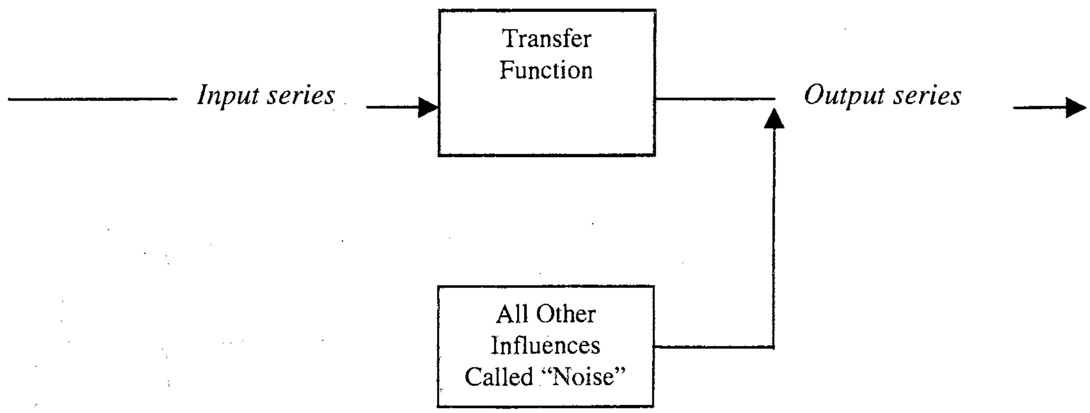


Figure 2. 3: The Transfer Function Concept

Source: Spypros Makridakis, Steven C. Wheelwright, and Victor E. McGee. 1983. Forecasting: Methods and Application Page 480, second edition, John Wiley and Sons, Inc.

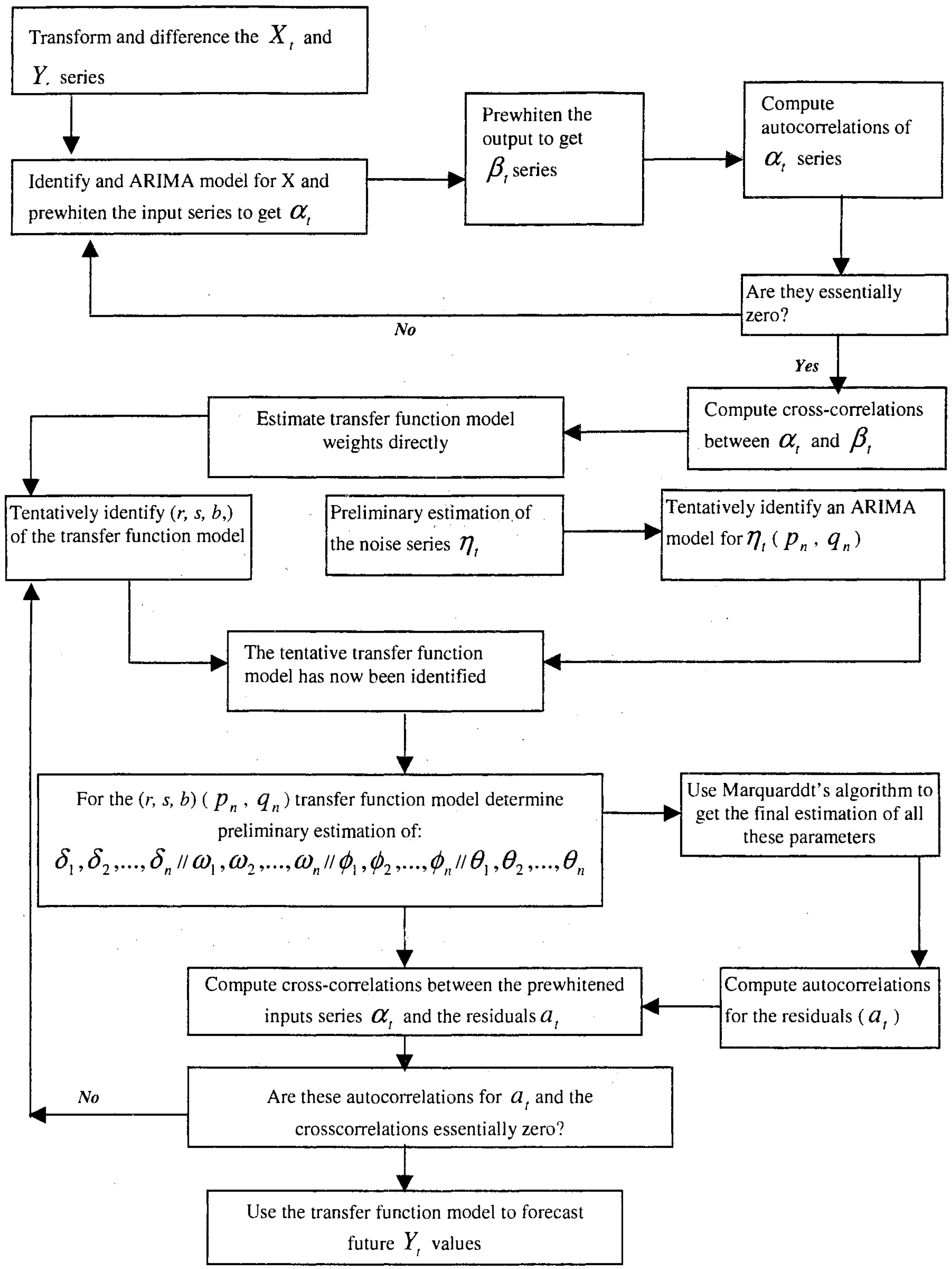


Figure 2. 4: The Basic Steps in Developing a Transfer Function Model

Source: Spypros Makridakis, Steven C. Wheelwright, and Victor E. McGee. 1983. Forecasting: Methods and Application Page 490- 419, second edition, John Wiley and Sons, Inc.

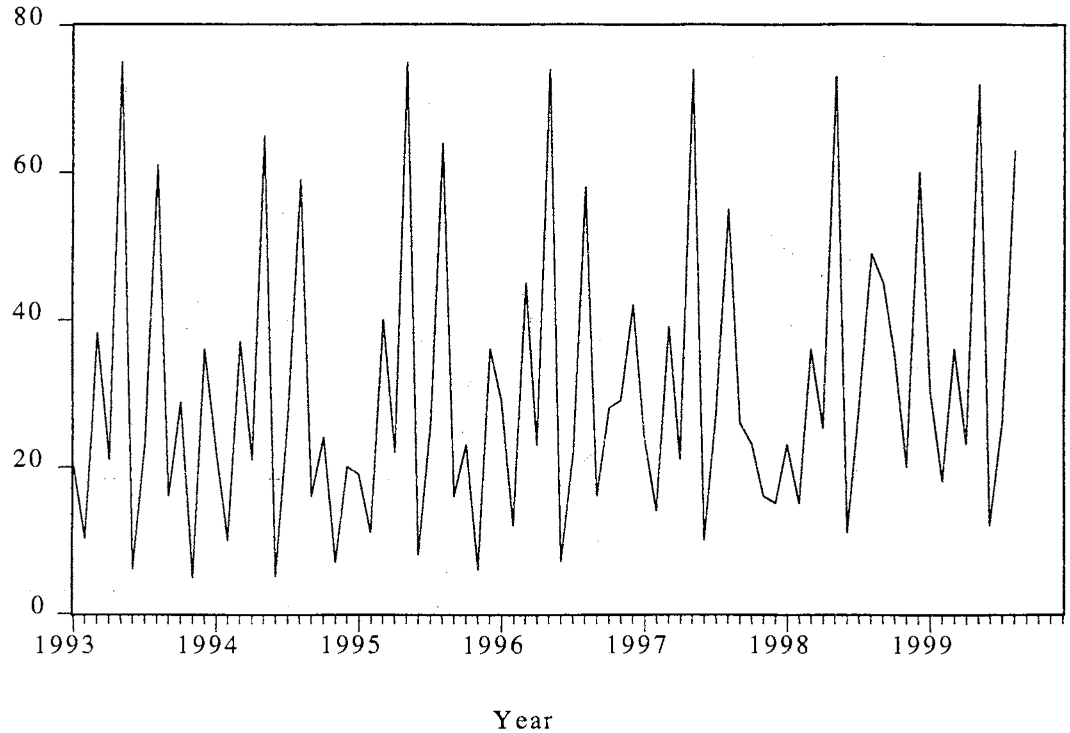
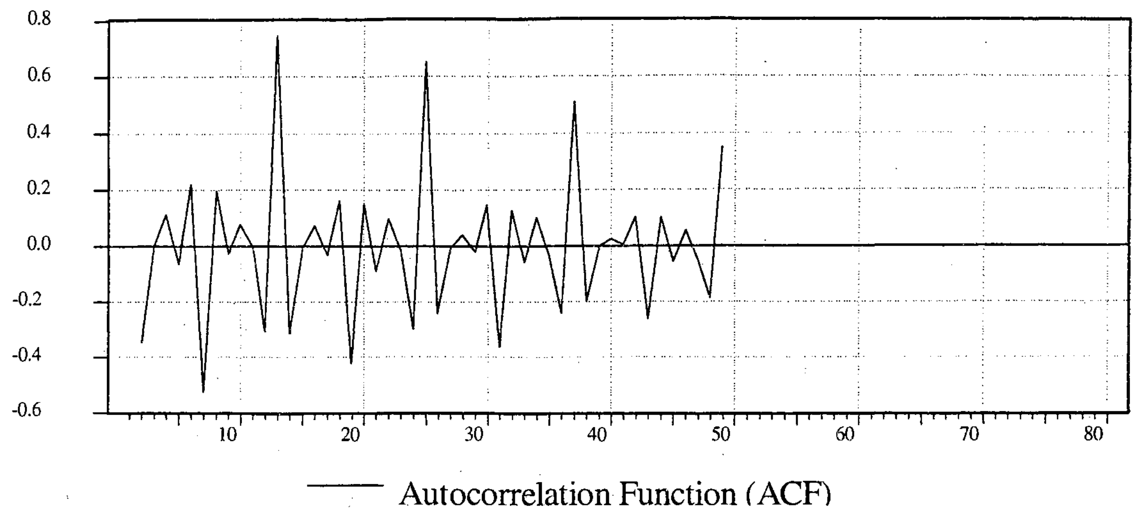


Figure 2. 5: Time Series Plot of the Monthly United States Total Wheat Exports to Colombia, 1993-2000 Period.



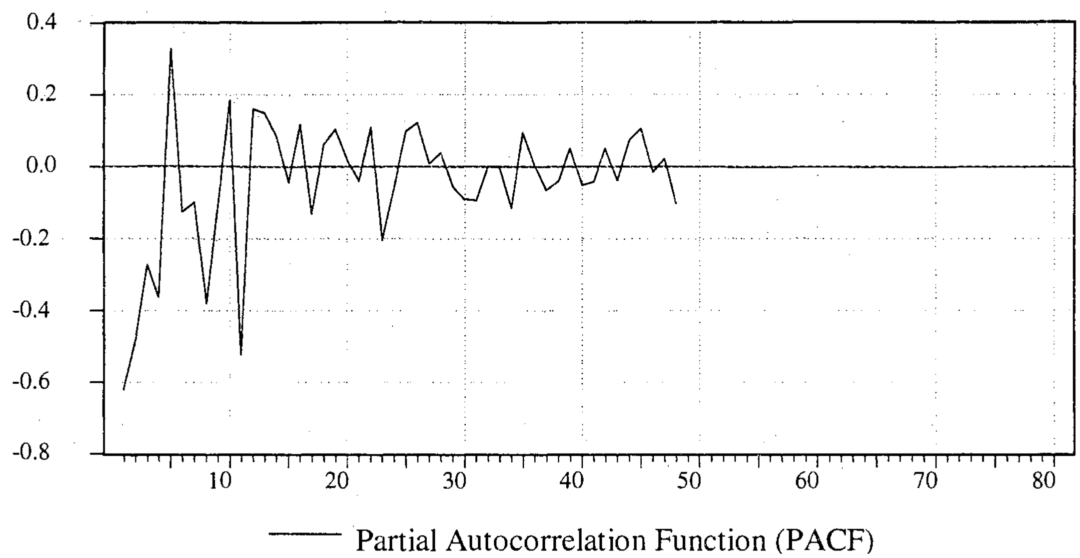


Figure 2. 6: ACF and PACF of Residuals of the Data Set for the Monthly United States Total Wheat Exports to Colombia.

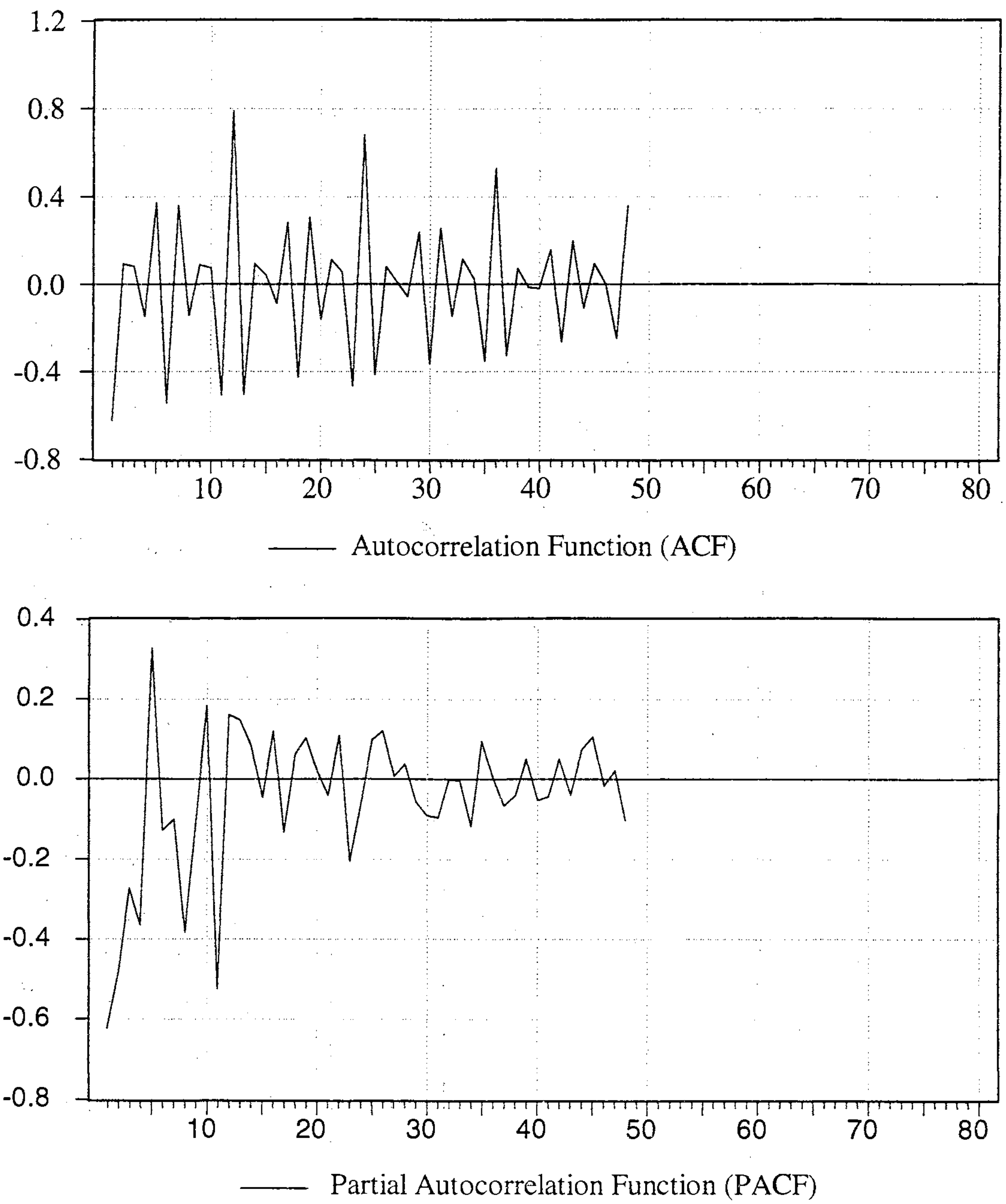


Figure 2. 7: ACF and PACF of Residuals of the First Differencing of the Data Set from the Univariate Model for the Monthly United States Total Wheat Exports to Colombia.

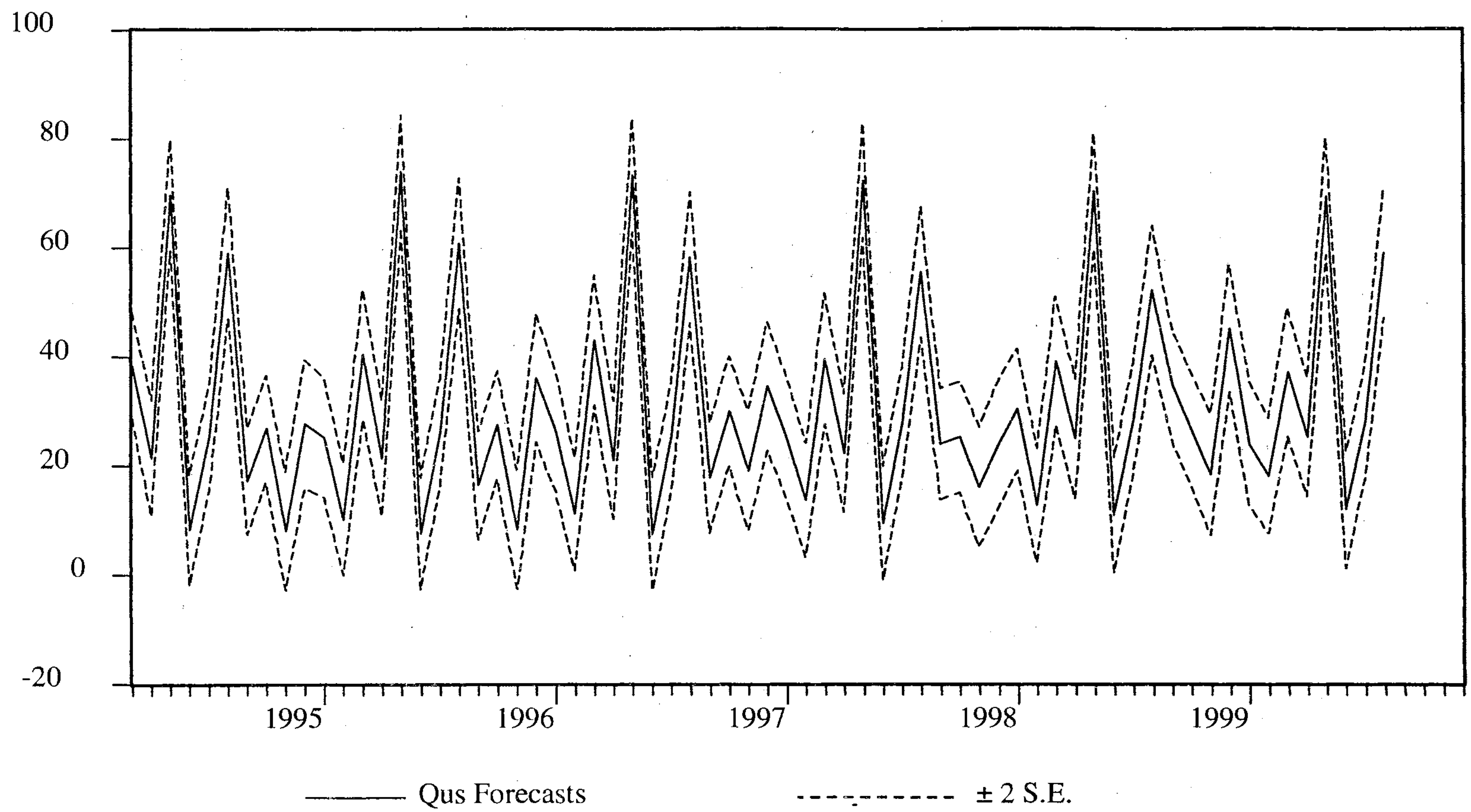


Figure 2. 8: Point and 95% Interval Forecasts of the Monthly United States Total Wheat Exports to Colombia for the Univariate Model.

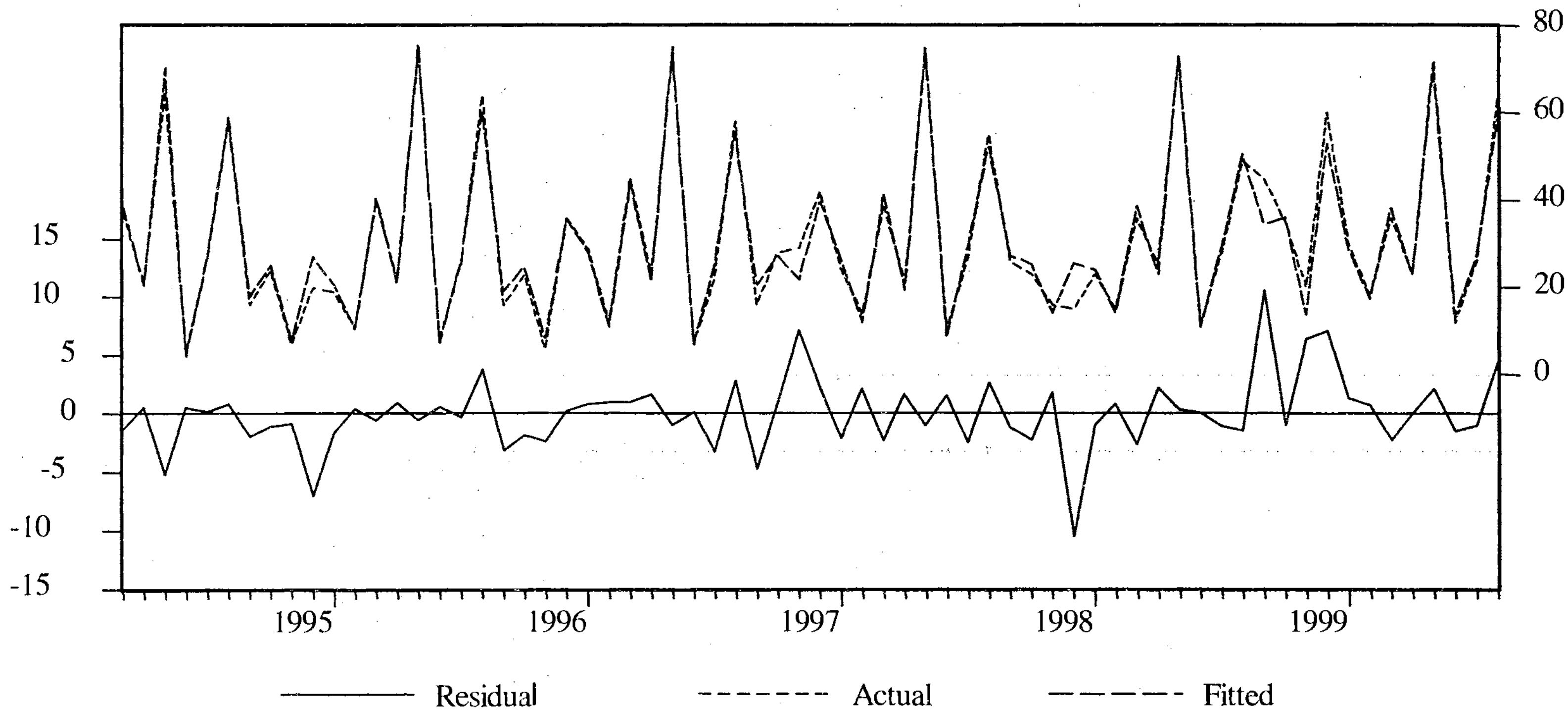


Figure 2. 9: Plot of Qus Residual of the Monthly United States Total Wheat Exports to Colombia for the Univariate Model.

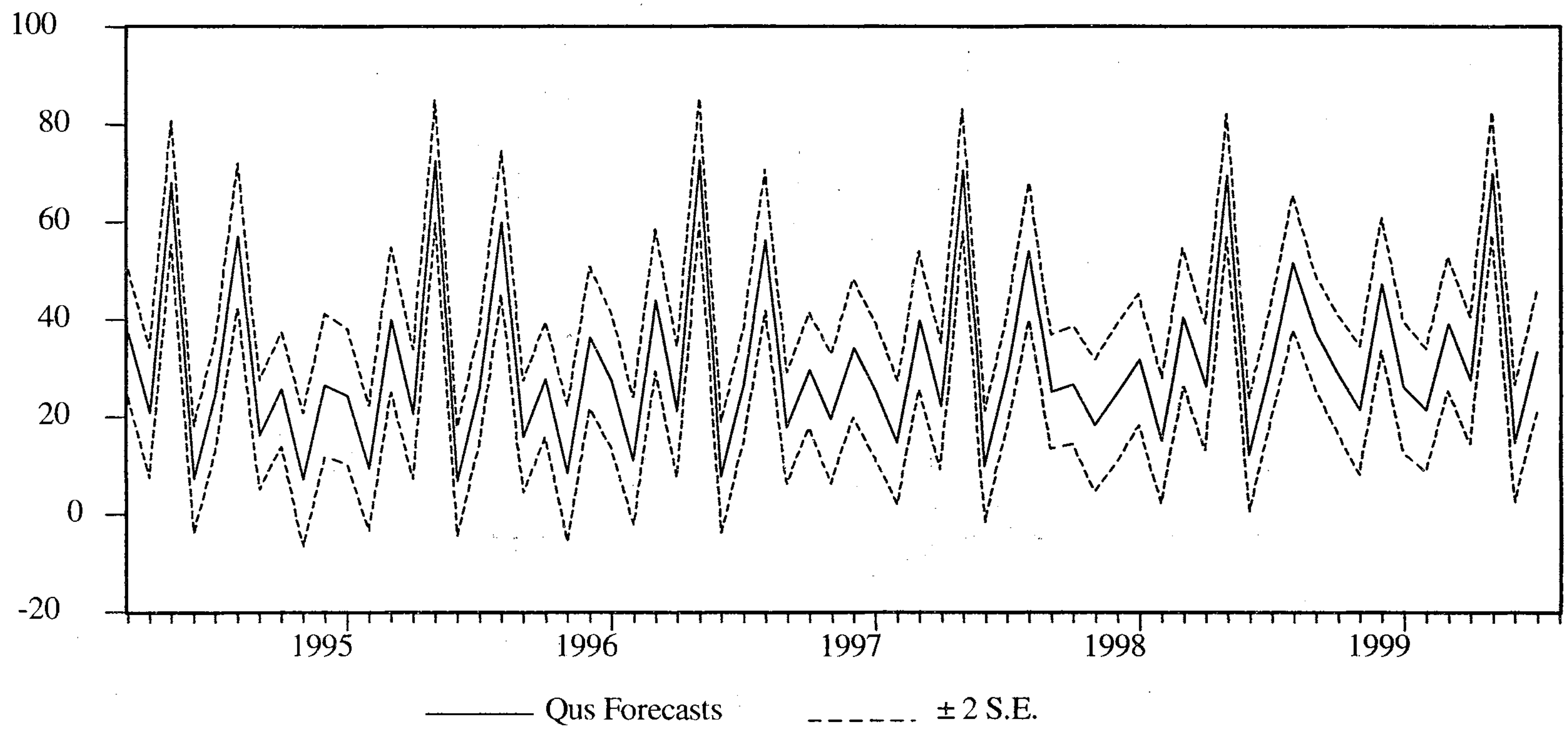


Figure 2. 10: Point and 95% Forecasts of the Monthly United States Total Wheat Exports to Colombia for the Transfer Function Model.

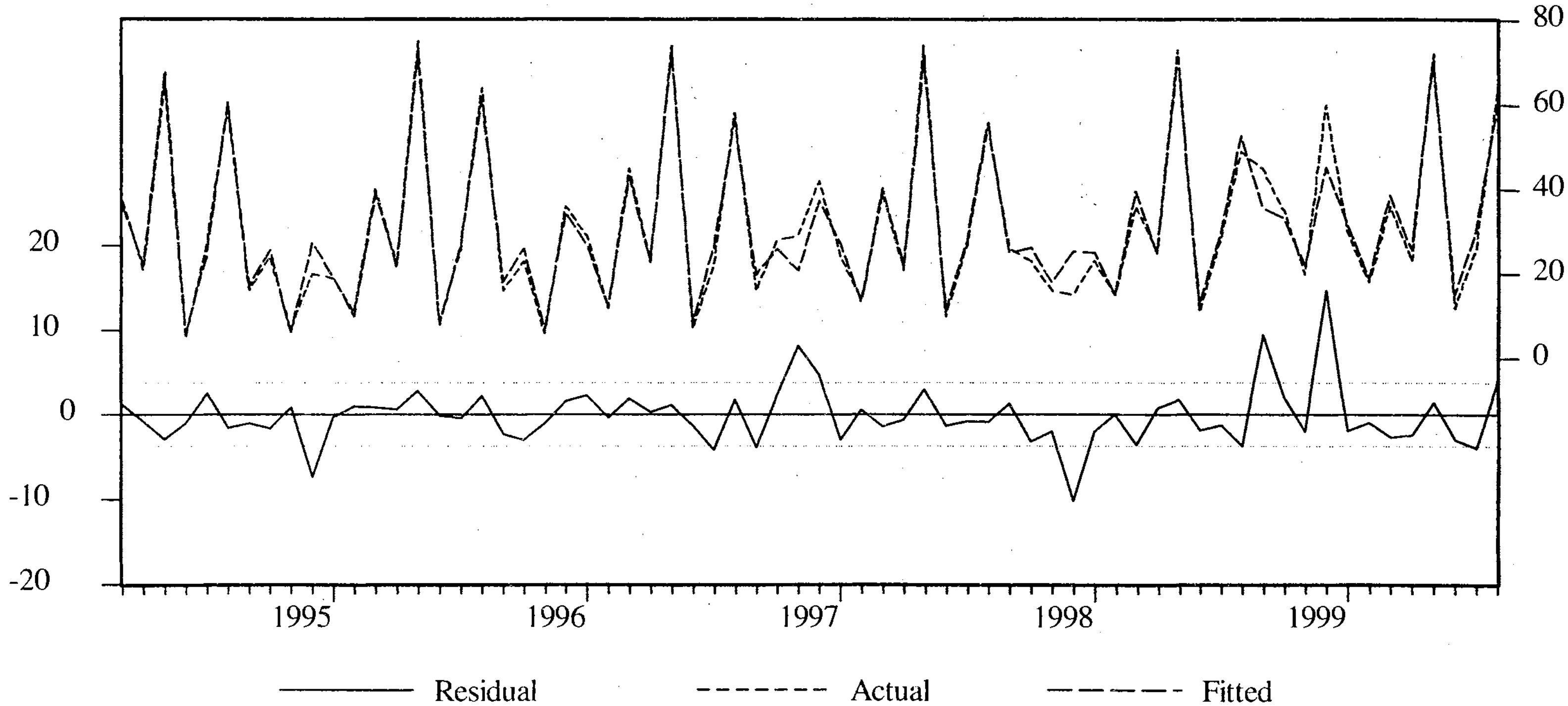


Figure 2. 11: Plot of Qus Residual of the Monthly United States Total Wheat Exports to Colombia for the Transfer Function Model.

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CHAPTER

III.

THE IMPACT OF PRICE CHANGES AND TRENDS ON DEMAND FOR MEAT IN NIGERIA

Introduction

Before the 1970's oil boom, agricultural exports were the backbone of the Nigerian economy with livestock products accounting for a significant share of exports. Prior to the oil boom in the early 19970's, Nigeria had well-developed domestic agricultural markets. Despite this sound potential for growth in the domestic market, Nigeria is witnessing a drastic decline in agricultural production, especially in livestock and meat sectors of the industry. This decline in agricultural production coincided with the nation's oil boom.

Furthermore, Nigeria has enjoyed yearly economic growth (GDP) of 10.8 percent in real terms between 1980 and 1987 as a result of export earnings from petroleum. Real per capita income rose at 6.9 percent per year from 1980-1987. However, the decline in the world oil prices experienced in 1987 and combined with the reduction in world market prices of agricultural products in 1989 brought an end to growth in GDP and real per capita income. Between 1987 and 1992 real per capita income dropped at a rate of 7.8 percent per year.

During this period, the federal government of Nigeria maintained a trade policy dominated by quantitative restrictions and price controls on food items. In January 1990, a tax was imposed on meat imports, ostensibly to raise government revenues and stimulate domestic meat production. The abrupt drop in meat imports, coupled with inadequate domestic supply pushed up price of meat and thus depressed domestic demand. For example, per capita meat consumption that had risen from 12.05 kg in 1981 to 13.8 kg in 1986 dropped to 11.6 kg in 1992. Also meat prices rose by 70 percent from 1987 to 1999, resulting in a decline in Nigerian per capita meat consumption from 10.5 kilograms of meat per year in 1987 to 9.4 kilograms per year in 1999 (*FGS*, 1999).[1] Although the federal government of Nigeria has designed various programs to help stabilize meat prices and consumption, the country still experiences meat scarcity and price fluctuations.

The purpose of this work is to understand the source of the change and fluctuation in meat consumption in Nigeria. In order to determine the cost or likely success of the various government programs, this research paper will examine the responsiveness of demand for meat to variations in prices and incomes on the basis of food demand data for the time period between 1980 to 1999. Additionally, it will also assist in formulating recommendations for policies with the potential to create more stable meat consumption and prices for the nation. In order to understand the source of the decline and instability in consumption and to determine whether the shock is from changing incomes or from changing prices, this paper will determine whether demand for meat is price-elastic on the basis of food demand data during the time period studied from 1980-1999.

[1] Nigeria, Federal Office of Statistics. *Economic and Social Statistics Bulletins* (Special Series) (January 1999).

World demand for meat has risen sharply during the last few decades. The key reasons for these increases in meat demand are increasing population, improving technology and increasing incomes. However, despite this overall improvement in technologies and incomes, per capita consumption of meat has lagged especially in the less-developed countries of the world because protein is the most costly food item.

The early study of empirical demand analysis was characterized by the extensive use of single equation methods centered on the measurement of elasticities since they are easily understood and conveniently dimensionless. Hence, they can be directly measured as the parameters of a regression equation linear in the logarithms of purchase, outlay and prices.

Agricultural economists have long been interested in the proper measurement and interpretation of elasticities and flexibilities between endogenous variables in systems of simultaneous equations. Elasticities are vital parameters in developing models for policy analysis, have been used in past applied models frequently based on subjective judgment not supported by quantitative and empirical evidence (Mdafri and Brorsen, 1993). Adegeye (1988) attempted to estimate elasticities, but his estimates of elasticity of demand for beef, poultry, and fish products such as freshwater fish are inaccurate to be used as policy analysis and recommendations. The inaccuracies occurred because he adopted provincial elasticities and failed to aggregate based on most recent policy analysis. It is well known that partial measures commonly used in a single-equation context are not valid for obtaining elasticities among endogenous variables in a systems framework because indirect effects are not accounted for by standard partial measures.

This applies to elasticities with respect to exogenous variables but does not apply to structural elasticities.

Demand Theory and Model

The classical theory of consumer demand behavior is based on a utility function $U = U(X_1,...,X_n)$, where $X = [x_i]$ is an n- element column vector of quantities bought of various commodities. The rational consumer always searches for the maximum utility subject to his or her budget constraint. Furthermore, demand theory holds that individual demand for a commodity or service is the outcome of budget-constrained utility. Facing an array of prices for different goods and services, which are fixed for the individual, and with a given income per unit of time, the consumer maximizes utility by choosing a specific combination of goods and services. The utility maximization problem can be represented as

(1) $$Max\ U = U(x_1,...,x_n),$$

$$S.t. \sum_{i=1}^{n} p_i x_i = M,$$

where $x_i,...,x_n$ represent the quantities of goods that the consumer actually consumes, $U(x_1,...,x_n)$ simply implies the consumer's own subjective evaluation of satisfaction, or utility, derived from consuming those commodities, p_i is the unit price of commodity x_i, and M is the total budget of the consumer per time period.

This combination will change as a result of changes in prices or income. Also, the utility function itself may change over time. Utility function may be separable so that decisions are made for groups of related commodities and services. When generating demand functions from utility functions, the forms of the demand functions depend on the underlying utility function. The utility function is a summary of some aspects of the consumer's taste or preferences regarding the consumption of various bundles of goods. The utility function has the following important properties: More is always preferred to less. All goods that the consumer chooses to consume at positive prices have the property that, other things being equal, more of any good is preferred to less of it. That is, the marginal utility of any good x_i is positive, or

$$U_i = \partial U_i / \partial x_i > 0. \tag{2}$$

The consumer, at any point, is willing to give up some of one good to get an additional increment of some other good. That is, the consumer's indifference curve has a negative slope. Diminishing marginal rate of substitution: All consumers possess a utility function $U = U(x_1, ..., x_n)$ that is differentiable everywhere, and which is strictly increasing $(U_i > 0,\ i = 1, ..., n)$ and strictly quasi-concave. However, the variable specification of the demand functions generally remain the same. Assuming weak separability, a general utility function can be written as

$$U = U[\Phi_1(x_{11}, .., q_{k1}), \Phi_2(x_{12}, ..., x_{k2}), ..., \Phi_n(x_{1n}, .., x_{kn})] \tag{3}$$

in which x_{ij} is the *i*th commodity or service in the *j*th group of such commodities or services. The Φ_j represent functional forms for branches of this utility function, which are unobservable due to the originality of utility. Hence, the very general specifications of the demand function can be obtained from equation (1) by means of the implicit function theorem and Roy's identity. The mathematics of the process yields the following specification for the *i*th commodities:

(4) $$x_i = x_i^M(p_1, p_2, \ldots, p_n, M) \qquad i = 1, 2, \ldots, n.$$

After substituting Marshallian demand equations above into the original utility function, one obtains the indirect utility function:

(5) $$U^*(p_1, \ldots, p_n, M) \equiv U\left(x_1^M(p_1, \ldots, p_n, M), \ldots, x_{nn}^M(p_1, \ldots, p_n, M)\right)$$

The function $U^*(p_1, \ldots, p_n, M)$ gives the maximum value of utility for any given prices and money income, $p_1, \ldots, p_n, M$ because it is precisely those quantities $x_1^*, \ldots, x_n^*$ that maximize utility subject to the budget constraint that is substituted into $U^*(x_1, \ldots, x_n)$. However, for empirical studies of consumer demand, it is increasing common to use a flexible form to approximate the consumer's (unknown) indirect utility function. Roy's identity is applied to the approximating form to obtain share equations for estimation, and the parameters of the share equations are used to calculate elasticities and test hypotheses such as separability or symmetry. The results are treated as those underlying indirect utility function.

The form of the group's utility function in equation (5) affects the form of the demand function in equation (4), the form being denoted by x_i. However, the variables included in the specification are the same irrespective of functional form. Without prior knowledge of the utility function the functional form of demand equations is as much an empirical issue as are prices and income parameters.

Under these conditions relatively flexible functional forms, such as the Cobb-Douglas function are appropriate. A Cobb-Douglas function is denoted as:

(6) $$q_i(p_1, p_2, ..., p_n, y) = \exp(\beta_{0i})(p_1)^{\beta_{1i}}(p_2)^{\beta_{2i}}...(p_n)^{\beta_{ni}}(y)^{\eta_i}.$$

By taking the logarithm of both sides of equation (6) the double log function as obtained:

(7) $$\ln(q_i) = \beta_{0i} + \beta_{1i}\ln(p_1) + \beta_{2i}\ln(p_2) + ... + \beta_{ni}\ln(p_n) + \eta_i \ln(y).$$

This double log functional form assumes constant elasticities since they are defined as the relative change in consumption of a commodity for an infinitesimal change in expenditure or price. The total (unconditional) expenditure elasticity for the commodity within the *k*th commodity is given:

(8) $$\eta_k = \frac{\partial \ln q_k}{\partial \ln y},$$

where a price change in commodity will cause a direct effect on the quantities purchased within the same commodity group, given unchanged group expenditure. The price change will, however, also affect the group price index, hence in allocation of expenditures between groups. The latter effect will influence all commodities, both within and without the same group. Separability does not imply that price changes for commodities in different groups do not affect each other, but merely that such effects are channeled through the group expenditures. In addition, within-group price elasticity between the *i*th and *j*th commodities group will be denoted as:

(9) $$e_{ij} = \frac{\partial \ln q_i}{\partial \ln p_j} = \beta_{ij}$$

The following restrictions must hold, for consistency with demand theory:

(10) $$\sum_j \beta_{ij} + \eta_i = 0 \quad \text{(homogeneity);}$$

(11) $$e_{ij} = e_{ji} \quad \text{(symmetry);}$$

$$(12) \qquad \sum_i \beta_{ij} = 0 \qquad \text{(adding up).}$$

The constraints (10), (11), and (12) ensure that the system satisfies the homogeneity symmetry and adding up restrictions respectively. However, it is known that the demand function equation (6) cannot be rigorously deduced from maximization of classical utility function. For if one or more of η_i differs from unity the function cannot satisfy the budget relation in the whole range of the variables involved. However, despite this defect, many use the double-log demand function because of its superior fit, ease of estimation, and the ready interpretation afforded by the estimated parameters. Finally, since demand parameters are estimated from market variables, it may be argued that the double-log function in some sense approximates aggregated individual maximizing behavior.

Chen (1998) derives a set of linear and nonlinear restrictions to a n-goods linear almost ideal demand system symmetric when all prices are allowed to vary. The consequences of imposing such restrictions on the demand elasticities are illustrated using United States meat consumption data. However, their results do not give a total picture of the effect of changing income on the demand for meat despite the restrictions and other assumptions incorporated. It only shows partial trend of demand changes when the data are strictly obtained and reanalyzed.

Burton et al. (1996) used family expenditure survey data over the time period 1973 to 1993, a Box-Cox double-hurdle model of the participation and expenditure decisions regarding meat consumption was estimated to show changing preferences for meat in United Kingdom. With particular attention was given to single-adult households.

Key results show that employment class and adult gender were significant determinants of factors affecting the United Kingdom meat purchase behavior but in expenditure; income affects both decisions, but in opposite direction while education affects expenditure directly. The effects of socioeconomic characteristics on meat demand decisions are shown to have varied quite markedly over this period while some trends, particularly with respect to the age and gender of the householder, are discernible.

Dono and Thompson (1994) used Lewbel's composite model as a basis for comparing the AIDS and Translog demand system in estimating Italian meat consumption data. Preliminary non-parametric diagnoses suggest that exogenous shifters of prices and expenditure need not be introduced into a parametric model. By contrast, the parametric analysis demonstrates that demographic shifters can account for substantial changes in patterns of meat consumption. Although a parametric model without demographic variables performs adequately, likelihood ratio tests indicate that an AIDS model with demographic variables performs significantly better.

Burton (1994) proved that it is possible to estimate the power on non-parametric demand analysis when applied to a particular data set using the budget hyperplane and alternative definitions of irrational behavior. The paper has two objectives: identify the number of sampling draws needed and calculate the power statistic under four alternative irrationality models for five British meat and fish data sets that have been used elsewhere for parametric and nonparametric analysis. The mean and variance of the estimated power statistics indicate that at least 1,000 sample must be drawn if an accurate figure for power statistic is to be obtained. However, this is often larger than that used in earlier work. The estimated power statistics also throw some light on earlier empirical results obtained using the same data sets.

Eales and Unnevehr (1994) developed a demand system that is related to the almost ideal demand system (AIDS) of Deaton and Muellbauer. The inverse almost ideal demand system (IAIDS) retains all of the desirable theoretical properties of the AIDS model with the exception of consistent aggregation. An empirical issue is whether a linear approximation will work as well for the IAIDS as it has for the AIDS model, since quantities are not as highly correlated as prices. An application to United States meat demand demonstrates that the linear approximation of the IAIDS is excellent, which enhance the ease and range of application.

Alston and Chalfant (1993) noted that during the past decade, most agricultural economists have adopted the Linear Approximate Almost Ideal Demand Systems and the Rotterdam model as the demand systems of choice in most applications. The apparent explanation is that the two models are both (second-order) locally flexible and compatible with demand theory. They have identical data requirements and are equally parsimonious with respect to parameters. While the two models are equally attractive in most respects, and indeed appear very similar in structure, they lead to different results in some applications. This develops a test of each against the other. In an illustrative application to United States meat demand, the almost ideal demand model is rejected while the Rotterdam model is not.

Sakong and Hayes (1993) elicited a test for preference stability that strengthens existing non-parametric procedures. The test uses indifference curve convexity to restrict compensated consumption bundles. Adding up, non-inferiority, and the Slutsky equation are used to limit the range of the compensated consumption boundless. A program is proposed that simultaneously measures the changes in consumption quantities satisfying the theoretical restrictions and the expenditure elasticities that minimize the required changes. The program is applied to consumption data and is shown to be detecting small changes in preference.

Eales (1996) used an inverse of the AIDS to test the endogeneity of prices and quantities in the United States meat demand system. The inverse AIDS has all the desirable theoretical properties of the AIDS expect aggregation from the micro to the market level. Using annual data, both prices and quantities appear to be endogenous within the entire meat market. Including livestock production costs and technical change indicators as instruments eliminates evidence of amid 1970s demand change.

The Almost Ideal Demand System

Through the pioneering efforts of economists such as H. Shultz and J.R.N. Stone, the theoretical works of Marshall, Slutsky and Hicks have become falsifiable; falsifiable in the logical positivist sense that the propositions of theory can be tested empirically and refuted. Recent advances in demand systems research lend support to this observation, since economists seem to be forever developing new ways to test consumer theory. In this vein one can trace the birth of demand systems analysis from Stone's in 1958 to the AIDS model of Deaton and Muellbauer, 1980.

Following the important paper by Diewert (1971), several demand system estimation models, known as "flexible functional form", have been developed. The basic method is to approximate the direct utility function, indirect utility function or the cost function by some specific functional form. One of these approaches is Christensen et al's (1975) indirect translog model

(13) $$U = \alpha_0 + \sum \alpha_k \log(P_k / X) + ½ \sum_k \sum_j \beta_{kj} \log(P_k / X) \log(P_j / X),$$

where k, j are goods. The demand function from equation (13) is complicated and clumsy to estimate while the direct translog model is usually estimated under the practically nonsensical assumption that, for all goods, prices are determined by quantities rather than the other way round.

In 1980, Deaton and Muellbauer proposed and estimated a new model that they call the Almost Ideal Demand System (AIDS). The AIDS model is now one of the most popular frameworks for estimating price and income elasticities when expenditure or budget data are available. Deaton and Muellbauer (1980) started not from an arbitrary preference ordering, but from a specific class of preferences, by which the theorems of Muellbauer (1975, 1976) permit exact aggregation over consumers: the representation of market demands as if they were the outcome of decisions by a rational representative consumer. They proposed that the cost or expenditure function, which defines the minimum expenditure necessary to attain a specific utility level, can be used to represent consumer preferences, known as the price-generalized logarithmic (PIGLOG) class,

(14) $$\log c(u, P) = (1 - u) \log\{a(p)\} + \log\{b(P)\}.$$

With some exceptions, u lies between 0 (subsistence) and 1 (bliss) so that the positive linearly homogeneous function $a(P)$ and $b(P)$ can be regarded as the costs of subsistence and bliss, respectively. Next they take specific functional forms for log $a(P)$ and log $b(P)$

(15) $$\log a(P) = \alpha_0 + \sum \alpha_k \log P_k + ½ \sum_k \sum_j \gamma^*_{kj} \log P_k \log P_j,$$

(16) $$\log b(P) = \log a(P) + \beta_0 \prod_k P_k^{\beta_k}.$$

After the selection of a specific functional form, the cost function in the AIDS model can be written as

(17) $$\log c(u,P) = \alpha_0 + \sum \alpha_k \log P_k + \tfrac{1}{2} \sum_k \sum_j \gamma_{kj}^* \log P_k \log P_j + \beta_0 \prod_k P_k^{\beta_k}.$$

The demand functions can be derived directly from equation (17). It is a fundamental property of the cost function that its price derivatives are the quantities demanded $\partial c(u,P)/\partial P_i = q_i$: Multiplying both sides by $P_i/c(u,P)$ we find:

(18) $$\frac{\partial \log c(u,P)}{\partial \log P_i} = \frac{p_i q_i}{c(u,P)} = w_i,$$

where w_i is the budget share of good i. Hence, logarithmic differentiation of equation (17) gives the budget shares as a function of prices and utility,

(19) $$w_i = \alpha_0 + \sum_j \gamma_{ij} \log P_j + \beta_i u \beta_0 \prod_k P_k^{\beta_k},$$

where

(20) $$\gamma_{ij} = \tfrac{1}{2}\left(\gamma_{ij}^* + \gamma_{ji}^*\right),$$

for a utility-maximizing consumer, total expenditure X is equal to $c(u,P)$ and this equality can be inverted to give u as a function of P and X, the indirect utility function. Solving equation (17) and (19) and eliminating u, we obtain the budget shares as a function of P and X. These are AIDS demand functions in budget share form:

(21) $$w_i = \alpha_i + \sum_j \gamma_{ij} \log P_j + \beta_i \log\{X/P\},$$

where w_i is the expenditure share of commodity i, P_j is the commodity price, X is the total expenditure of the selected goods, and P is overall price index, which is defined by

$$\log P = \alpha_0 + \sum_k \alpha_k \log P_k + \tfrac{1}{2}\sum_k \sum_j \gamma_{kj} \log P_k \log P_j, \tag{22}$$

By taking three sets of restrictions on the parameters of the AIDS equation (19),

$$\sum_{i=1}^{n} \alpha_i = 1,\ \sum_{i=1}^{n} \gamma_{ij} = 0,\ \sum_{i=1}^{n} \beta_i = 0,\ \sum \gamma_{ij} = 0,\quad \gamma_{ij} = \gamma_{ji}. \tag{23}$$

Provided equation (23) holds, equation (21) represents a system of demand functions which add up to total expenditure $\sum w_i = 1$ are homogenous of degree zero in prices and total expenditure taken together, which satisfy Slutsky symmetry. When there is no change in relative price and X/P the budget shares are constants. Changes in relative prices take effect through γ_{ij}. Changes in expenditure operate through the β_i coefficients, which are summed to zero and are positive for luxuries and negative for necessities (Deaton and Muellbauer, 1980).

Deaton and Muellbauer(1980) summarized the following advantages of the AIDS model as follows:

(1) It gives an arbitrary fist-order approximation to any demand system

(2) It satisfies the axioms of choice exactly;

(3) It aggregates perfectly over consumers without invoking parallel linear Engel curves;

(4) It has a functional form which is consistent with known household-budget data;

(5) It is simple to estimate, largely avoiding the need for non-linear estimation; and

(6) It can be used to test restrictions of homogeneity and symmetry through linear restrictions on fixed parameters.

An important feature of the AIDS model is that the expenditure levels are allowed to impact the distribution of shares. It is of flexible functional form, allowing testing of theoretical restrictions on demand equations. The AIDS model in share form for a group of n commodities can be written as

(24) $$w_i = \alpha_i + \sum_j \gamma_{ij} \ln P_j + \beta_i \ln(X/P), \qquad i = 1, 2, \ldots, n$$

where w_i is market share, X is total expenditure, $i = j$, is the number of products in the demand system, and P_j is the price of product j in the system. α_i, γ_{ij}, and β_i are parameters. ln$P$ is defined as:

(25) $$\log P = \alpha_0 + \sum_k \alpha_k \ln P_k + \tfrac{1}{2} \sum_k \sum_j \gamma_{kj} \ln P_k \ln P_j .$$

In practice, equation (24) is difficult to estimate because of its nonlinearity. A common alternative is to estimate a linear approximation version of the AIDS model. That is, instead of estimating the complete AIDS model in equation (24), its linear approximation is employed by replacing ln$P$ with lnP^*, where lnP^* is the Stone's Index defined as:

(26) $$\ln P = \sum_i w_i \ln P_i, \qquad i = 1, 2, \ldots, n.$$

therefore, (25) becomes:

(27) $$w_i = \alpha_i + \sum_j \gamma_{ij} \ln P_j + \beta_i \ln\{X/P\}.$$

Marshallian and Hicksian measures of elasticities may be computed from the estimated coefficients of the AIDS model as follows:

(28) $$\varepsilon_{ii} = -1 + \gamma_{ij}/w_i - \beta_i ,$$

(29) $$\varepsilon_{ij} = \gamma_{ij}/w_i - \beta_i (w_j/w_i),$$

(30) $$s_{ii} = -1 + \gamma_{ii}/w_i + w_i,$$

(31) $$s_{ij} = \gamma_{ij}/w_i + w_j,$$

where ε and s denote Marshallian and Hicksian elasticities respectively. The expenditure elasticities can be obtained from the estimated coefficients as well:

(32) $$\eta_i = 1 + \beta_i/w_i.$$

In the case of Nigeria, the meat demand system to be estimated includes beef, pork, chicken, and fish. Furthermore, time trends in a more appropriate manner would be incorporated into the model more appropriately by interacting each variable in the model with time period variable (Pollak and Wales, 1981).

Double-Log Demand Specification for Nigeria Meat Demand System

The theory of consumer behavior suggests that the Marshallian demand function can be estimated as a function of own price, prices of substitutes or complements, and expenditure. Behavioral equation (33) denotes that the per capita consumption of meats in Nigeria is a function of the real retail prices of meats, real retail prices of substitute products, real retail prices of complement products, and real per capita income. Furthermore, the ordinary least squares (OLS) is often used to estimate the model.

(33) $$\ln(Q_{it}) = \beta_{i0} + \beta_{i1}\ln(Pa_{it}) + \beta_{i2}\ln(Pb_{it}) + \beta_{i3}\ln(Pc_{it}) + \beta_{i4}\ln(Pd_{it}) + \beta_{i5}\ln(Pe_{it}) + \beta_{i6}\ln(Pf_{it}) + \beta_{i7}\ln(y_{it}) + trend + U_{it}$$

Q_{it} is per capita consumption of i commodities in kilograms in year t, P_a is consumer real price index for beef, P_b is consumer real price index for chicken, P_c is consumer real price index for other meats, P_d is consumer real price index for demersal fish,

P_e is consumer real price index for freshwater fish, P_f is consumer real price index for other fish, y is per capita income in Naria, *trend* is time trend, and U_{it} random disturbance.

Among the assumptions of the classical linear regression model is that the residuals (U_{it}) are mutually independent (Maddala). The use of time series data may result in high correlation between the successive residuals, a situation known as serial correlation or autocorrelation. For models whose Durbin Watson statistics showed evidence of autocorrelation, the Cochrane iterative method was used as a corrective measure (for first order autocorrelation).

Data Estimation and Procedure

Very few demand estimates have been obtained for Nigeria, the earliest dating back to 1965. One reason is the absence of adequate data in terms of both quality and duration of the time period covered. The official source of data on meat and fish in Nigeria is the Statistics Division of the Ministry of Livestock, Fisheries and Animal Industrial which publishes information on herd inventories and livestock slaughtered numbers. Divisional data are aggregated first into provincial and then national data, and later reported by Nigeria Federal office of Statistics, Economic and Social Statistics in Lagos. Data were obtained from the Nigeria Federal Office of Statistics, Economic and Social Statistics (Lagos: FOS, various years) and the Central Bank of Nigeria. The data are Nigerian time series data on meats and fish categories from 1980 to 1999. The price data are in index form and are constructed so that 1985 = 100 (Base year).

All prices are the retail level and all quantities are per capita and based on retail cuts. Disposable income per capita will be used in the estimation to determine the income effect on meat consumption. Time series data were obtained for meat consumption of meats (demand for all meats), the price level (price index), disposable income per capita, and expenditures on meat products.

Direct application of ordinary least squares (OLS) to equation (33) provides estimates that are consistent but inefficient. The seemingly unrelated regression (SUR) method of estimation is used to estimate the model in equation (33), with the homogeneity, Engel aggregation, and the symmetry conditions imposed.

Results and Analysis of the Double Log Demand Model for Nigeria Meat Demand Systems

The double-log demand equation (33) developed in this study is used to estimate Nigeria meat demand systems. Per capita consumption of specific meat products in relation to corresponding product price, price of possible substitutes, expenditure, and time trend factor are presented in the Table 3.1. This consumption demand for meat products, like any other products, is consistent with economic theory. All demand coefficients, especially those of own-price, display the appropriate sign with a plausible magnitude. Most of the variation in the demand for individual meat and fish products is explained by the variation in the explanatory variables indicated. A number of inferences can be drawn from the results shown.

First, consumption demand for each meat product selected is negatively related to its own price. However, the magnitude of these indirect price elasticities varied substantially. The demand for beef, chicken, and other meat are characterized by inelastic demand. The demand for demersal fish is elastic -1.133. Hence, beef is a normal good with an expenditure elasticity value inferior to that reported by Adegeye (1988) for Nigeria. However, it is closer to the value reported by Tambi (1991) in Table 3.2. The demand for freshwater fish and other fish is inelastic. Second, the estimated expenditure elasticities of demand are all positive but with different magnitudes. Both chicken and freshwater fish are highly responsive to expenditure changes with 1.100 and 1.121 expenditure elasticities respectively and can be qualified as having unitary elasticity. Beef, other meats, and other fish are classified as expenditure inelastic commodities. Third, substitution effects are evident when beef and freshwater fish are considered. Most significant is the substitution relationship between chicken and demersal fish.

The plausible substitution relationship of fish for chicken might be linked to the tendency of most consumers to consider fish products to have a comparable nutritional and food value attributes. The substitution relationship is a socioeconomic factor contributing to the willingness of Nigerians to reduce the intake of meat for other reasons. The trends and variabilities in demand for individual product suggest several policy implications that ought to be considered in the pricing, marketing, and commodity regulations of the industry.

Several critical areas identified as a result of this study include the following: the increasing price sensitivity of consumption of beef and other meat products reaching the point of being moderate elastic indicates that price moderation or even slight but temporary price decreases would have a beneficial impact on producers' revenue in the long run. The market pricing regulations and meat subsidization designed by the federal government of Nigeria to help stabilize meat prices and consumption is having a detrimental effect on other products like fish products. This finding is supported by the fact that both beef and other meat products are experiencing a shrinking market. Hence, policies aimed at improving meat product income by adjusting fish prices upward are becoming less effective and these pricing policies are having a substantially negative effect on the consumption of other preferred products.

In summary, the main conclusion is that meat consumption patterns do not significantly differ in regards to economic factors (food expenditure and prices). Some small income and price effect differences have been found for beef and chicken. Finally, limitations to these findings include the use of CPI to deflate prices; the use of proxies, and the use of secondary data are likely to result in multicollinearity.[2]

Results and Analysis of the Almost Ideal Demand System for Nigeria Meat Demand Systems

Parameter estimates for Nigeria meat demand system were obtained using the Deaton-Muellbauer iterative procedure. Most of the parameter estimates were significant at the 10 and 15 percent level of significance (Table 3.3). The principal goal of the study, however, was to estimate Nigerian demand elasticities for beef, chicken, demersal fish, and freshwater fish and analyze the effects of expenditures on household meat

[2] Multicollinearity occurs when the independent variable is a perfect linear function of one or more of the independent variables. The consequences of multicollinearity are (Studenmund, 1995, p. 264-267):

- The estimates will remain unbiased
- The variance of the estimates will increase
- The computed t-scores will fail
- Estimates will become very sensitive to changes in specification
- The overall fit of the equation will be largely unaffected
- The estimation of nonmulticollinear (orthogonal) variables will remain unaffected
- The severity of multicollinearity worsens its consequences.

consumption behavior in Nigerian. Thus, the Marshallian and Hicksian elasticities are reported in Table 3.4 and Table 3.5 respectively with all expenditure elasticities having positive signs as expected. However, the magnitudes of these elasticities are different for the six commodities. The expenditure elasticities for chicken, freshwater fish, and demersal fish are greater than one, implying that they are luxury goods. However, demersal fish has the greatest expenditure elasticity of 2.389 compared with other meat products. This suggests that demand for demersal fish would increase greatly when per capita expenditure rises. The magnitudes of expenditure elasticities for beef and other meat are similar, although they are relatively lower compared to those of demersal fish and freshwater fish. These findings are reasonable given the position that beef holds as the dominant and traditional meat in the diet for most Nigerians. These elasticities also imply that beef and chicken are luxury goods, while other fish and demersal fish are normal goods for Nigeria households consistent with the findings of previous studies.

With the exception of some cross-price elasticities, the majority of the price elasticities exhibit the expected signs and magnitudes. Uncompensated own-price elasticities presented in Table 3.4 have negative signs in accordance with economic theory. However, the magnitudes of own-price elasticities of demand vary for different types of meat. Own-price elasticities for beef are much higher than those for other meats and less than one. This indicates that demand for beef and other meat Nigeria is very price elastic.

The magnitudes of own-price elasticities for beef and chicken meat consumption are between -0.224 and -0.118 respectively for the Marshallian elasticities illustrated in Table 3.4 and –1.632 and –0.411 for Hicksian elasticities illustrated in Table 3.5.

Furthermore, some of the cross-price elasticities have negative signs, but the magnitudes are very small. In general, the results suggest that own-prices as well as incomes are the predominant factors determining consumer choice and meat consumption patterns in Nigeria rather than relative prices.

The results of this estimation broadly coincide with those obtained using the double log demand model specification and previous studies where expenditure elasticities ranged from 0.30 to 2.80, and own price elasticities from 0.25 to 1.11 (Table 3.4). The results also fall into the range of income elasticities (0.57 - 1.0) and price elasticities (0.34 - 1.04) in South Korea and Japan from previous studies such as Hayes et al., (1990) and Hayes et al. (1991). The Hayes et al. studies were based on 1961-1987 and 1947-1978 average data in South Korea and Japan respectively and also employed an LA/AIDS model. Therefore, it appears that meat demand and consumption in Nigeria in the past decade may, in part, be comparable to that in South Korea and Japan during 1960s and 1970s.

Nigeria is not only one of the largest meat producing countries in Africa but also one of the largest meat consumers in this region of the world. The empirical results of this study suggest several points of interest for researchers, policy makers, planners and traders with involvement in Nigerian food production and marketing. First, expenditure elasticities for demersal fish and freshwater fish are highly elastic suggesting that Nigeria households will consume more demersal fish and freshwater fish as incomes increase. In terms of beef, the expenditure elasticity is also highly elastic, implying that Nigeria consumers with low incomes will increase their consumption of beef as their incomes rise. Second, own-price elasticities of all meat items are fairly elastic. This suggests that any changes in meat prices could bring about a significant shift in meat consumption patterns. Third, given the emergence of large unemployment in Nigeria, a major challenge confronting the government is how to design appropriate policies for the relative enhancement of low-income groups. Identifying elasticities for different income groups would enable Nigerian decision-makers to gauge more precisely the impact of their policies on various income groups, and more effectively design policies targeted at low-income groups.

The strength of this study relative to previous meat demand studies in Nigeria and other West African countries is the use of observations pertaining to expenditure share rather than average income estimates for the population as a whole. Further partitioning of income groups with time series data of greater duration and incorporating socio-demographic variables would enhance the accuracy of results. Caution should be taken, however, when interpreting those empirical results because the statistical information on consumption data in Nigeria is rather scarce, incomplete and controversial. The described data problems limit strong interpretation of empirical findings. Nevertheless, this study opens up discussion on the important issue of consumption patterns for different meat and fish products in Nigeria. Further studies will enhance the potency of these preliminary findings.

Table 3. 1: Estimated Price and Expenditure Elasticities for Meat and Fish in Nigeria Using Double-Log Demand Model Specification, 1980-1999

Commodity	Beef	Chicken	Other Meat	Demersal Fish	Freshwater Fish	Other Fish	Expenditure	Time Trend
Beef	-0.118**	-1.185**	0.741*	0.315	-0.576**	0.388*	0.327*	-0.035**
	(0.025)	(0.016)	(0.760)	(0.371)	(0.011)	(0.129)	(0.751)	(0.011)
Chicken	-0.335	-0.321**	0.193*	-0.278*	-0.723*	0.054**	1.100*	-0.022
	(0.262)	(0.017)	(0.079)	(0.015)	(0.1354)	(0.003)	(0.124)	(0.001)
Other Meat	0.297**	-0.019**	-0.047**	-0.013*	-0.447*	0.637*	0.395*	0.018
	(0.110)	(0.007)	(0.005)	(0.004)	(0.001)	(0.042)	(0.011)	(0.002)
Demersal	-1.133*	0.294*	-0.902**	-0.721*	0.534	-1.921	2.387*	0.700**
Fish	(0.138)	(0.046)	(0.112)	(0.001)	(0.092)	(0.233)	(0.625)	(0.141)
Freshwater	0.193	-0.165**	-0.463	-0.036**	-0.422*	0.072*	1.121**	0.015
Fish	(0.015)	(0.021)	(0.441)	(0.115)	(0.010)	(0.017)	(0.132)	(0.391)
Other Fish	-0.101*	-0.480*	0.171**	-0.168*	-0.199**	-0.303**	0.475**	-0.032*
	(0.007)	(0.091)	(0.016)	(0.061)	(0.018)	(0.004)	(0.025)	(0.003)

Note: The numbers in parenthesis are standard errors.
Single (*) and double asterisks (**) denote significance at the 15% and 10% level, respectively.

Table 3. 2: Comparison of Price and Income Elasticities for Beef in Nigeria, by Various Authors

Author	Product	Type of model	Price	Income
Adegeye (1988)	Beef	Linear	-2.367	0.470
		Log-linear	-2.675	0.457
Tambi (1991)	Beef	3SLS[a]	-0.411	0.596
Present study	Beef	Double-log	-0.118	0.327

[a] Three-stage least squares.

Table 3. 3: Parameter Estimates For Nigeria Meat and Fish Demand System Using an Almost Ideal Demand System Model, 1980-1999

	Dependent Variables (The budget share of per capita wheat import of:)							
Independent Variables	Beef	Chicken	Other Meat	Demersal Fish	Freshwater Fish	Other Fish	Expenditure	R^2
Beef	0.163**	-0.1704**	0.062**	-0.050**	-0.057*	0.080**	0.143*	0.91
	(0.048)	(0.031)	(0.001)	(0.001)	(0.014)	(0.010)	(0.041)	
Chicken	-0.111*	0.133*	0.084*	0.133*	-0.042*	-0.079*	0.025*	0.842
	(0.023)	(0.022)	(0.050)	(0.022)	(0.031)	(0.004)	(0.009)	
Other Meat	0.007**	-0.112*	0.081*	-0.023**	-0.024**	0.029	0.021*	0.851
	(0.001)	(0.010)	(0.009)	(0.001)	(0.001)	(0.003)	(0.005)	
Demersal Fish	0.007*	-0.005**	-0.062*	0.050*	-0.057*	0.077**	0.262**	0.956
	(0.001)	(0.011)	(0.019)	(0.015)	(0.007)	(0.004)	(0.018)	
Freshwater Fish	0.163*	-0.171*	0.012**	-0.036*	-0.422*	0.072*	0.143**	0.947
	(0.018)	(0.032)	(0.008)	(0.001)	(0.012)	(0.005)	(0.019)	
Other Fish	0.007*	-0.480*	0.062**	-0.006*	-0.011*	0.047*	0.016**	0.957
	(0.001)	(0.029)	(0.011)	(0.001)	(0.002)	(0.009)	(0.007)	

Note: The numbers in parenthesis are standard errors.
Single (*) and double asterisks (**) denote significance at the 15% and 10% level, respectively.

Table 3. 4: Marshallian Elasticities for Meat and Fish in Nigeria Using an Almost Ideal Demand System, 1980-1999

Commodity	Beef	Chicken	Other Meat	Demersal Fish	Freshwater Fish	Other Fish	Expenditure
Beef	-0.224**	-0.093**	-0.112**	0.213**	-0.911**	0.388**	1.255**
	(0.061)	(0.051)	(0.006)	(0.021)	(0.083)	(0.019)	(0.079)
Chicken	-0.189*	-0.118*	-0.103**	-0.342*	-0.623**	0.102*	0.407*
	(0.089)	(0.081)	(0.041)	(0.037)	(0.117)	(0.021)	(0.014)
Other Meat	-0.111**	-0.814*	-0.069*	-0.012**	-0.581**	0.671**	0.793**
	(0.008)	(0.102)	(0.013)	(0.001)	(0.011)	(0.087)	(0.084)
Demersal Fish	-0.295**	0.413*	-0.151*	-0.438*	0.924*	-0.734*	1.569*
	(0.016)	(0.052)	(0.032)	(0.046)	(0.163)	(0.053)	(0.051)
Freshwater Fish	0.126*	-0.452	-0.173*	-0.011*	-0.163**	0.181*	0.235*
	(0.071)	(0.097)	(0.011)	(0.045)	(0.105)	(0.075)	(0.011)
Other Fish	-0.071**	-0.032*	0.525**	-0.219**	-0.201**	-0.419*	0.141*
	(0.003)	(0.001)	(0.086)	(0.015)	(0.041)	(0.021)	(0.091)

Note: The numbers in parenthesis are standard errors.
Single (*) and double asterisks (**) denote significance at the 15% and 10% level, respectively.

Table 3. 5: Hicksian Elasticities for Meat and Fish in Nigeria Using an Almost Ideal Demand System, 1980-1999

Commodity	Beef	Chicken	Other Meat	Demersal Fish	Freshwater Fish	Other Fish
Beef	-1.632**	-0.233*	0.151**	0.421**	-0.891**	0.087*
	(0.012)	(0.011)	(0.023)	(0.062)	(0.025)	(0.001)
Chicken	-0.221*	-0.411**	0.201*	-0.178*	-0.941*	-0.911*
	(0.062)	(0.047)	(0.019)	(0.015)	(0.054)	(0.013)
Other Meat	0.241*	-0.341**	-0.012**	-0.116*	-0.321*	-0.221**
	(0.010)	(0.107)	(0.005)	(0.011)	(0.017)	(0.042)
Demersal Fish	-0.192**	0.821**	-0.215**	-0.321*	0.054	-0.307*
	(0.022)	(0.016)	(0.021)	(0.061)	(0.001)	(0.001)
Freshwater Fish	0.121*	-0.106*	-0.271*	-0.117*	-0.551*	0.052**
	(0.011)	(0.021)	(0.001)	(0.064)	(0.003)	(0.001)
Other Fish	-0.090*	-0.161*	0.511**	-0.371*	-0.851**	-0.101**
	(0.001)	(0.011)	(0.026)	(0.001)	(0.073)	(0.091)

Note: The numbers in parenthesis are standard errors.
Single (*) and double asterisks (**) denote significance at the 15% and 10% level, respectively.

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