FORECASTING ANIMAL WATER DEMAND: ECONOMETRIC AND TIME SERIES ASSESSMENT

by

MURALI ADHIKARI

(Under the Direction of Jack E. Houston)

ABSTRACT

Lack of credible information on present and future livestock water demand and severe limitations of existing physical water demand models necessitate the development of sound livestock water demand forecasting models. The issue of accurate livestock water demand estimation and forecasting is further highlighted by the growing water scarcity problems and constant and/or decreasing supplies of water in Georgia. In the absence of accurate livestock water demand information, policy proposals and decisions regarding livestock water allocation would be inefficient, leading to the misallocation of limited water resources. Developing sound livestock water demand forecasting models requires a complete understanding of livestock supply response behavior under physical, economic, and institutional determinants.

Especial efforts have been made to improve the existing livestock supply response models and their forecasting accuracy. For broilers and swine, dynamic supply response models were developed considering underlying biological features. The forecasting accuracy of broiler and swine supply response models were further assessed by developing univariate and structural time series models, respectively. A structural time series model with explanatory variables was used to model dairy cattle and beef cattle supply responses. The superior dairy cattle and beef cattle supply models were selected by analyzing different scenarios of deterministic and stochastic trend and seasonality components.

In our analyses of broiler, swine, dairy cattle, and beef cattle supply response models, all economic variables yield expected signs and statistically significant results, demonstrating the importance of economic information variables to forecast numbers of livestock and poultry, and thereby animal water demand. The study yielded mixed results in terms of water demand forecasting, mostly because of the failure of the underlying ACT/ACF physical models to capture the ongoing changes in poultry, swine, dairy cattle, and beef cattle industries in Georgia.

INDEX WORDS: Animal supply response, Poultry, Swine, Dairy Cattle, Beef Cattle, Livestock water demand, Water demand forecasts, Slippage

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CHAPTER ONE

INTRODUCTION

Background

With approximately $6.22 billion in annual gross farm income in 2001, agriculture has significant economic impacts on the economy of the state of Georgia. Out of this $6.22 billion annual gross farm income, nearly 60% of gross farm income arises from livestock and poultry, making the livestock and poultry sectors a major source of farm income in Georgia. In 2001, gross cash receipts from poultry and eggs production totaled $2.83 billion, which represents 45% of total annual gross farm income of Georgia. Other sectors of livestock, such as cattle and calves, hogs, and dairy products, also contributed $347 million, $88 million, and $225 million, respectively, to the Georgia economy. However, due to the value-added aspect of livestock production, along with the nature of animal care, the effects of livestock production on rural economies are larger in magnitude than from most other agricultural enterprises (Shurley et al., 2000).

Broiler Production

Georgia ranks top in the national broiler production, producing 1.25 billion broiler birds in 2001 (Georgia Agricultural Statistics Service, 2002). Agricultural statistics of Georgia show a rapid expansion of broiler production in Georgia, from 1.005 billion broiler birds in 1994 to 1.246 billion broiler birds in 2001, nearly 23% expansion in the last seven years. Poultry production also represents the largest source of farm income in Georgia, generating a total value of approximately $2.81 billion from broiler and egg production in 2001, a 16% growth from 2000. Out of the $2.81 billion, total value of commercial broiler production was $2.43 billion, which is nearly 86% of the total value of poultry production in Georgia. In the meantime, the value of egg production was $386 million, and the sale of chickens, excluding broilers, was $11.5 million in 2001 (Georgia Agricultural Statistics Service, 2002). In the last five years, income from broiler production has been increased by an annual average rate of about 10% in Georgia, and Georgia breaks the eighteenth consecutive year of record-setting numbers.

Beef cattle and Dairy Production

With a total herd population of 1.24 million head in January, 2002, Georgia ranks 28th in the national cattle inventory. In Georgia, 26,000 beef cattle producers represent the single largest group of commodity producer. The total value of all cattle and calves in 2002 was $893 million, representing an average value of $720 per head (Georgia Agricultural Statistics Service, 2003). The total cash receipts from cattle and calves in 2001 were nearly $348 million. In Georgia, beef production represents the 5th largest single source of farm income. In spite of the important role of cattle production in rural economy of Georgia, the number of cattle has been declining in Georgia because of unfavorable prices (Shurley et al., 2000). A decrease in the total number of all cattle and calves from 1.47 million in 1994 to 1.24 million in 2002, nearly a 15% reduction in seven years, is evident (Georgia Agricultural Statistics Service, 2002). Out of 1.24 million total cattle and calves in Georgia, beef cattle and dairy cattle comprise of 47% (0.59 million) and 6% (86,000 head) of total population, respectively, in 2002.

The Georgia dairy industry was in a growth phase from the mid 1980's through the mid 1990's, reaching a peak of 1.56 billion pounds in 1994. However, in 1995 high feed prices and low milk prices resulted in the decline in herd numbers, cow numbers and milk production. Factors that led to continuing declines in milk production include: the average age of dairy farmers, other farming options, low and variable milk prices, high feed prices, cost of renovation and expansion, availability of farm labor, high land prices and uncertainty about future dairy policy (Shurley et al., 2000)

Swine Production

In December 2001, the total number of hogs and pigs was 310,000 in Georgia, making the state 22nd among all states of the United States in the total number of hogs and pig production (USDA, 2002). Total numbers of breeding stock and market hogs were 50,000 and 260,000, respectively. The total value of hogs and pigs in Georgia was $21.4 million in 2001. However, Georgia hog production has declined from 950,000 in 1994 to 310,000 in 2001 in response to a highly unstable local hog market. Hog production in Georgia has declined from 35.79 million lbs in 1994 to 17.8 million lbs in 2001. Unfavorable prices, lack of processing plants, and emergence of larger but fewer numbers of swine farms remain the major causes of decline in swine production in Georgia. If continuous unfavorable market prices exist, Georgia swine numbers will drift further, as the state moves to an industry producing pigs to be shipped to Mid-Western states for finishing closer to the harvested/processing markets and in the areas with lower feed costs (Shurley et al., 2000).

Water Use in Livestock Water is the most fundamental necessity of life for livestock. Water is critical for animals because, depending upon age and type of animal, 60% to 75% of animal body tissues are composed of water. Water in livestock is needed to perform all essential processes of the body, such as digestion, absorption of food nutrients, removal of waste, reproduction, and regulating of body temperature. Life in farm animals might be possible for a short time in the absence of other feed stuffs, but farm animals cannot survive for longer period without water, especially broilers (Taylor and Field, 2001). In swine, water deprivation for 12 to 24 hours has significant negative effects on pig behavior, feed intake and growth. Water intake in swine is at least twice the feed intake (Whittmore, 1993).

Several factors affect the demand of water in animal production. These factors include weight, ambient temperature, rate and consumption of feeds, physiological condition of body, activity, type of ration, and feed intake (Taylor and Field, 2001). Most importantly, factors affecting water demand differ with animal types. Ambient temperature is the most important factor affecting water intake in broilers. Electrolyte contents of both diet and water are major determinants of water intake in poultry. For broiler or other types of chicken birds, water is the most important, because bodies of chickens are 50-60% of water and eggs are two-thirds water. Unless the ample and regular supply of water is available for poultry, they often suffer, especially during summer season, when temperature is high. Tests have shown that poultry die more quickly when deprived of water than when deprived of all other nutrients (Gillespie, 1995). Animal feed contains some portion of water and oxidation of certain nutrients in the feeds also produces water. Therefore, drinking water does not meet all water requirements of livestock. Feedstuffs such as silage, green grass or pasture, contain high moisture levels, and thereby amount of water. However, the moisture content of grains, hays, and dormant pasture is low. Furthermore, high-energy feeds produce much metabolic water, while low-energy feeds produce less metabolic water.

In addition to drinking, livestock require water for cleaning purposes. It is most important for dairy, where substantial amounts of water are used for cleaning and sanitary purposes prior to milking and flushing of waste in confined areas. The US Geological Survey (USGS) estimates approximate water use of 8 gal/day for cattle, 2.5 gal/day for hogs, 0.06 to 0.22 gal/day for poultry in Georgia. Whatever the issue, regular supply of water is most important for successful livestock business in Georgia. Failure to supply regular and sufficient amounts of water might lead to collapse of livestock enterprises of Georgia and thereby the backbone of rural economy of Georgia. In the past, water supply was abundant in Georgia, and livestock farmers were receiving sufficient amounts of water. However, adverse climatic conditions, growing population in metro areas, growing water demand by other sectors of water use, including farm crops, and increasing water and environmental regulations in Georgia have changed the scenario of abundant supply of water supply for animal producers, creating new water constraints for livestock enterprises. Using the present information available, it is difficult to assess animal water use in Georgia because there exist only USGS water records taken in surveys every five years without following any systematic study approach. A possible additional source of information to assess water use is time series of numbers of broilers, layers, beef cattle, dairy cattle, and swine in Georgia. USGS reports water use for livestock watering, feedlots, dairy operation, catfish farms, and farm operation for poultry, horses, cattle, and hogs in Georgia. Estimates of water use, which show 34.67 million gallons of water use per day by livestock in Georgia, were calculated by animal type (cattle, hogs, horses, and several kind of poultry) and by pond acreage for catfish farming. Estimated water use by animal type was calculated by multiplying the number of animals by average water use by each animal type. Average daily water use by poultry, dairy, beef, swine, and pigs were calculated from different sources (Personal communication with Julia L. Fanning).

Using USGS reports, it is difficult to assess the amount of water use on a county basis by each animal type. However, this level of aggregated data helps to understand the variation in water demand in different counties, giving a rough picture of water use trends by livestock enterprises in Georgia. In order to find the actual amount of animal water use in Georgia, it is imperative to evaluate temporal and site-specific water use information for all animal types of Georgia. Site-specific, temporal water use information is especially important in vulnerable areas, both in terms of water quality and quantity. Presently a study of this nature is underway in Tifton College of the University of Georgia (Personal communication with Dr. George L. Newton).

Water Issues in Georgia

The importance of efficient water use and management is supported by rapidly growing water demand and constant or decreasing supplies of water in many parts of the United States. The problems associated with water scarcity are further exacerbated due to the need of water to meet minimum in-stream flow for habitat restoration, recreation, and navigation. Furthermore, recent changes in water management from supply-oriented to demand oriented raises a need for more economic analysis and better management of existing allocation practices (Frey, 1993).

Until the last few years, there had been very little concern or conflict related to water supply in Georgia. The substantial expansion of urban areas, including Atlanta, prolonged drought in South Georgia, and a tri-state water dispute between Georgia, Alabama, and Florida have drastically increased the public awareness and concern about potential scarcity and availability of water in the last few years, making water allocation a serious political and public issue in Georgia. There is a growing concern about insufficient water supplies to sustain agriculture, including animal agriculture, and simultaneously to meet all other demands during low rainfall years. Since agriculture is the largest consumer of water, it can play a crucial role in efforts to efficiently utilize water in Georgia. Animal agriculture requires water for drinking, cleaning, and processing purposes. An efficient allocation of water resources in animal agriculture can enhance the water conservation efforts in Georgia for both future needs of agriculture and for those of competing uses.

Statement of Problem

The rapidly rising population and more recent adverse climatic conditions are major reasons for the current water crisis in Georgia. Concurrent with the rapid growth in the Atlanta metropolitan area, a prolonged drought and increasing water demand for agriculture and other activities have created a strong pressure on the existing water resources of the state. The USGS reports that the rainfall deficit for Georgia in calendar year 1999 was about 11.5 inches, and that deficit increased through 2002. In spite of depleting water resources, there is an opposing trend of increased water use in Georgia. USGS reports show that Georgia's use of 1.19 billion gallons per day (bgd) of ground water and 4.63 bgd of surface water in 1995 were up from 0.996 bgd of ground water use and 4.36 bdg of surface water use in 1990, respectively (USGS, 2000). USGS estimates show that water withdrawals in Georgia increased almost nine percent between 1990 and 1995. If this trend of increasing use and withdrawals of its water resources continues without conservation efforts, the sustainability of Georgia's water resources will likely be threatened.

Animal agriculture represents a critical sector of water use in Georgia because of its direct link with the welfare of thousands of farmers in Georgia. The Georgia Cooperative Extension Service (2000) reports that presently 1.29 billion broilers, 8.01 million beef cattle, 0. 92 million dairy cattle, and 0.44 million hogs generate billions of dollars in state income, making a substantial contribution to the growth of the state's economy. Out of the $7.5 billion in Georgia annual farm income in 1997, beef contributes 4.7 percent ($350 million), pork 2.7 percent ($200 million), dairy 3.3 percent ($250 million), and poultry 33 percent ($2.5 billion). USGS estimates show that animal agriculture in Georgia requires 47.5 mgd of water (USGS, 2000). In spite of the significant role of animal agriculture in efficient use and allocation of water, no scholarly works have been carried out to predict the amounts of water demanded by animal agriculture under the influence of economic, institutional, and other policy variables in Georgia. In this study, an attempt will be made to understand the economics of animal water use and demand in Georgia.

Objectives of the Study

The main objective of this proposal is to develop a method for forecasting water demand for beef cattle, dairy cattle, swine, and broilers and to accurately forecast the amount of water demand by animal agriculture in Georgia. Specially, the research objectives are:

I. To develop sound animal supply response models for broilers, swine, dairy cattle, and beef cattle within a dynamic and economic framework;

II. To predict present and future annual water use by dairy, beef, swine, and poultry enterprises in Georgia;

III. To compare the animal water demand forecasting accuracy of physical, econometric, and time series models; and

IV. To assess the impacts of economic variables in animal agriculture water demand.

Procedures

Presently, a study to project the regional irrigation and animal water use in Southeast Georgia is underway under the supervision of a multidisciplinary team of scientists. One of the aims of the project is to develop methods for predicting water use by dairy, beef, swine, poultry, and aquaculture enterprises in Georgia. Under the overall objective, one major task was to install the water measuring instruments in selected dairy, beef, swine, poultry, and aquaculture farms of Georgia to measure the amount of water used for drinking, sanitation, waste management, and spillover for each animal type of Georgia. So far, the water measuring instruments have been installed in three selected beef farms of Southeast Georgia and four monthly time series data on water used by beef are available. After the completion of installments of water measuring devices in all selected farms of dairy, beef, swine, poultry, and aquaculture, more precise information on water demand is expected to be available. Upon completion of the project, it will be possible to use the data of the Regional Irrigation and Animal Water Use Project for further analysis of water use by animal agriculture in Georgia.

The information provided by the USGS and ACT/ACF comprehensive study offer benchmark information for understanding the water use patterns of animal agriculture in Georgia. The impacts of economic and institutional variables can be captured in animal supply response functions. A comprehensive study of animal agriculture, therefore, must consider the economic variables in addition to the physical factors examined by the USGS and ACT/ACF comprehensive study. Understanding of the relationship between physical water forecasting model and economic water forecasting model contributes to correct the weaknesses of physical water forecasting model and thereby to more accurately forecast water demand.

This study will adopt a systematic analysis approach based on economic principles (supply response functions) to forecast the number of animals in coming years in Georgia. Econometric and statistical procedures will be adopted to disaggregate and simulate the data necessary to forecast the animal water demand in each county and commodity level in Georgia.

Objective 1 is achieved by developing econometric and univariate time series supply response models for broilers. A structural time series model with stochastic trend and seasonality component and a separate econometric model are developed for swine. Different scenarios of deterministic and stochastic trend and seasonality were considered while analyzing dairy supply response functions using structural time series model. The beef cattle supply response model is developed assuming no seasonality and analyzed using structural time series model with explanatory variables. Objective 2 is accomplished by combining the broiler, swine, dairy cattle, and beef cattle forecasts obtained from the analysis of objective 1 and animal water use coefficients available from the USGS and ACT/ACF study. For objective 3, measures of root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE) are used to compare the structural and time series models. Coefficients of elasticities for economic variables obtained from objective 1 will be used to accomplish objective 4.

Summary

This first chapter has introduced the reader to the study. The objectives set forth offer the glimpses of the activities to be covered in the study. These objectives outline the types of activities necessary to carryout the research and define some of the more technical aspects of the analyses. The statement of problem summarizes the underlying issues of the livestock water demand and possible new research frontiers of this study. A secondary aim of the chapter one is to familiarize the novice reader with the livestock water demand issue. This entails the understanding of livestock supply responses, limitations of the existing livestock water demand models, and discussion on the new models livestock water demand forecasting. A thorough understanding of the livestock industry is of importance in this instance because the livestock water demand depends on the animal supply responses of livestock producers.

The remaining chapters of the dissertation are organized in the following format. Chapter two covers the review of literature on livestock supply response and water demand forecasting. Chapter three presents the development of a theoretical paradigm of a representative cattle producer. Chapters four, five, six, and seven analyze the water demand forecasting for broilers, swine, dairy cattle, and beef cattle respectively. And finally, chapter eight summarizes the findings of the study and provides some conclusions, implications and direction of future research. The findings from this study will be useful to policy makers and regional planners at all levels to guide the allocation of limited water of Georgia in the most efficient ways. The results may assist in evaluations and planning of the region's water management policies. It will also provide suitable guidelines for similar studies of economics of animal water use elsewhere.

CHAPTER TWO

REVIEW OF LITERATURE

Livestock Supply Response

Growth in livestock production and consumption represents an integral part of the overall economy. Analysis of impacts of various economic and institutional variables on livestock and broiler demand and supply and the resulting influences on the overall economy of the United States might be of interest to agricultural researchers. Several economic and institutional factors affect the supply and demand of livestock and broilers. Government policies, prices of inputs, size and distribution of population, foreign trade, and income are some of the economic and institutional variables that affect the livestock and broiler industries severely. Directly or indirectly, economic and institutional variables affect the production, consumption, distribution, and price of livestock, in turn affecting the supply and demand dynamics of livestock production.

Government participates in the economic affairs of the agricultural sector through different agricultural farm policies like export subsidies, import quotas, and price supports. Government programs, or institutional variables, create various levels of production, distribution, and prices, and thereby affect the market supply of beef, pork, and broilers. In spite of the critical role of institutional factors on supply and demand of livestock and broiler, the complex nature of the economy and inconsistent government policies make it very difficult to accurately trace relationships between institutional variables and the supply of livestock and poultry. However, our literature reviews cover the areas of livestock and poultry supply, institutional variables, economic variables, biological phenomena, and technological constraints in livestock production.

Beef and Dairy Cattle Supply

Many researchers have made attempts to model the US livestock and poultry industries using different methodological approaches, emphasis, issues, and factors. Earlier studies of beef cattle mostly concern the supply and its related elasticities. Reutinger (1966) analyzes the issue of negative price elasticity of short run beef supply by disaggregating the cattle harvested into steer, heifer, and cow components and developing an annual supply function. In this model, Inventory of steers, heifers, and cows and the expected beef-corn price ratio were included as explanatory variables. The study results yield a positive coefficient for beef- corn price ratio and negative coefficients for heifers and cows, a result inconsistent with the conventional economic theory where the output supply related positively with output price.

Langemeier and Thompson (1967) estimate demand and supply elasticities for fed and non-fed beef using a simultaneous equation system. In this analysis, the number of cattle on feed, cow inventory, and cow price were predetermined. The number of fed cattle harvested, average weight per head of feed cattle harvested, domestic supply of non-fed beef, import beef prices, and margin were determined simultaneously. The ratio of the market price of corn to the government support price for corn explains the average weight per head of fed cattle harvested. The analysis yields negative coefficients on the ratio variable in the non-fed beef demand equation. Study results show non-fed beef as inferior goods, which is less likely to be demanded with rising per capita income. Langemeier and Thompson also calculate the demand and supply elasticities and compare these elasticities with the results from models which treat beef as a single commodity. This analysis yields results similar to earlier estimates in many aspects.

Corm (1970) develops a recursive model with relatively few simultaneous relationships to forecast prices, output, and the effects of different policy proposals. In this analysis, population, corn prices, income, and seasonal dummy represent exogenous variables. Corm's model includes the fed beef corn price ratio lagged one quarter as the only economic variable in his relation for the average weight of fed cattle marketed each quarter. The lagged corn price was also included in the model for marketing of non-fed cattle especially to obtain a positive coefficient. The results show that high corn price encourages cow harvested and steers and heifers, which would normally go in feedlots, to be sold for harvested. Furthermore, negative effects of corn price on the levels of placements of cattle in feedlots were observed.

Bain (1971) analyzes the impacts of various policy proposals by using a quarterly recursive econometric model. Bain assumes that short run market equilibrium is achieved by an adjustment in prices at the wholesale level. The model divides the US beef output into fed and non-fed group and examines the cow and calf inventory, feeder cattle prices, placements of cattle in feedlots, and output of fed and non-fed beef. The estimates indicate that none of the meat products is an inferior good, and all meats are substitutes for one another. The findings are consistent with the demand theory. In this analysis, supply of grass-fed steers and heifers increases with the increase of corn price. In the meantime, increase in the corn price decreases the supply of feedlot placements.

Freebairn and Rausser (1975) estimate supply and demand relationships for meat. Researchers analyze the effects of changes in level of US beef imports on supplies and prices. The model treats farm price of corn, inventory of dairy cows, beef import as exogenous variables and solves fed and non-fed beef supplies, prices and consumption, and livestock inventory simultaneously within the system. Along with the disaggregated beef model, Freebairn and Rausser specify supply and demand relationship of pork and chicken with their interdependencies at both production and consumption levels. The findings show the negative impacts of beef imports on retail price of all meats with larger reduction in non-fed beef price, harvested steer, cull cow, and feeder cattle prices. In this study, a higher beef import level causes a small decline in the number of cattle placed in feedlots.

Arzac and Wilkinson (1979) examine the feed grain market and US livestock industry using more comprehensive model and simultaneously solving consumer demand for meat, prices, meat supplies, and livestock inventories. Their model treats corn exports, wage rate, dairy cow inventory, and dairy herd replacements as exogenous variables, and it specifies some partial adjustment relationship in livestock supply and feed grain market. The findings of this study yield results somewhat inconsistent with the finding of Freebairn and Rausser (1975) and Bain (1971). However, in this analysis, current quarterly prices have no impact on supplies of beef, pork, and chicken. The results further reveal more responsiveness of feeder cattle price to the non-fed beef price than to the fed beef price. In Arzac and Wilkinson's view, this result arises because the non-fed beef price represents the current opportunity cost of feeding, while the fee beef price is only an indicator of the future price of fed beef.

In 1979, Ospina and Shumway analyze the US beef cattle market, disaggregating into male and female classes. In this analysis, demand, supply, and inventories were determined simultaneously within the system. The problem of price expectation was dealt by using a polynomial distributed lag model of annual own prices prior to the year of decision-making. Researchers also analyze the effects of alternative feed grain price on the supply of cattle. The estimates of the analysis show a negative response of own price changes on supply of cow. However, a substantial positive response of own price changes on steer and heifer supply was observed. Inconsistent with the finding of Reutinger (1966), study results show a positive response of price change on the supply of beef in short run but no substitutability existed among beef components or between beef components and other meats.

Extending Arzac and Wilkinson's model, Martin (1982) analyses the policy questions related to the behavior of US demand and supply for US beef. Martin develops two separate equations for cow harvested, plus non-fed steers and heifers. He sums these equations to obtain the total supply for non-fed beef. The model, which was divided into a recursive block and a simultaneous block of equations, was estimated using quarterly data. Findings of Martin's study were inconsistent with the findings of Arzac and Wilkinson. In this analysis, beef supply was responsive to the current price. Analysis of multipliers also confirms the earlier finding that increase import of beef reduces both the retail prices of non-fed beef and farm price. Study results further reveal that the short-term effect of changes in beef imports on US hamburger prices is smaller than the long-run effects.

Bobst and David (1984) develop an annual econometric model including beef cow, calf corp, cattle and calf harvested, beef output, and demand. To capture the competition between cattle and crop enterprises for land and other farm resources, cropland was included in the inventory functions as an explanatory variable. Findings of the analysis show that beef cow supply is responsive to revenue, and beef supply decreases with the increase of crop acreage. In this study, broiler price yields a negative coefficient, indicating that beef and poultry are complementary goods rather than substitutes.

Most of the research works reviewed so far use simultaneous systems of equations as the major modeling approach. However, simultaneous systems of equations lack power to capture the biological features of livestock production. It is especially evident when dealing with an industry characterized by lagged responses, such that the desired levels of inventories, supply, and demand may not be instantaneously achieved. It is, therefore, almost imperative to specify dynamic relationships while modeling the livestock supply response.

In 1984, Rucker, Burt, and LaFrance develop an econometric model of cattle inventory by incorporating cattle cycle and biological constraints of cattle production. Dynamic regression equations were estimated for each beef cattle breeding herd and beef cattle inventories at two levels of aggregation, the US and Montana. Researchers use the analysis of Montana as a guide for specification of national equation to reduce the inference problem associated with letting the sample data help specify the model.

Rational lag on average price received by farmers for calves and the ratio of fed beef price to corn price constitute the primary exogenous variables. In the analysis, the US beef breeding herd equation looks more promising than Montana model. The study result shows beef to corn price ratio as apparently a preferable specification. The finding further supports the proposition that the beef to corn price ratio provides a net addition to information on future calf prices.

In 1986, Chavas and Klemme develop a dynamic model of herd composition and supply response for the US dairy sector. Their model treats the dairy herd as a capital good and incorporates the biological information, influence of economic environment on culling rates, and dynamics of dairy cows. The study results show that farmers' responds strongly (especially in the long run) to changing relative prices in the management decisions concerning the size of dairy herd. Results also indicate the importance of a constant monitoring of the dairy support price in the design of dairy policy. The results show that, given a rather small short run supply elasticity, setting the support price higher than the market equilibrium price may not create noticeable excess supply of dairy product in the short run. However, the long-run effects of such a policy may be very costly; since herd size had been expanded, the elimination of excess supply can become rather a difficult task.

Poultry and Broiler Supply

Several researchers attempt to analyze poultry supply response. Malone and Reece (1976), Chavas and Johnson (1981), and Ardhula and Holt (1989) model broiler supply response using different methodological approaches and focusing on the different aspects of broiler supply function. Lee and Seaver (1971) develop a linear behavioral and definitional equation to model supply and demand of broilers. The model was solved by using a simultaneous system of equation. The model was applied to structural changes of broiler markets with emphasis on regional relationships. Lee and Seaver divide the country into three regions: the northeast, south, and remaining region of USA. In the analysis, the lagged quantity was a significant variable in explaining the current supply of broilers. Results show simultaneous shifting of demand and supply tends to decrease equilibrium price and increase broiler supply.

Using simultaneous equation model, Thompson, Sprott, and Callen (1972) examine per capital broiler supply at the farm level, per capita broiler demand at retail, and the market margin, defined as the difference between the retain and farm prices of broiler. Annual time series data and techniques of OLS, 2SLS, and Jack-Knife (JK) procedure were used to estimate the coefficients of the model. In this analysis, standard errors of coefficient estimated by using OLS and 2SLS methods were significantly smaller than coefficient estimated by JK method.

Malone and Reece (1976) develop a two-equation, simultaneous model to estimate supply and demand of broilers. Equation one defines the wholesale price of broilers as a function of the quantity of broilers, pork price, disposable income, and lagged wholesale price of broilers (price expectation). Equation two models quantity of broilers as a function of wholesale price of broilers, pork price, transportation cost, and lagged wholesale price of broilers. In this analysis, Malone and Reece use annual time series data and implement 2SLS procedure to estimate the parameters of the model. Study results show that as broiler quantity changed by 1 percent, price changed inversely by 1.66 percent. Analysis further shows the direct influence of pork price expectations and consumer income on demand of broiler; also broiler price positively influences the supply of broiler.

Chavas and Johnson (1982) develop a model of broiler and turkey production based on the dynamic broiler production decision procedure. This model decomposes the broiler production into a number of successive stages, where different stages of production are biologically and functionally related to each other. At each stage, the owner makes a decision about selected variable input and some form of capital is transformed into a different form of capital. In this model, supply response was caused by changes in the output wholesale price and a feed cost variable, seasonal dummies, and trend variable. The findings of Chavas and Johnson show that the short-run supply elasticity approaches zero in the last stage of production and the largest economic adjustment exists in the first stage of production.

Martinez, Norton, Capps, and Weaver (1986) construct a quarterly econometric model of the US broiler industry with special focus on factors affecting wholesale price, export demand, retail to wholesale margin, and domestic demand. The model consists of four behavioral equations and two identities and includes dummy variables to capture the possible seasonal influences on the dependent variable. Because the model was recursive, except for the simultaneous wholesale price and export demand relationship, both OLS and 2SLS procedures were used to estimate the parameters of the model. The analysis shows inelastic nature of broiler demand, significant influence of US broiler exports, and the direct influence of retail price and income on domestic broiler consumption.

Jensen, Johnson, Shin, and Skold (1989) use a quarterly broiler model having six behavioral equations and two identities. Supply side of broiler model comprises of four equations: chick placement, hatching, production, and other chicken production. The demand block consists of retail demand equations and wholesale price. Exogenous variables of the model include: farm production, trade flow shipments, and military consumption. Generalized Least Square (GLS) estimators were obtained by single equation estimation procedures in the supply block. In this analysis, parameter estimates yield expected signs. Price elasticities were derived from the estimated equations and were compared with those of previous studies. Simulation equations validate the estimation results.

Aradhyula and Holt (1989) examine the empirical implication of extending the rational expectation hypothesis to entail price risk. They develop a general estimation framework that incorporates both the restrictions on structural parameters and on the variance-covariance terms. Generalized auto-regressive conditional heteroscedasticy (GARCH) time series process was used to generate time-varying expectations of both the means and variances of exogenous variables. The estimated coefficients of the quarterly supply-demand model for the US broiler industry were obtained by the use of the maximum likelihood method. The findings show that the rational expectation of price variance is an important determinant of broiler supply. A formal test indicates that the restrictions implied by the rational expectations hypothesis cannot be rejected.

In 1998 Kapombe and Colyer use a structural time series model to estimate the supply response function of broiler production. They use quarterly time series data from 1970 to 1993. In their view, structural time series model has the advantage of expressing trend and seasonal elements as stochastic components, allowing dynamic interpretation of the results and improving the forecast capabilities of the model. The results of the estimated model were highly promising. The model shows that four-quarter lag for broiler prices and feed prices determine the per capita broiler production. This study confirms the influence of technological innovations on the broiler cycle and reproduction traits. The results of the estimation indicate the continued importance of feed cost to poultry products and of technology, as expressed by the stochastic trend variable. However, seasonal influences appear to have become less important.

Irrigation Water Demand

Using the profit function approach to estimate a system of factor demands and supply responses for three irrigated field crops and four inputs (water, fertilizer, labor, and machinery), Harrington (1995) established a method for estimation of economic demand for irrigation water for the wiregrass region of Alabama. A translog cost function method was employed to estimate cost share equations for irrigation equipment (traveler and center pivot) and crop insurance. In this study, the price elasticities of demand for water vary across counties. Water price was a significant factor in the supply response of corn and peanuts (quota and additional). Furthermore, crop price levels for corn and peanuts (quota and additional) were the most important components affecting the demand for irrigation water.

Using a combination of simulation, econometric, and optimization models to develop a methodology that can be applied to examine the effect of water scarcity on net farm income, Acharya (1997) simulates the relationship between water from rainfall and/or various irrigation management practices, and crop yields. The study results indicated that, even if the historical flow could be maintained in the future, it would not be enough to meet the total irrigation demand in many instances. The aggregate optimal demand for irrigation water in the Middle Chattahoochee Sub Basin was estimated to be 3.211 million gallons per week. The contribution of this optimal irrigation level to net farm income would be $1.175 million per year for dry years and $0.711 million per year for normal years. That is, the aggregate impact of a water shortage, measured relative to the optimal use level, would be higher in dry years by $0.464 million as compared to normal years. Since the impact of water scarcity on net farm income was expected to be much higher in dry years than in normal years, two separate marginal relationships were estimated. Once the existing supply and weather conditions are known, these marginal functions can be used to derive the impact of reduced stream flow on net farm income.

Quality and Quantity Issue

Zachariah (1999) analyzed extractive and non-extractive uses of water with the aid of a dynamic programming model that maximized the net present value of drinking water benefits and agricultural waste assimilation benefits under a common pool institutional arrangement and integrated management strategies. The central result of the optimization problem was that optimal choices of groundwater extraction and agricultural waste assimilation were determined simultaneously in an integrated management approach. Thus, a common pool groundwater management regime or any regime that emphasizes only one area of concern (e.g., extraction or pollution) would be sub-optimal.

In this study, the model was applied to an aquifer management problem in Wilmot Township, Ontario. Extractive benefits were measured by using water demand functions, and agricultural waste assimilation benefits were obtained using farmers' marginal abatement cost functions for nutrient waste. The study results showed that the present value of aquifer benefits achieved under current common pool institutional arrangements were sub-optimal. Where the cost of switching from one management approach to another would be zero, the integrated approach was always optimal.

The optimal method of achieving water quantity and quality standards in a dynamic framework was examined by Opaluch (1981). The instruments under control were groundwater use, investment in treatment facilities, waste water disposal, an effluent tax, and imported water from two sources such as inexpensive, poor quality water and expensive, good quality water. Assuming salinity control of the Colorado River, the benefit to the Upper Watershed for the availability of the Peripheral Canal in 1980 was $33.9 million. If the Peripheral Canal was not built, the willingness to pay for salinity control of the Colorado River would be $923,000. Opaluch also concluded that a somewhat more stringent constraint for water flow out of the Upper Watershed was probably justified. Monte Carlo methods were used to evaluate the net benefits derived from incorporating an effluent charge into the pollution control policy. Results from the Upper Santa Ana Watershed were extrapolated to other affected river basins to evaluate the total benefits derived from the Peripheral Canal in a speculatory manner, tentatively estimated at $7.5 billion.

CHAPTER THREE

SUPPLY RESPONSE: THEORETICAL MODEL

Theoretical Background

The firm represents a basic organizational unit in responding to supply of product demanded by consumers. A firm incurs cost while acquiring inputs or factors of production. Basically, factors of production convert into output through a production process, a source of revenue for firm. The theory of the firm assesses the behavior of the firm in acquiring factors of production and transforming them into outputs. It is basically a study of supply of goods by profit maximizing agents. Study of theory of the firm resembles the theory of consumer behavior, where an agent maximizes utility given budget constraints. The firm (or farmer) acquires inputs to produce goods, has a production function, and a desire to maximize profits subject to resource constraints and a given level of technology.

Factor input and product output levels represent the rate of flow per unit of time. Factors of production comprise of short-run or long run variables. The short run refers to a time period sufficient to allow any desired change of technically possible output without altering the sale of plant. However, short run is not long enough to permit any adjustment in the scale of the plant. The long, however, run allows each producer to make such technologically possible changes in the scale of plant.

A production function is a mathematical expression depicting the maximum amount of output that is technically feasible from any specified set of input factors.

Technical aspects of production impose restrictions on economic behavior. Technical aspects of production are of interest to production economists, as they impinge the behavior of economic agent. Behavior of the firm can be analyzed by identifying technologically possible production vectors. Production set comprises of the set of all production vectors having a feasible plan. Production set can be restricted by $Y \in R^2$. Any $y \in Y$ is possible; any $y \notin Y$ is not possible. The production set is considered as a primitive datum of the theory (Mas-colell, Whiston, and Green, 1995). Technological constraints limit the possibility of production plan. Alternatively, production set Y can be described using a transformation function F (.). The transformation function F (.) has the property that *Y = {y R²: F(y)*

F(y) = 0, iff an element of the bounder of Y.

While assessing the economic behavior of firm, some restrictions on the farm of the production set technology are needed. Following axioms summarizes the production technology restriction (Varian 1992)

Monotonicity

If x is in V(y) and than x'=?x, then x' is in V(Y). Axiom of monotonicity assumes that if y is in Y than y' must also be in Y. Alternatively, if the firm can produce y with a input bundle x, it should be able to produce y if there exists more of input bundle. The monotonicity axiom assumes free disposal. The monotonicity implies the non-negativity of marginal production of

$y = f(x')$ that is $\frac{\partial y}{\partial x_j} = \frac{\partial f(x)}{\partial x_j} = MP_j(x') \geq 0$ for all j

Convexity

If x and x' are in V(y), then tx+1 (1-t) x' is in V(y) for all 0 = t = 1; that is V(y) is a convex set. Under the assumption of the convexity, if x and x' can produce y unit of output, then any weighted average of tx + 1 (1-t) x' can also produce y units of output. The isoquants may have flat spots, if V(Y) is convex. However, strict convexity V(y) yields nonlinear round isoquants. Strict convexity implies the law of diminishing returns. In other words, Y is a convex set. However, convexity of production is a much more problematic hypothesis than the convexity of the input requirement. This problem arises because convexity of the production set rules out "start up cost" and other sorts of returns to scale (Varian, 1992).

Regularity

V (y) is a closed, nonempty set for all y ? 0. This is a weak regularity condition concerning V (y). Assumption of the empty V (y) requires some conceivable way to produce any given level of output. And the firm cannot produce something from nothing. This assumption rules out a strict positive output without the commitment of scarce resources. The closedness assumption rules out the possibility of a gap in the boundary of p(q). Unlike the subjective nature of the utility function (in terms of measurement), a production function is objective. The production function represents a single valued, continuous function and defines over domain. It has continous first and second order partial derivatives. Henderson and Quandt (1975) outline the three general features of the short run production

(I) Sufficiently short run so that agent is not able to alter the level of his variable resources

(II) Sufficiently short so that technical improvement does not change the shape of production function.

(III) Sufficiently long to allow the completion of necessary technical process to take place.

A short run production function for a single output can be presented as follows

$$y = (x_1, x_2, . x_m, Z) \qquad (1)$$

where y represents the output quantity produced by the firm, x_1, x_2,. x_m represents the quantity of variable inputs, and Z refers to the plant size for all inputs which are fixed in the short run.

A production function can be presented as a family of isoquants, a set of possible combinations of all possible combinations of factors of production. Each isoquant represents a different level of output. The slope of an isoquant equals the negative ratio of marginal products. A production function does not determine the optimal mix of factor of production. The optimum input mix represents a particular combination of variable inputs which enables firm to produce a desired level of output at minimum variable cost. Therefore, the function relationship relating total cost to the quantity of the various factors of production used by firm can be modeled by using cost equation. The short run total cost can be presented as

$$C = P_i X_I + P_2 X_2 + ... + P_m X_m + F$$

$$C = \sum_{i=i}^{m} P_i X_i + F \qquad (2)$$

where C represents short-run total cost, p_1, p_2,.p_m represent market prices of variable factors x_1, x_2, .x_m, and F is the fixed cost. A cost function can be graphed as a family of isocost curves. An Isocost curve represents an input combination possible to purchase for a specified cost. The slope of isocost lines equals the negative of the input price ratio.

The objective of the firm is to minimize total costs of producing any outputs or maximize the amount of output for a given expenditure. The choice of factors that minimize production cost can be determined by finding the point on the isoquant that has the lowest associate cost. At the point of tangency between the isoquant curve and isocost curve, the marginal rate of substitution between two inputs is equal to the ratio of their respective input prices. The tangency condition does not exist in boundary solutions, where only one factor of production is used. Similarly the tangency condition has no meaning for kinked production function. The basic hypothesis in the theory of production is that firms seek to maximize profits while making the production decisions. The profit function of the firm may be represented by

$$p = R - C$$
$$p = PQ - C$$

$$p = P * f(x_1 x_2 .....x_m, s) - \sum_{i=1}^{m} r_i x_i + F \qquad (3)$$

Where p is profit, R is revenue, C is cost, P is the price of output, and Q is rate of output. Profit remains a motivating force behind the firm decision, with respect to the level of production. Profit equals the difference between value of output and value of the inputs. Producers aim to maximize profit at any given output level. The first production condition of profit maximization shows that the isoprofit line, which is tangent to the production function, will maximize profit subject to the production function. The first order conditions of profit maximization could be found by setting the partial derivative of the profit function with respect to x_i equal to zero

$$\frac{\partial_p}{\partial_{x_1}} = pf_1 - w_1 = 0 \rightarrow pf_1 = w_1$$

$$\frac{\partial_p}{\partial_{x_2}} = pf_2 - w_2 = 0 \rightarrow pf_2 - w_2$$

....

....

$$\frac{\partial_p}{\partial_{x_m}} = pf_m - w_m = 0 \rightarrow pf_m - w_m$$

Where f_m is the partial derivative of the production function with respect to $x_{m.}$ It is also defined as a marginal production of X_m *(MP_m).* The marginal production shows a rate of change of extra amount of output per unit of extra input (Variance, 1992). The first order condition states that the value of marginal product of each factor must be equal to the price. The optimum combination of inputs exists when the marginal rate of substitution must be equal to the ratio of their respective factor prices $mp_1/mp_2 = w_1/w_2$

The technical rate of substitution measures the tradeoff between two inputs in production. It measure the rate at which the firm will have to substitute one input for another in order to keep output constant. If factor cost remains constant for all amounts of the factor, the locus of cost minimization can be easily be traced out by using expansion path. Formally expansion path is an implicit function

$$gi\left(x_1, x_2, ...x_m = 0 \quad \right) \; for \quad i = 1,\; 2, ...m - 1$$

In the two-dimensional case, the second derivative of the production function with respect to the input must be non-positive,

$$\frac{\partial^2 f(x)}{d^2 x} \leq 0$$

A similar second-order condition exists in the multiple input case. In this case, the matrix of second derivatives of the production function must be negative semi-definite at the optimal point; that is the second order condition requires that Hessian Matrix

$$\partial^2 f(x'') = [\frac{\partial^2 f(x')}{\partial x_i \partial x_i}]$$

must specific the condition that hD^2 f (x') h'=0 for all vector h. For a single commodity, the solution of the profit maximization offers the basis for derivatives of short run cost functions and the firm's short-run supply function. The production functions, the cost equation, and expansion path can be summarized in the system of equations:

$Q = f (x_1, x_2, x_3, S)$

$C = r_1x_1 + r_2x_2 + \ldots\ldots. + r_mx_m + F$

$g_i (x_1, x_2, x_3, \ldots\ldots\ldots\ldots\ldots\ldots\ldots.x_m) = 0$ where, $i = 1,2,.m-1$

Let's reduce the production function, the cost function and expansion path into a single equation where cost is stated as an explicit function of the level of output plus the cost of fixed factor.

C = f (x) + F

The relationship is the cost function. C represents the minimum cost of producing any given rate of output. The relevant information about the firm's cost structure can be summarized into the short-run total cost. It is convenient to derive a set of short-run costs like average variable cost, fixed cost and marginal cost from the curve. The marginal cost function can be determined by taking the partial derivative of the total cost with respect to output.

$$\frac{\partial_c}{\partial_y} = mc = f'(y)$$

The competitive firm takes the market price as given, so the profit maximization problem can be specified as

Max (*py - cy)*

The first order and second order conditions for an interior solution are

$p = c'(y^*)$

$c''(y^*) = 0$

The second order condition satisfies as a strict inequality. The inverse supply function, p(y), measures the price that must prevail in order for a firm to find it profitable to supply a given amount of output. The first order condition of inverse supply function is

$p(y) = c'(y)$ as long as $c''(y) > 0$

If we assume perfectly competitive market, the upward sloping position of a firm's marginal cost curves lying above the average variable cost curve represents the short-run supply curve of the firm. The supply function gives the profit-maximizing output at each price. Therefore, the supply function *y(p),* must satisfy the first order condition

$$p = c'(y(p))$$

and the second order condition

$$c''(y(p)) >= 0$$

The direct supply curve and inverse supply curve assess the relationship between price and the profit-maximizing supply of output. The industry supply function sums individual firm supply functions. If $y_i(p)$ is the supply function of the firm in an industry with m firms, the industry supply function is given by

$$y(p) = \sum_{i=1}^{m} y_i(p)$$

While making a livestock or broiler supply decision, a representative firm or farmer aims to maximize profit. Therefore supply function serves as the theoretical background for modeling the supply response behavior of farmers.

Time Series Forecasting

Time series analysis modeling offers a powerful means of understanding value-generating mechanisms, forecasting of future values, and optimal control of systems. Time series arising in agricultural or livestock production might be dependent or correlated. This intrinsic nature of a time series makes statistical procedures that rely on the independence assumption invalid. Basically, time series analysis is used to model the mechanism that generates the value and forecasts the future value using the fitted model. In our study, forecasting of future values of livestock is critical to predict future numbers of broilers, layer, dairy cattle, beef and swine, and thereby the amounts of future water demand by livestock. Time series analysis of livestock product also allow us to compare forecasting results with econometric and the USGS physical model.

There exist different time series modeling approaches to analyze the stationary time series. However, many applied time series, mostly arising in agriculture and livestock, are non-stationary in nature. Non-stationary time series can have non-consistent mean $\mu_{t,}$ non-consistent variance $?^2_{t,}$ or both of the properties (Wei, 1989). Therefore, in our analysis, the autoregressive integrated moving average (ARIMA) model was used. Box Jenkins (ARIMA) offers a powerful modeling tool for stationary, non-stationary, seasonal, and non-seasonal time series data analysis. A process that is non-stationary in the mean presents serious problems for estimation of the time dependent mean function without multiple realizations. Techniques of mean differencing must be used correct the time series non-stationary in means.

Box and Jenkins (1976) refer the non-stationary behavior as the homogeneous non-stationary. In ARMA models, the non-stationary process arises if some roots of the AR polynomial do not lie outside the unit circle. However, by the nature of homogeneity, the local behavior of this kind of homogenous non-stationary series is independent of its level (Wei 1989). Let ? (B) be the autoregressive operator defining the behavior

$$? _B (Z_t + C) = ? (B) Z_{t+} \qquad (1)$$

If C is constant, it implies that ? (B) must be of the form

$$? (B) = ? (B) (1-B)^d \qquad (2)$$

if d >0, where ? (B) is a stationary autoregressive operation. By appropriate differencing of the general series, a homogeneous non-stationary series can be reduced to stationary. In an alternative, the series $\{Z_t\}$ is non-stationary, but the d^{th} difference series $\{(1-B)^d Z_t\}$ for some integer d=1 is stationary.

If the d^h difference series follows a white noise phenomenon

$$(1-B)^d Z_t=a_t \quad (3)$$

Let consider d=1 in equation 3. The implication of this kind of homogeneous non-stationary series

$$(1-B)Z_t= a_t \quad (4)$$

or

$$Z_t=Z_{t-1}+a_t \quad (5)$$

Given the past information Z_{t-1}, Z_{t-2},…………………………the level of the series at time 't' is

$$\mu_t=Z_{t-1} \quad (6)$$

The General ARIMA Model

The stationary process resulting from a properly differenced, homogeneous non-stationary series may not be white noise (Neimi,1984). More generally, the series $(1-B)^d Z_t$ follows the general stationary ARMA (p,q) process.

$$Fp(B)\ (1-B)^d Z_t = ?_0 + ?_q(B)a_t \quad (7)$$

In equation 7, the AR operator Fp(B) = (1- FB - ……… - FpBp) and the invertible MA operator ?a (B)=(1- $?_1$B-…….- $?_q$ B^q) share no common factors. The parameter $?_0$ plays an important role for d=0 and d >0. When d=0, the original process is stationary, and $?_0$ is related to the mean of the process, i.e

$?_0$= µ(1-F1 -………….-Fp).

If d =1, $?_0$ is the deterministic trend term. The resulting homogeneous, on-stationary model is an autoregressive integrated moving average model (ARIMA) of order (p,d,q). Where p, d, and q represent the order of autoregressive process, degree of differencing, and order of the moving average process, respectively.

Variance of autocovariance of the ARIMA (p, d, and q)

Stationary in mean is not necessary in the variance and the autocovariance. However, a non-stationary time series in mean will also be non-stationary in the variance and autocovariance. Although the model is stationary, the finite numbers of parameters (i.e. Fi, ?j, and s2) define the complete characteristics of time series process (Weiss, 1984). Therefore, given data set {Z_1, Z_2, Z3,…………Zn}, the future evaluation of the process can be developed using ARIMA. Suppose we fix IMA (1, 1) or ARIMA(0,1,1) model

$$(1\text{-}B)Z_t = (1\text{- }?B)\, a_t \qquad (8a)$$

or

$$Zt = Z_{t-1} + at\text{- }?_{at-1} \qquad (8b)$$

To a series of n_o observation, if time origin number for t > n_o, we can write

$$Z_t = Z_{\ t-1} + at - ?_{at-1}$$

$$= Z_{t-2} + a_t + (1\text{- }?)_{at-1}\text{- }?_{at-2}$$

$$= Z_{no} + a_t + (1\text{- }?)_{at-1} + (1\text{- }?)\, a_{no} + (1 - ?)a_{no} \qquad (9)$$

If t-k > n_o,

$$Z_{t-k} = Z_{no} + a_{t-k} + (1\text{- }?)a_{t-k-1} + (1\text{- }?)_{ano+1}\text{- }?_{ano} \qquad (10)$$

Hence, with respect to the time origin number

$$Var(Z_t) = [1 + (t\text{- }n_o^{\ -1})(1\text{- }?)^2]\ s^{\,2}_{\ a} \qquad (11)$$

$$\mathrm{Var}\ (Z_{t-k}) = [1+(t\text{-}k\text{-}\ n_o\ \text{-}1)(1\text{-}\ ?)^2]\ s^2{}_a \qquad (12)$$

$$\mathrm{Cov}\ (Z_{t-k},Z_t) = [1\text{-}\ ?)+(t\text{-}k\text{-}\ n_o\ \text{-}1)(1\text{-}\ ?)^2]\ s^2{}_a \qquad (13)$$

Equation 11 and 12 summarize (Wei,1989) that

I. Variance, var (Z_t), of ARIMA process is time dependent and var (Z_t)?var (Z_{t-k})

II. The variance var (Z_t) is unbounded as t → 8

III. The autocovariance cov (Z_{t-k},Z_t) and the autocorrelation corr (Z_{t-k},Z_t) of the process are also time dependent, and hence not variant with respect to time.

Although, it is difficult or impossible to make statistical inference of a process that is non-stationary in both mean and the autocovariance or autocorrelation function, by using the technique of differencing, we can reduce it to stationary time series data. Therefore, if the original series Z_t is non-stationary, the differenced series $W_t=(1\text{-}B)^dZ_t$ is stationary ARIMA process where $F(B)W_t= ?(B)a_t$

$F(B) =(1\text{-}\ F_1B\text{-}\ \ldots\ldots\text{-}\ FpB^p)$ and

$?(B)= (1\text{-}\ ?_1B\ \text{-}\ldots\ldots\ldots\ldots\ldots\text{-}\ ?qB^q)$

Therefore, the parameter F_i, $?_j$, and s^2 that control the evolution of the non-stationary phenomenon of Z_t can be estimated from the differenced series W_t (Wei 1989).

Forecasting

Time series analysis is also used for forecasting purposes. Considering the general ARIMA (p, d, q) model

$$F(B)\ (1\text{-}B)^dZ_t = ?q(B)at \qquad (14)$$

Here F(B) = (1- FB-……………… FpB^F) and ? (B) = (1- ?$_1$B-…………….?qB^q) represent stationary AR operator and MA operators respectively. Although, the mean and the second order moments, such as the variance and autocovariance functions, vary over time, the evaluation of the process is completely determined by a finite number of fixed parameters (F$_i$, ?$_j$, s^2). Basically, forecasting is a process of estimation of these parameters and obtains the minimum mean square error forecasting using Bayesian approach (Wei 1989).

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CHAPTER FOUR

WATER DEMAND FORECASTING FOR POULTRY: STRUCTURAL, TIME SERIES AND DETERMINISTIC ASSESSMENT

Introduction

Concurrent with the rapid growth of metropolitan areas, adverse climatic conditions and increasing water demand for agricultural and other sectors have created pressure on existing water resources in many parts of the United States (Acharya, 1997). Recent trends in climatic conditions and growing water demands in many sectors might threaten the sustainability of water resources, if policy makers and water managers fail to devise appropriate policies to efficiently allocate the available water. However, the task of efficient allocation of existing water is severely constrained by the lack of information about present and future water demand by different sectors of water use, including animal agriculture (Hatch, 2000). Animal agriculture (broiler, layer, turkey, beef cattle, horse, dairy cattle, and swine) requires water for drinking and cleaning purposes. Even though small in demand in comparison to water demand in many other sectors, precise estimates of future water demand for animal agriculture can play an important role at the crucial hours of water allocation decisions, given relatively fixed water availability.

Finding accurate information related to water use for animal agriculture is a difficult task in the light of the scarcity of past research and systematic records of water use data. Except for the aggregate animal water use data published by the United States Geological Society (USGS), there exists very little information about animal water use in the United States. Unfortunately, estimates of USGS water demand is based on a static physical model, where future water demand is a function of temperature, daylight, and physiological conditions of animals. The USGS water forecasting model carries limitations of other similar water models by failing to capture the animal production behaviors of farmers, which change with changes in economic and institutional variables.

Indeed, the production of animals by farmers is an economic decision that is mostly driven by economic variables, such as expected future profits and costs of inputs. Supply of animals is also affected by changing international trade agreements, environmental laws, and government programs. A sound supply response model and rigorous econometric analysis is needed to accurately predict the number of animals, and thereby the amount of water demanded by animal agriculture. To our knowledge, this is the first study of broiler water demand forecasting by incorporating economic variables. As a result, this represents a significant departure from previous studies in the same areas that have ignored changes in animal water demand in response to changes in prices, policies, and government support programs.

This study adopts a systematic analytical approach based on economic principles (supply response functions) to forecast the number of animals in future years under the influence of changing economic variables. Forecasting water demand for all animal types, such as broilers, beef cattle, dairy cattle, and swine, is the main aim of our dissertation work. Therefore, first we select broiler production in Georgia for future water demand modeling purposes. Although the production processes and biological constraints are different for different animal types, our model serves as a representative model for other animal types if researchers incorporate the production stages of other animal types in a given model.

Theoretical Model Development

For theoretical model development, we consider a competitive firm where production function can be decomposed into N production stages. At each stage, owner makes a decision about selected variable input and some form of capital is transformed in to different form of capital (Jarvis, 1974). Conceptually, we can represent this type of production function as (Chavas and Johnson, 1982):

$$Y_k = f_k(Y_{k-1}, X_k) \tag{1}$$

Where k = 1,2…n;

Y_k = vector of capital stock at stage t

Y_{k-1} = lagged vector of capital stock

X_k = Vector of variable inputs used in the t^{th} production stage

Here, vector of variable inputs X_k changes the capital Y_{k-1} in to different form of capital Y_k. In the case of poultry production, Y_1, Y_2, and Y_3, represent the placement, the grow out flock, and broiler production, respectively. Vector of variable inputs like feeds, medicine, and other nutritional supplements change poultry production from one stage of production to another stage of production. In each stage, broiler growers (integrators) make an economic decision related to investment, and some form of capital is transformed into a different form of capital. Considering Y_t as a scalar and capital stock as a single variable, we develop a profit function as:

$$A = PY_n + \sum_{i=1}^{n-1} S_k Y_k - \sum_{i=1}^{n-1} R_k X_k - R_0 Y_0 \tag{2}$$

P = output price

Y_n = final output

S = salvage value of the capital stock Y_k

R_k = price of the input X_k,

R_0 = purchase price of Y_0.

Ignoring salvage value and considering the constrains of production technology (equation 1) and profit maximization (Equation 2),

$$A = PY_n - \sum_{i=1}^{n-1} R_k X_k - R_0 Y_0 s.t. Y_k = f_k(Y_{k-1,} X_k)$$

Now, our optimality condition as indicated by asterisk would be:

$$X_k^* = g_k(P, R_k, Y_{k-1}^*), \tag{3}$$

where k = 1,…,n

$$Y_k^* = f_k(Y_{k-1}^*, X_k^*) = h_k(Y_{k-1}^*, P, R_k) \tag{4}$$

Where k = 1,….,n, $R_k = (r_k, \ldots\ldots\ldots\ldots r_n)$ represents vector of input prices

Here, equation 4 clearly shows economic decisions made at earlier stages defines the optimality condition at each stage of broiler production. Equation 4 represents a static optimally condition and introducing time variable at each stage of production allows us to examine the dynamics of broiler production system. However, in many cases, underlying production technology alters or strongly influenced the time lag separating two successive stages of production. Suppose, if, after a delay of 'j' time periods, it takes 'i' time periods to transform the capital stock Y_{k-1} in to Y_k, then equation 4 can be express as:

$$Y_{kt} = f_k(Y_{k,t-j,} Y_{k,t-j-1}, \ldots\ldots\ldots, Y_{k,t-j-1}, P_t, R_{kt}) \tag{5}$$

Where P and R respectively show the output price and input prices expected by the decision maker at time t. Generally, the time lag between two stages in equation 5 is mostly defined by the underlying production technology. However, there are instances in broiler production process, when production or economic decisions made by integrators influence change the lag between two successive stages. It is mostly true when sudden changes in price of out put or input occurs. For example, an increase in short-run profitability of eggs might reduce the culling rate of pullets or hatching flocks.

A Representative Broiler Model

Today's broiler industry represents a rapidly changing and highly technical agricultural industry. In this vertically integrated industry, integrators control all or most of the production stages, and thereby investment decisions. Integrators generally own breeder flocks, feed mills, and processing plants. The integrators provide the chicks, feed, medication, and other technical support to growers. The integrators also co-ordinate processing and marketing activities. Given the current nature of broiler production, the broiler production decision of this study area can be examined in three successive stages namely: placement, hatching, and broiler production (personal communication with Dr. Mckissick). Placement refers to the introduction of chicks in to the broiler production or number of chicks placed into hatchery supply flocks. Hatching refers to the hatching of eggs from the hatchery supply flock. After hatching chicks enter in to broiler production. In broiler production system, 'placement', 'hatching', and 'production' follow a sequence of production.

Understanding of underlying technology of broiler production process is critical for dynamic broiler supply decisions. In broiler production process, after few weeks of placing chickens in hatchery supply flocks, egg production starts following a cycle of high and low production, which generally lasts for 10 months in broiler type chickens. After hatching, approximately eight weeks is needed to produce 3.8 lbs live weight broiler (72% dressing). These underlying time gaps between the different stages of broiler production and equation 5 offer an insight into develop a dynamic broiler supply response function.

A representative broiler production stages comprise of:

PLACEMENT (BP)

$$BP_t = b_0 + b_1 BP_{t-i} + b_2 WBP_t + b_3 WBP_{t-i} + b_4 BFC_t + b_5 BFC_{t-i} + b_6 T_{67} + b_7 DV2 + b_8 DV_3 + b_9 DV_4 + e_t \quad (6)$$

where

β_0 = The intercept of the equation;

BP_t = The broiler placement (quarterly broiler chick placed in Georgia) in current quarter in millions;

BP_{t-i} = The broiler placement in lagged i^{th} (I = 1,2,3,4) quarters in millions in Georgia;

WBP_t = The 12 city composite wholesale price (ready to cook) in the current quarter, deflated by CPI (1982-84= 100) in cents per pound;

WBP_{t-i} = The 12 city composite wholesale price (ready to cook) in lagged i^{th} (I = 1,2,3,4) quarters, deflated by CPI (1982-84= 100) in cents per pound;

BFC_t = Broiler feed prices paid by farmers in current quarter deflated by CPI (1982-84= 100) in dollar per ton;

BFC_{t-i} = Broiler feed prices paid by farmers in lagged i^{th} (I = 1,2,3,4) quarters deflated by CPI (1982-84= 100) in dollar per ton;

T_{67} = The time trend variable, year 1967 =1

DV_2, DV_3, DV_4 = The quarterly seasonal dummy variables (binary or 0-1) in quarters 2,3, and 4, respectively;

e_t = the stochastic error term

HATCHING (BH)

$$BH_t = b_0 + b_1 PBP_{t-i} + b_2 WBP_t + b_3 WBP_{t-i} + b_4 BFC_t + b_5 BFC_{t-i} + b_6 T_{67} + b_7 DV_2 + b_8 DV_3 + b_9 DV_4 + e_t \qquad (7)$$

β_0 = The intercept of the equation;

BH_t =The broiler type chick hatched by commercial hatcheries in Georgia in current quarter in millions;

PBP_{t-i} = The predicted broiler placement in lagged i^{th} (I = 1,2,3,4) quarters in millions in Georgia;

WBP_t = The 12 city composite wholesale price (ready to cook) in the current quarter, deflated by CPI (1982-84= 100) in cents per pound;

WBP_{t-i} = The 12 city composite wholesale price (ready to cook) in lagged i^{th} (I = 1,2,3,4) quarters, deflated by CPI (1982-84= 100) in cents per pound;

BFC_t = Broiler feed prices paid by farmers in current quarter deflated by CPI (1982-84= 100) in dollar per ton;

BFC_{t-i} = Broiler feed prices paid by farmers in the lagged i^{th} (I = 1,2,3,4) quarters deflated by CPI (1982-84= 100) in dollar per ton;

T_{67} = The time trend variable, year 1967 =1

DV_2, DV_3, DV_4 = The quarterly seasonal dummy variables (binary or 0-1) in quarters 2,3, and 4, respectively;

e_t = the stochastic error term

Broiler Production (BRP)

$$BRP_t = b_0 + b_1 PBH_{t-i} + b_2 WBP_{t-i} + b_3 BFC_t + b_4 BFC_{t-i} + b_5 T_{67} + b_6 DV_2 + b_7 DV_3 + b_8 DV_4 + e_t \quad (8)$$

β_0 = The intercept of the equation or constant

BRP_t = Quarterly poultry harvested under federal inspection in Georgia in Thousands;

PBH_{t-i} = The predicted broiler hatching in lagged i^{th} (I = 1,2,3,4) quarters in millions in Georgia;

WBP_{t-i} = The 12 city composite wholesale price (ready to cook) in lagged i^{th} (I = 1,2,3,4) quarters, deflated by CPI (1982-84= 100) in cents per pound;

BFC_t = Broiler feed prices paid by farmers in current quarter deflated by CPI (1982-84= 100) in dollar per ton;

BFC_{t-i} = Broiler feed prices paid by farmers in the lagged i^{th} (I = 1,2,3,4) quarters deflated by CPI (1982-84= 100) in dollar per ton;

T_{67} = The time trend variable, year 1975 =1

DV_2, DV_3, DV_4 = The quarterly seasonal dummy variables (binary or 0-1) in quarters 2,3, and 4, respectively;

e_t = the stochastic error term

Time series forecasting model

In order to make comparative forecasting of broiler production and there by water demand by broiler in Georgia econometric and physical models, Autoregressive Integrated Moving Average Models (ARIMA) was also developed. ARIMA (p, d, q) where p, d, and q represent the order of the autoregressive process, degree of differencing, and order of the moving average process respectively were written as

$$\nabla^{d} y_{t} = d + f(B) e_{t}$$

where y_t represents acreage planted in time t, e_t are random normal error terms with mean zero and variance σ^2_t and Δ^d denotes differencing i.e. $y_t = y_t - y_{t-1}$,

$$f(B) = 1 - f_1(B) - f_2(B)^2 - .... - f_p(B)^p \ and$$
$$f(B) = 1 - f_1(B) - f_2(B)^2 - .... - f_q(B)^q$$

Where B represents the backward shift operator such that $B^n{}_{et} = e_{t-n}$. In ARIMA model, the acreage response is modeled dependent on past observation of itself. Future price and yield of cotton and peanut were estimated by using Box-Jenkins (ARIMA) time series models.

Data

In order to carry out the objectives of the study, quarterly data of 1967-2002 of broiler chick placement, hatching flock, and final broiler number of selected counties of Georgia was collected from National Agricultural Statistics Services (NASS) of United States Department of Agriculture (USDA) and Georgia Agricultural Facts. Information about the wholesale price of broiler and feed costs were collected from the Economic Research Service (ERS) of United State Department of Agriculture (USDA)'s publications. The wholesale price of broiler and broiler feed costs were deflated by using consumer price index (all urban consumer, US city) average (1982-84=100).

Realizing the nature of underlying technology of broiler production, we consider a quarterly observation while analyzing broiler supply function. In our analysis, lagged observed wholesale output (broiler) price is considered as expected price for output. Although such expectations are in general not rational, they reflect most of the information available to decision makers (Muth, 1961). In our model, dummy variables for second, third, and fourth quarters capture the effects of seasonality and a trend variable is used as a structural change proxy. Futures feed costs and out put prices were estimated by using Box-Jenkins (ARIMA) specification. Water use coefficients for broiler were collected from the USGS.

Results and Discussion

It is possible to examine the estimated equations by various ways; however the basic aim was to examine how well the behavior of the equations tracks the historical behavior of the modeled supply relationship. In order to achieve the goals of study, our analysis first presents a common econometric evaluation of the estimated parameters, the sign of each parameter, and the derived elasticities followed by time series water demand forecasting.

Ordinary regression analysis (OLS) is based on the several statistical assumptions including independence of the stochastic errors term. However, with the use of time series data, the ordinary regression residuals might correlate over time violating the assumptions of OLS. Problem of autocorrelation especially arises in the autoregressive model where one or more lagged values of the dependent variable serve as independent variables. The OLS estimates of the autoregressive model are generally biased and inconsistent leading to incorrect statistical test results and/or false inferences. In our analysis, broiler placement equation represents a distributed lag model raising the possibility of the autocorrelation problem. Therefore, in order to solve the problem of autocorrelation, autoreg procedure was used using SAS.

The autoreg procedure of the SAS solves the problem of autocorrelation by augmenting the regression model with an autoregressive model for the random error, thereby accounting for the autocorrelation of the errors. By simultaneously estimating the regression coefficients and the autoregressive error model parameters, the autoreg procedure corrects the regression estimates of distributed lag model. In statistical term, it is called autoregressive error correction or serial correlation correction. Results of the placement equation using autocorrelation procedure are presented in Table 4.1.

In order to select the best model for the hatching and broiler production, backward, forward, and stepwise selection procedure were used. The forward selection procedure starts with the null (b_0) model, and then adds the most significant variable. After adding the first most significant variable, it adds the next most significant variable (with the first already entered into the model). The process continues until none of the variables left unentered meets the entry-level selection value i.e. (alpha=0.10) in our model. The backward selection procedure starts with the full K variables model and deletes the least significant variable until all p variables remaining are significant at the stay selection level (alpha=0.10). The stepwise selection procedure combines the procedure of backward selection and forward selection to select the best model. Results of the hatching and broiler production equation using backward, forward, and stepwise procedure are presented in table 4.2 and table 4.3. In most of the cases, all of these three procedures yield the same results. In our analysis, the F statistics and P values (p =0.0001) strongly reject the null hypothesis that all parameters expect the intercept are zero. The estimated model explains historical variations in broiler production well, with adjusted R^2 of 0.99 (Table 4.1).

Placement in the hatchery supply flock (BP_t) represents the first stage of broiler production. Only statistically significant variables at 90 percent confidence level are presented in the Table 4.1. The estimated coefficients of chick placement and wholesale broiler price in the lag structure yield positive sign, findings consistent with the study of Chavas and Johnson, 1982. Though statistically insignificant, the estimated coefficients of the broiler feed price had negative signs. In our analysis, elasticity of one-quarter lag broiler wholesale price was statistically significant at 10 % level. Analysis shows that one percent increase in the wholesale broiler price increases the introduction of chick in to production process (placement) by 0.061 percent. A historical trend and technological advancement in broiler placement was captured by the positive coefficient of 0.3514 of the annual trend variable. The study results show no significant impacts of seasonal variables on placement.

In the hatching equation, the signs of the coefficients were consistent with what model expected. The signs of the predicated placement variables on lag structure were positive and statistically significant at 90 percent confidence level. As expected wholesale broiler price had a positive sign and statistically significant. Analysis of elasticity shows an increase in 1 percent of wholesale broiler price increases the broiler type chick hatching by commercial hatcheries by 0.729 percent. Feed cost elasticity in hatching stage of production was – 0.041 and statistically significant. It shows a decrease of 0.41 percent of hatching for every 10 percent increase in the feed cost. With the statistically significant coefficients for seasonal dummies, study shows the impacts of season in the hatching.

Hatched chicks are generally fed for approximately eight weeks to get a marketable broiler weight. In our analysis of broiler production equation (table 4.3), lagged hatching variables, lagged wholesale broiler price, and broiler feed cost yield expected signs. At 10 percent level of significance, the wholesale price of broiler of the previous quarter showed a significant impact on broiler production. Estimated elasticity for wholesale broiler price shows a 0.078 increase in broiler production for every 1% increase in the wholesale broiler price. Contrary to our expectation, broiler feed cost fails to show statistically significant impacts on broiler production. This result was not consistent with the finding of other researchers (Aadland and Bailey, 2001;Freebairn and Rausser, 1975; Bhati, 1987; Mbaga, 2000) Study results further reveal the significant and negative impacts of third quarter (June, July, August). It might have resulted from the summer months and resulting higher expenses for cooling of broiler houses. Our study basically aims to forecast the water demand for broiler for drinking and sanitation purposes. In order to meet the objective of study, we selected estimated broiler equation for econometric forecasting of water, ignoring the role of chicks and hatching flocks.

Results of Box-Jenkins (ARIMA) time series models are presented for comparison purposes. As determined with Akaike's information criterion (AIC) and Schwarz's Bayesian information criterion (SBC), the ARIMA (1,1,1) model seems more effective in forecasting number of broiler in study area than other ARIMA specifications. Other ARIMA specifications like ARIMA (2,1,0), ARIMA (2,1,1) and ARIMA (0,1,2) also have AIC and BIC values very close to the selected model. However, forecasted values from these ARIMA models deviate drastically from the actual observed number of broiler of study area. In our selected model, forecasted number of broiler (in-sample forecasting) closely traced the observed values between 1995 and 2000, which further supports the validity of the model.

Broiler Water Demand Forecasting

So far, there exists no specific formula to measure the actual amount of water use by broiler. However, ACT/ACF study conducted by Natural Resources Conservation Service (NRCS) of Georgia estimates per day per broiler water use of 0.05000778 gallon, 0.049999489 gallon, 0.050032176 gallon, 0.049997553 gallon, and 0.04999755 gallon for the year 1992, 1995, 2000, 2005, and 2010 respectively (ACT/ACF river basic comprehensive study, 1995). Per day average broiler water use coefficient (0.050007) used by ACT/ACF study is very near to USGS estimates of 0.06 gallon per day broiler water use in Georgia. In our analysis, we assume per day broiler water use of 0.05007 as reported by NRCS for the comparison purposes.

In our study, we first capture the effects of economic variables in broiler supply decision. Then, we use the number of broilers available from the structural and time series forecasting models and the water use coefficients available from the NRCS to forecast the amount of water demand for broiler up to year 2007. In our study, forecasted number of broilers and broiler water demand information available from the ACT/ACF comprehensive study serve as baseline information. ACT/ACF study represents a physical model as it ignores the role of any economic and institutional variables while forecasting the number of broiler and thereby the levels of broiler water demand.

Table 4.4 and 4.5 show the forecasted number of broiler and corresponding broiler water demand in Georgia using econometric, time series, and physical (ACT/ACF) model. Different in water demand between the physical, structural, and time series models have been termed as “slippage” (Tarren, 2001). Our analysis assesses this slippage by comparing the changes in total per day broiler water demand resulting from capturing the impacts of economic variables. ACT/ACF study of NRCS assumes approximate annual broiler growth of 0.008 in the selected counties of flint, Chattahoochee, and act regions of Georgia. Assuming the same (0.008) growth rate for Georgia in coming years, physical model forecasts 119,1951; 120,1487; 121,1099; and 1220,788 thousands of broilers in 2004, 2005, 2006, and 2007, respectively in Georgia. Given the per day broiler water use of 0.05007 gallon, physical model forecasts 59,681; 60,158; 60,639; and 611,24 thousands gallons per day of water demand in 2004, 2005, 2006, and 2007, respectively in Georgia.

After assessing the impacts of economic variable in broiler supply decision, our structural model yields 130,7030; 133,9991; 137,3436; and 140,7376 thousands broilers and 65,442; 67,093; 68;767; and 70,467 thousands gallons per day of water demand in 2004, 2005, 2006, and 2007, respectively in Georgia. Similar analysis using time series ARIMA (1,1,1) model yield 136, 4484; 140,9646; 145,5692; and 150,2624 thousands broilers and 68319; 70580; 72886; and 75,230 thousands gallons per day of water demand in 2004, 2005, 2006, and 2007, respectively in Georgia. Based on the findings of our analysis, we conclude that physical model, which is based on the educated guess in forecasting broiler production, underestimate the future water demand by approximately 11 percent in comparison to econometric models. It arises because physical model does not follow any statistical or econometric modeling and ignore the role of economic and institutional variables, which in most of the cases define the broiler supply behaviors of farmers. The analysis also shows no substantive difference between the structural and time series forecasts models.

Conclusions

This study adopts a systematic analytical approach based on the economic principle (supply response functions) to forecast the number of broiler in future years under the influence of changing economic variables. We basically adopt a profit-maximization framework, given the technology constrains. In our broiler profit maximization model, broiler production decisions are made in three successive stages, namely: primary breeding flock, hatchery flock, and finishing broiler production. In each stage, broiler growers make an economic decision related to investment, and some form of capital is changed in to a different form of capital.

In our analysis, all economic variables were statistically significant reflecting importance of incorporating economic variables while forecasting number of broilers and thereby future broiler water demand. Analysis further shows that ignoring economic variables lead to under estimation of future water demand. Study also reflects no substantive difference between using structural and time series models for broiler water forecasting purposes.

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Table 4. 1. Parameter Estimates of Placement and Elasticities at Means, 1967-2002

Variable	Coefficients	Standard Error	P- Value	Elasticity
Intercept	-1.0985	7.376	0.8819	
BP_{t-4}	0.8762	0.0341	<0.0001	
WBP_{t-1}	92.70	44.99	0.0517	0.061
T	0.3514	0.0675	<0.0001	
R Square	0.9928			
Total R-Square	0.9928			
Durbin h	5.6347			

Table 4. 2. Parameter Estimates of Broiler Hatching Flock and Elasticities at Means, 1967-2002

Variable	Coefficients	Standard Error	P- Value	Elasticity
Intercept	1.761	6.961	0.8008	
PPL_{t-1}	0.767	0.082	<0.0001	
PPL_{t-2}	0.253	0.084	0.0031	
$WBPL_{t-1}$	89.872	24.008	0.0003	0.729
$BFCL_{t-1}$	-14.943	5.395	0.0066	0.0416
DV_3	-13.726	1.438	<0.001	
DV_4	-16.576	1.711	<0.001	
R Square	0.9913			
DW	0.700			

Table 4. 3. Parameter Estimates of Broiler Production and Elasticities at Means, 1975 2002

Variable	Coefficients	Standard Error	P- Value	Elasticity
Intercept	-12171	9929.775	0.2236	
PHL_{t-1}	910.299	23.447	<0.0001	
$WPBL_{t-1}$	89376	34898	0.0122	0.078
DV_3	-5564.818	1923.476	0.0048	
DV_4	-11347	1921.440	<0.001	
R Square	0.98			
DW Test	0.833			
1^{st} order				
Autocorrelation	0.579			

Table 4. 4. Total Number of Broiler (Thousands) Using Physical, Structural, and ARIMA (1,1,1) Forecasts

Year	ARIMA	Econometric Model	Physical Model
1999	114,5397	116,0233	114,5397
2000	118,2587	117,9836	115,4560
2001	123,4102	121,0903	116,3796
2002	127,6794	124,2490	117,3107
2003	132,0202	127,4531	118,2491
2004	136,4484	130,7030	119,1951
2005	140,9646	133,9991	120,1487
2006	145,5692	137,3436	121,1099
2007	150,2624	140,7376	1220,788

Table 4. 5. Total Water Demand in Thousands Gallons Per Day by Broiler Production Using Physical, Structural, and ARIMA (1, 1, 1) Forecasts

Year	ARIMA	Econometric Model	Physical Model
1999	57,350.03	58,092.8663	57,350.03
2000	59,212.13	59,074.3885	57,808.83
2001	61,791.49	60,629.9132	58,271.3
2002	63,929.08	62,211.4743	58,737.47
2003	66,102.51	63,815.7672	59,207.37
2004	68,319.71	65,442.9921	59,681.03
2005	70,580.98	67,093.3494	60,158.48
2006	72,886.5	68,767.9405	60,639.74
2007	75,236.38	70,467.3163	61,124.86
1999	57,350.03	58,092.8663	57,350.03

CHAPTER FIVE

SWINE WATER DEMAND FORECASTING: AN ECONOMETRIC AND STRUCTURAL TIME SERIES ANALYSIS

Introduction

Efficient management and allocation of existing water resources have become highly critical aspect of water policy in the United States, due to the rapidly growing water demand and constant and/or decreasing supplies of water in the many parts of the United States. Seasonal and cyclical scarcity of water and increasing levels and variations in demand of water by different sectors of water users including animal agriculture further exacerbate the water scarcity problem leading to more scrutiny of the efficiency of water use in the United States (Frey, 1993). Recent changes in water management from a supply-oriented focus to a more demand-oriented focus also require more economic analysis and better management of existing allocation practices (Frey, 1993).

In spite of the urgent need to efficiently allocate the existing water, policy makers and water managers are often constrained by the lack of information about present and future water demand for different sectors of water use including animal agriculture. Animal agricultural, including swine, needs water for drinking and cleaning purposes. Even though small in relative water demand, more accurate information about future water demand for animal agriculture can play a crucial role, given the relatively fixed availability of water. Uncertainties related to future animal water demand arise mostly due to lack of information and the use of an existing US Geological Society (USGS) water model. The USGS model comprises only engineering features and considers only physical parameters, such as temperature and daylight hours, while forecasting future animal water demand. Future animal water demand directly depends on the supply of farm animal by farmers, which in turn relies on different economic and institutional variables. Therefore, a sound supply response model is needed to accurately forecast the number of animals, and thereby the amounts of future animal water demand.

Without knowing the number of present and future farm animals accurately, it is impossible to accurately predict the amounts of future animal water demand. Therefore, we have selected swine production of Georgia for future water demand modeling purposes. Although the production processes and biological constraints are different for different animal types, our model serves as a representative model for other animal types, if researchers incorporate the production stages of other animal types in a given model. In our analysis, first we develop a sound econometric swine supply model, capturing the information available from the biological features of swine production. The swine supply model is further analyzed by using a structural time series model (STSM). Information available from both econometric and STSM are then used to forecast the future number of hogs and pigs in Georgia. Later, future swine water demand is estimated by using the forecasted swine inventory and swine water use coefficients available from USGS.

Hog Supply Model

In 1959, Dean and Heady analyzed observed patterns in hog slaughtering and price in the USA. Since then, many researchers have developed numerous econometric models of hog supply response to capture the relationship between hog production and exogenous variables, such as prices of hogs, feed costs, and lagged response variables. The typical hog supply model comprises of a distributed lag specification and exogenous variables, such as current or lagged output and input prices (Shonkwiler and Spren, 1982). Most of these studies of hog supply response focus on the assessment of causal relationship and appropriate specification of lagged response variable within the US hog market. In most of the cases, economic theory and sample data were used as a priori information to specify the lag structure of hog supply model (Shonkwiler and Spren, 1982).

In spite of frequent use of these structural models to explain the hog supply behavior of farmers, a number of conceptual problems arise, mostly due to the unique biological features of swine production (Holt and Johnson, 1988). Swine production follows a sequence of production; for example the breeding herd represents the first stage of production. Gilt farrowing, pig corp, and market inventory (barrow and gilt harvested) comprise subsequent stages of production. The production decisions made at any particular stage effectively limit the potential adjustment in the subsequent stages of swine production. For example, fixed biological lags limit the ability of hog producers to instantaneously adjust the number of gilts farrowing, yet this is precisely the response built into many previous hog supply models. The result is that these models are overly responsive in the short run (Holt and Johnson, 1988).

Even though an appropriate lag specification while modeling animal supply response function is an empirical issue, a priori biological information of animal production offers benchmark information that can be used to define a lag structure and develop a dynamic model of animal production (Chavas and Johnson, 1982). Therefore, our study develops a dynamic swine supply model capturing the priori biological information of swine production. In this analysis, we consider swine production as a sequential process and place emphasis on identifying and incorporating appropriate biological lags in to the model specification.

Theoretical Model Development Our study considers a competitive firm where the production function can be decomposed into N production stages, as discussed above. Even though the different stages of production are biologically or functionally related to each other, we can decompose and analyze the swine production process into sequences of production phases separately. At each stage, the swine producer makes a decision about selected variables input and some form of capital is transformed into a different form of capital (Jarvis, 1974). Conceptually, we can represent this type of production function as (Chavas and Johnson, 1982):

$$Z_k = f_k(Z_{k-1,} X_k) \quad (1)$$

Where k = 1,2…n;

Z_k = Vector of capital stock at stage t

Z_{k-1} = Lagged vector of capital stock

X_k = Vector of variable inputs used in the t^{th} production stage

Here, vector of variable inputs X_k changes the capital Z_{k-1} in to different form of capital Z_k In the case of swine production, Z_1, Z_2, $Z_{3,}$ and Z_4 represent breeding herd, gilt farrowing, pig corp, and barrow or gilt harvested. A vector of variable inputs such as feeds, medicine, and other nutritional supplements, change swine production from one stage of production to another stage of production. In each stage, swine producers make an economic decision related to investment, and some form of capital is transformed. Considering Z_t as a scalar and capital stock as a single variable, we develop a profit function as:

$$A = PZ_n - \sum_{i=1}^{n-1} R_k X_k - R_0 Z_0 \tag{2}$$

P = output price

Z_n = final output

S = salvage value of the capital stock Z_k

R_k = price of the input X_k,

R_0 = purchase price of Z_0.

Considering the constraints of production technology (equation 1) and profit maximization (Equation 2),

$$A = PZ_n - \sum_{i=1}^{n-1} R_k X_k - R_0 Z_0 \quad \text{Subject to } Z_k = f_k(Z_{k-1}, X_k)$$

Now, our optimality condition as indicated by asterisk would be:

$$X_k^* = g_k(P, R_k, Z_{k-1}^*) \tag{3}$$

Where k= 1, ………..,n and

$$Z_k^* = f_k(Z_{k-1}^*, X_k^*) = h_k(Z_{k-1}^*, P, R_k) \tag{4}$$

Where k = 1,….,n, R_k = (r_k,…………….r_n) represents a vector of input prices.

Here, equation 4 shows economic decisions made at earlier stages define the optimality condition at each stage of swine production. Equation 4 represents a static optimality condition and introducing a time variable at each stage of production allows us to examine the dynamics of swine production system. However, in many cases, underlying production technology alters or strongly influences the time lag separating two successive stages of production. Suppose, if, after a delay of 'j' time periods, it takes ‘i’ time periods to transform the capital stock Z_{k-1} in to Z_k then equation 4 can be express as:

$$Z_{kt} = f_k\,(Z_{k,t-j}, Zk_{, t-j-1},\ldots\ldots,Z_{k,t-j-I}, P_t, R_{kt},) \qquad (5)$$

Where P and R, respectively show the output price and input prices expected by the decision maker at time t. Generally, the time lag between two stages in equation 5 is mostly defined by the underlying production technology. However, there are instances in swine production process when production or economic decisions made by integrators influence or change the lag between two successive stages.

The US Hog Industry and Biology of Production

The US hog industry represents a rapidly changing and highly specialized agricultural industry. This industry has undergone drastic structural changes in the last decade, especially with respect to technological innovations and practices of economy of size. Presently, there exist three types of specialized hog operations in USA. A farrow-to-finish operation is the most prevalent hog operation in US, where hogs are raised from birth to harvested weight about 250 to 270 pounds. In farrow-to-feeder-pig operation, producers raise pigs from birth to about 20 to 60 pounds, and then sell to finishers for the finishing operation. In feeder pig-to-finish operation, producers (finishers) buy pigs from feeder pig producers and grow pigs up to marketable weight. Farrow-to-finish operation is still the most common hog production practice in Georgia, so our study considers farrow-to-finish operation while modeling the hog supply response.

In general, a hog production system comprises of breeding herd, gilt farrowing, pig corp, and barrow or gilt harvested. The breeding herd consists of sows, gilts, and boars. Gilts and boars are female and male hogs, respectively that can be keep for breeding purposes or can be sold for slaughter. Increase or decrease of culling rate of gilts controls the size of breeding herd or gilt farrowing. One apparent biological lag then would be the size of breeding herd that places a physical limit on the number of sows that can be slaughtered (Holt and Johnson, 1988).

The primary function of the breeding herd is to produce pigs. Therefore, the size of the breeding herd places a physical limit on the number of gilt farrowing. A gilt can produce an average of a little more than 2 litters per year, each consisting of an average of nearly 9 pigs. Following a 114-day gestation period, an average of 176 days is required to grow a pig to a harvested weight in farrow-to-finish operation. Typically 210 to 240 days are required to grow a gilt or young female (McBride and Key, 2003). The above biological features imply a six month lag between farrowing and slaughter, showing that a pig born in the beginning of the previous quarter could be marketed at the end of current quarter. However, current marketable barrow and gilt are largely consist of pigs born two or even three quarter periods ago.

Our study uses the above information to specify the technical relationship between barrow and gilt harvested and lagged level of pig corp. Throughout the hog production process, hog producers adjust the culling rate of sows and gilt retention in response to changing economic variables such as price expectations, feed costs etc. Our dynamic hog supply response equation models all economic variables and information available from the biological production features of hog production.

A Representative Swine Production Model

In this study, the specifications for the equations are developed primarily with the references to the studies of Jensen et al. (1989), Chavas and Johnson (1982), and Holt and Johnson (1990). Our quarterly econometric supply model incorporates the biological and technological relationship as prior information of model development.

A representative swine production comprises:

Breeding Herd Inventory (BH)

$$BH_t = b_0 + b_1 PBH_{t-i} + b_2 HP_{t-i} + b_3 CP_{t-i} + b_4 T_{67} + b_5 DV_2 + b_6 DV_3 + b_7 DV_4 + e_t \quad (6)$$

where

β_0 = the intercept of the equation;

BH_t = the breeding herd inventory in current quarter in thousands in Georgia;

BH_{t-i} = the breeding herd inventory in lagged i^{th} (I = 0,1,2,3,4) quarters in thousands in Georgia;

HP_{t-i} = the seven-market average price of barrows and gilts in lagged i^{th} (I =0, 1,2,3,4) quarters, deflated by CPI (1982-84= 100) in cents per pound;

CP_{t-i} = the average corn price received by farmers in lagged i^{th} (I = 0,1,2,3,4) quarters deflated by CPI (1982-84= 100) in dollars per ton;

T_{67} = the time trend variable; year 1967 =1;

DV_2, DV_3, DV_4 = the quarterly seasonal dummy variables (binary or 0-1) in quarters 2,3, and 4, respectively;

e_t = the stochastic error term.

Gilt Farrowing (SF)

$$SF_t = b_0 + b_1 PBH_{t-i} + b_2 HP_{t-i} + b_3 CP_{t-1} + b_4 T_{67} + b_5 DV_2 + b_6 DV_3 + b_7 DV_4 + e_t \quad (7)$$

β_0 = the intercept of the equation or constant;

SF_t = the gilt farrowing in Georgia in current quarter in thousands;

PBH_{t-i} = the predicted breeding herd in lagged i^{th} (I = 0,1,2,3,4) quarters in thousands in Georgia;

HP_{t-i} = the seven-market average price of barrows and gilts in lagged i^{th} (I = 1,2,3,4) quarters, deflated by CPI (1982-84= 100) in cents per pound;

CP_{t-i} = Average corn price received by farmers in lagged i^{th} (I = 0,1,2,3,4) quarters deflated by CPI (1982-84= 100) in dollar per ton;

T_{67} = the time trend variable; year 1967 =1;

DV_2, DV_3, DV_4 = the quarterly seasonal dummy variables (binary or 0-1) in quarters 2,3, and 4, respectively;

e_t = the stochastic error term.

Pig Crop (PC)

$$PC_t = b_0 + b_1 PBH + b_2 PBH * DV_i + b_3 PBH * T + b_4 PBH * T * DV_i + b_5 T_{67} + b_6 DV_2 + b_7 DV_3 + b_8 DV_4 + e_t \quad (8)$$

β_0 = the intercept of the equation or constant;

PC_t = the pig corps in Georgia in current quarter in thousands;

PBH = the predicted breeding herd in present quarter in thousands in Georgia;

T_{67} = the time trend variable; year 1967 =1;

DV_i = the quarterly seasonal dummy variables (i=1,2,3);

$DV_{2,}$ $DV_{3,}$ DV_4 = the quarterly seasonal dummy variables (binary or 0-1) in quarters 2,3, and 4, respectively;

e_t = the stochastic error term.

Barrow and Gilt harvested (BGS)

$$BGS_t = b_0 + b_1 PPC_{t-i} + b_2 T_{67} + b_3 DV_2 + b_4 DV_3 + b_5 DV_4 + e_t \qquad (9)$$

β_0 = the intercept of the equation or constant;

BGS_t = the gilt harvested in Georgia in current quarter in thousands;

PPC_{t-i} = the predicted pig corps in lagged i^{th} (I = 1,2,3,4) quarters in thousands in Georgia;

T_{67} = the time trend variable; year 1967 =1;

$DV_{2,}$ $DV_{3,}$ DV_4 = the quarterly seasonal dummy variables (binary or 0-1) in quarters 2,3, and 4, respectively; e_t = the stochastic error term.

Data

To carry out the objectives of the study, quarterly data (1974-1999) of breeding herd, gilt farrowing, pig corp, and market inventory (barrow and gilt harvested) of Georgia were collected from National Agricultural Statistics Services (NASS) of United States Department of Agriculture (USDA) and Georgia Agricultural Facts. Since 1999, USDA does not maintain the swine quarterly data of Georgia. Therefore, ARIMA time series technique was used to forecast quarterly time series data from 1999-2002. Information about the seven-market average price of barrow and gilts and average corn price received by farmers were collected from the Economic Research Service (ERS) of United State Department of Agriculture (USDA) publications. Corn comprises the major portion of swine feed; therefore, corn price was considered as a proxy variable for feed cost. The seven-market average price of barrow and gilts and average corn price were deflated by using consumer price index (All Urban Consumer, US city average 1982-84=100).

Realizing the nature of underlying technology of swine production, we consider a quarterly observation while analyzing swine supply function. In our analysis, lagged observed output price of barrow and gilts is considered as an expected price for output. Although such expectations are in general not rational, they do reflect most of the information available to decision makers (Muth, 1961). In our model, dummy variables for second, third, and fourth quarters capture the effects of seasonality and a trend variable is used to model the impacts of technological progress in swine industry in recent years. Future feed costs and output prices were estimated by using a Box-Jenkins (ARIMA) specification. Water use coefficients for swine were collected from the USGS.

Results and Discussion

A problem of autocorrelation commonly arises in the autoregressive model, where one or more lagged values of the dependent variables serve as explanatory variables. The problem of autocorrelation also arises because of the use of quarterly time series data. In the presence of autocorrelation, the ordinary least squares (OLS) yield biased and inconsistent results, leading to incorrect statistical test results and false inferences. In order to overcome the problem of auto-correlated errors and lagged endogenous variables, we used the techniques of instrumental variables and autoreg procedure available in SAS. Only statistically significant variables at 90 percent confidence level are presented and discussed in Tables 5.1, 5.2, 5.3, and 5.4.

Breeding herd is (BH_t) is the first stage of swine production. In our analysis, the F statistics and P values (0.001) clearly reject the null hypothesis that all parameters except the intercept are zero for breeding herd. The estimated model explains historical inventory behaviors of breeding herds well with adjusted R^2 of 0.95 (Table 5.1). Inventory level lagged two quarters reflects dynamic adjustment in hog supply. In the breeding herd equation, the estimated coefficients of lagged breeding herd variables (BH_{t-1} and BH_{t-2}) and lagged hog price (HP_{t-3}) show positive and statistically significant results. The results are consistent with the findings of Holt and Johnson (1988). Analysis shows that an increase of hog price by 1 percent increased the hog supply by 11.29%. Study results also reveal the inverse relationship between corn price and breeding herd inventory. In our analysis, the lagged corn price variables (CP_{t-2} and CP_{t-4}) were significant. Also, the significant and positive impacts of seasonal variable on breeding herd inventory are shown. Analysis of residual plotting and a Darwin Watson test show no problem of heteroscedasticity and autocorrelation at this stage.

Gilt farrowing represents the second phase of hog production. In this phase of swine production, producers adjust the breeding stock and liquidation schedules as per the changes in profit conditions or expectation in profit conditions. The breeding herd inventory available at the beginning of the quarter, $BH_{t-1,}$ represents the available stock of gilts for slaughter. Generally, 13% of gilts in the breeding herd are slaughtered and the rest are kept for farrowing purposes (Holt and Johnson, 1988). In our analysis of gilt farrowing (Table 5.2), the economic variables show the changing expectations about the profitability of the hog production and estimated coefficients for hog price and corn price yield hypothesized signs. Furthermore, the coefficient of lagged hog price (HP_{t-3}), lagged corn prices (CP_{t-2}, CP_{t-4}), and breeding herd variables (BH_{t-1}, BH_{t-2}) were significant at 90 percent level. The estimated elasticities of hog price and corn price indicate that sow farrowing is responsive to economic variables. Further diagnostic tests using residual plotting and heteroscedasticity test confirm the best fit of model.

Equation of pig crop (equation 7) represents a technical relationship hypothesizing pig crop directly proportional to the level of breeding herd. The pig crop model also aims to capture the changing relationship between breeding herd inventory and pig crops. The specification of the equation 7 allows the relationship between pig crop and breeding herd inventory to change seasonally as well as over time. The study results show the statistically significant role of breeding herd, trend, and seasonal variables in pig crop production. The resulting parameter estimates of the pig crop equation confirm the hog production pattern.

Generally five to six months are required for a pig crop to grow to a marketable weight. Therefore, pig crop lagged one, two, and three are included as the major explanatory variables for barrow and gilt harvested equation. Once the pig is born, little adjustments can be made, even if the economic variables are changed. Therefore, economic variables like corn price and hog price do not have much influence in the barrow and gilt harvested (Holt and Johnson, 1988). In our analysis of barrow and gilt harvested, the coefficients on the lag distribution were and trend variable yield expected sign and were statistically significant. Further chi-square test does not show the problem of heteroscedasticity in the model.

Structural Time Series Analysis of Swine Supply and Swine Water Demand Forecasting

Animal supply response has traditionally been modeled as a function of feed cost, market price of animal, interest rate, institutional variables, and lagged dependent variables. Despite economic and institutional variables, unobservable factors, such as technological improvements, seasonal dummies, demographic features, and other exogenous variables, also affect animal supply responses. In the animal supply response literature, impacts of these unobservable variables were either ignored or modeled by a simple linear deterministic time variable which assumes fixed underlying trend effect overtime (Kapombe and Colyer, 1998). In most cases, the trend variable was used to capture the underlying technological improvements in the animal production sector.

In a similar way, potential impacts of non-stationary seasonal data have been ignored. Animal supply response models, which use quarterly time series data, have traditionally incorporated deterministic seasonal dummy variables to account for the underlying seasonal effects. Deterministic seasonal dummies implicitly assume fixed effects of seasonal variables through out the period. However, assuming deterministic seasonality and trend as a priori when it is actually stochastic might yield a misspecified model and false inferences. To fully understand the animal supply response, and more importantly, to predict future animal supply and future animal water demand, it is critical that animal supply be modeled appropriately. Therefore, a preferable approach would be to test a model having stochastic trend and seasonal variables as an alternative model to the existing models having deterministic trend and seasonal components.

In this section, the swine supply model was further analyzed by developing a structural time series model especially to accommodate the unobservable underlying trend in a more general way. Similarly, stochastic seasonal dummies are incorporated in the place of conventional seasonal dummies hence allowing the seasonal pattern to evolve over time. So far, no researchers have examined the impacts of stochastic trend and seasonal variables in their analysis of swine supply response. Therefore, this study significantly departs from the supply response analysis of other researchers.

Rationale

US hog industry has undergone a rapid structural change in the last decade, making it increasingly concentrated among fewer and larger farms and becoming more economically efficient. Despite the drastic change in the number of hog farms, the hog inventory remained relatively constant averaging about 56 to 63 million heads in USA. However between 1994 and 1999, the numbers of the hog farms decreased by more than 50 percent from 200,000 to fewer than 100,000, and fell to just 80,000 in 2001 (McBride and Key, 2003).

Economic of size and innovational profits remain the major factors of structural change in the hog industry. Innovational profit mostly arises from technological progress in the areas of nutrition, health, breeding and genetics, reproductive management, housing, and environmental management (Rhodes, 1995). In addition to the rapid growth in the size of US hog operation, changes in the traditional approach of farrow-to-finish production (where gestation, farrowing, nursery, and growing-finishing phases of production are performed in one operation) to a new, coordinated hog production approach, where large integrators contract out production with many growers, resulted in to major organizational change in hog production.

Technological innovation in hog production covers improved genetics, housing and handling equipments, veterinary and medical services, and management that improve the performance of hogs and the efficiency of operation, and/or reduces production risk. Increased gilt farrowing by 50%, average litter size by 22%, and feed efficiency by 20% between 1992-1998 demonstrate the technological progress in the hog production sector (USDA, 1999).

While analyzing hog supply responses, the ideal condition would be to include all variables of technological innovations. However, it is not feasible to measure the impacts of all these variables separately using different proxies. Hence past studies of swine supply response either ignored the impacts of all these variables completely and/or implicitly included all factors as a part of a technological progress variable. A deterministic, mostly linear, proxy trend variable was developed to capture the impacts of organizational, management, and technical progress in the swine industry.

In particular, whether it is appropriate to model such progress using a simple linear variable is an empirical issue. The issue is critical as sources of technological progress can take many functional forms (not necessarily linear). It can be embodied, disembodied, endogenous, and endogenous, and hence unlikely to be modeled adequately by a simple linear deterministic time trend (Hunt and Ninomiya, 2003). Therefore, in our study, Harvey (1997)'s structural time series model (STSM) with exogenous variables was used to further analyze the swine supply response mode,l especially by allowing stochastic trend and seasonality variables to vary over time.

Structural Time Series Model

The STSM allows for the unobservable trend and seasonal components to change stochastically over time (Harvey, 1997). The STSM models are generally developed directly in terms of components of interest, trend, seasonal, cyclical and residual or irregular components (Kapombe and Colyer, 1998). In an STSM model, the exogenous variables enter into the model side by side with the unobserved components. STSM models revert to a standard regression model in the absence of unobservable components (Harvey and Scott,1994).

Consider the following STSM quarterly swine supply model

$$QS_t = \mu_t + ?_t + Z'_t\, d + e_t \qquad (8)$$

where

QS_t = Quarterly hog supply;

μ_t = the trend component;

$?_t$ = the seasonal component;

Z'_t = a vector of explanatory variables (hog price, feed cost);

d = k*1 Vector of unknown parameters; and

e_t = Random white noise disturbance ternm.

The trend components e_t are assumed to have the following stochastic process

$$\mu_t = \mu_{t-1} + ß_{t-1} + ?_t \qquad (9)$$

$$ß_t = ß_{t-1} + ?_t \qquad (10)$$

where $?_t \sim NID\ (0, s_?^2)$ and $?_t \sim NID\ (0, s_t^2)$

Equations (9) and (10) represent the level and the slope of the trend, respectively. A stochastic trend variable (μ_t) is incorporated into the hog supply model to capture the technological progress and structural change in the industry in recent years. The exact form of the trend depends upon whether the variances, $s_?^2$ and s_t^2, also known as the hyper parameters, are zero or not. If either $s_?^2$ and $s_{t,}^2$ are non-zero then the trend is said to be stochastic. If both are zero, then the trend is linear and the model reverts to a deterministic linear trend model as follows;

$$QS_t = a + ?_t + ß_t + Z'_t d + e_t \tag{11}$$

A stochastic seasonal component ($?_t$) is included in the hog supply model to capture the effect of weather and other seasonal factors in the hog supply function. It is especially critical, as the seasonal impacts are gradually diminishing in swine production because of rapid adoption of confined type of hog production in Georgia. Accordingly, equation (8), the seasonal components ($?_t$) follows the following stochastic process:

$$S(L)\ ?_t = ?_t \tag{12}$$

Where $?_t \sim$ NID (0, $s_?^2$), S(L) = 1 + L + L^2 + L^3 and L = lag operator. If $s_?^2 = 0$ the model becomes a deterministic seasonal dummy variable model. If not, seasonal components are moving stochastically over time.

Results and Discussion of STSM Modeling

Following the analysis of the econometric model, we have further analyzed the swine supply response model using STSM techniques. As STSM assumes stochastic trend and seasonal variables, we removed trend and seasonal variables from the following equations, keeping other variables unchanged during STSM analysis.

Breeding Herd Inventory (BH)

$$BH_t = b_0 + b_1 BH_{t-i} + b_2 HP_{t-i} + b_3 CP_{t-i} + b_4 T_{67} + b_5 DV_2 + b_6 DV_3 + b_7 DV_4 + e_t$$

Gilt Farrowing (SF)

$$SF_t = b_0 + b_1 PBH_{t-i} + b_2 HP_{t-i} + b_3 CP_{t-i} + b_4 T_{67} + b_5 DV_2 + b_6 DV_3 + b_7 DV_4 + e_t$$

Pig Crop (PC)

$$PC_t = b_0 + b_1 PBH + b_2 PBH * DV_i + b_3 PBH * T + b_4 PBH * T * DV_i + b_5 T_{67} + b_6 DV_2 + b_7 DV_3 + b_8 DV_4 + e_t$$

Barrow and Gilt harvested (BGS)

$$BGS_t = b_0 + b_1 PPC_{t-i} + b_2 T_{67} + b_3 DV_2 + b_4 DV_3 + b_5 DV_4 + e_t$$

Structural Time Series Analyzer, Modeller, and Predictor (STAMP) 6.0 version was used for the analysis purposes. STAMP allows formulating STSM directly, in terms of components of interest, offering many options necessary for interactive structural time series modeling. STAMP uses the Kalman filter and related algorithm to fit the unobserved components of time series models (Koopman et al. 1995). Inclusion of the explanatory variable in the structural time series model results in the mixing of time series and regression model (Harvey and Scott, 1994). A structural time series model converges in to a standard regression equation, if the variances of hyper parameters (trend, level = s_n^2 and slope = $s_?^2$ and seasonal = s_w^2) are zero. However, presence of an unobserved stochastic component with explanatory variables offers possibility of alternative dynamic models.

Stationary, Trend, and Seasonality

Specification of the swine supply response model assumes stationarity in mean and variance for sound statistical inferences from a single realization of a random process (X_t). However, plotting of all time series data of breeding herd inventory, gilt farrowing, pig crops, and Barrow and Gilt harvested evidently exhibit non-stationary patterns in both mean and variance (Figure 5.1). Therefore, all data were transformed by using the best Box-Cox lambda value and first difference technique to obtain a time invariance probability distribution of the process (X_t). Let E denote the expectation of a random process. The mean, variance, and covariance of the process are defined as follows:

mean: $\mu(t) = E X_t$,

variance: $\sigma^2(t) = Var(X_t) = E(X_t - \mu(t))^2$, and

covariance: $\gamma(s, r) = Cov(X_s, X_r) = E(X_s - \mu(s))(X_r - \mu(r))$

the relative variance ratios (Q) for trend (s_n^2/ s_e^2), level ($s_?^2$/ s_e^2), and season (s_w^2/ s_e^2). The relative variance ratio 'Q' shows the level of stochastic movement of trend, seasonal, and irregular components in the model (Koopman et al., 1994). The zero 'Q' value shows the deterministic component and levels of stochastic behavior of components increase with the increase of Q ratio. If both trend and seasonal components become zero, the model is converges to standard regression model with fix trend and seasonal effects.

Results obtained from the analysis of the relative variance ratio (Q) for breeding herd, gilt farrowing, pig crop, and barrow and gilt harvested are presented in Table 5.5. The relative variance ratio ranges 'Q' from 0.34 to 1 for level component, 0.0023 to 0.0188 for trend component and 0.002 to 0.1290 for seasonal component. The level of relative variance ratio is different for the different phases of swine production. The results clearly show that none of seasonal and trend components are fixed in hog production. There exist changing seasonal and time patterns in swine production. The results, therefore, suggest incorporating trend and seasonal components as stochastic variables while developing hog supply response model. This inference clearly contrasts with the conventional econometric model, which assumes trend and seasons and fixed variables.

Structural Time Series Analysis with Explanatory variables

After confirming the presence of the stochastic nature of trend and seasonal variables, we further analyze the swine supply model by using STSM with explanatory variables and incorporating seasonal and trend variables as stochastic components (Koopman et al., 1990). The results of estimating swine supply response structural time series model with explanatory variables and hyper parameters are given in Table 5.6, Table 5.7, Table 5.8, and Table 5.9 for breeding herd, gilt farrowing, pig corps, and barrow and gilt harvested respectively.

Structural time series analysis of breeding herd shows a strong convergence reflecting successful maximum likelihood estimation by the numerical optimization procedure of STAMP. The test of Box-Ljung Q statistics, a test for residual serial correlation against chi-square, was 0.2449. The chi-square test shows the no problem of serial correlation in the model. In the breeding herd equation, the estimated coefficients of lagged breeding herd variables (BH_{t-1}, BH_{t-2} and BH_{t-4}) and lagged hog price (HP_{t-3}) show positive and statistically significant results. The results are somewhat consistent with the findings of earlier analysis of breeding herd equation in the econometric model. Analysis of residual plotting and Darbin Watson test further show the best fit of model.

In our analysis of gilt farrowing using STSM time model (Table 5.7), hog price, a variable of expectation about the profitability of the hog production, yields statistically significant result and hypothesized sign. The study results failed to demonstrate a significant impact of feed cost in hog production in Georgia, a result inconsistent with the findings of other researchers. In our analysis, coefficients of lagged breeding herd (BH_{t-1}, BH_{t-3}) were statistically at 90 percent level and positive. Further, chi-square value of 0.1626, a value obtained by using Box-Ljung Q statistics against chi-square, show no problem of heteroscedasticity and serial correlation, respectively, confirming the best fit of model.

STSM assumes stochastic time and seasonal components. Therefore, we remove the cross term variables which were used in econometric analysis to capture the relationship of pig crops with seasons and time. The equation of pig crop thus represents a technical relationship hypothesizing pig crop directly proportional to the level of breeding herd. In our analysis, breeding herd inventory (BH_t) and legged breeding herd inventory (BH_{t-1} and BH_{t-3}) show statistically significant and positive impacts on pig crops inventory. This finding was inconsistent with the finding of Holt and Johnson, 1988. Further analysis using the test of Box-Ljung Q statistics against the chi-square test shows the no serial correlation problem in the model.

Immediately after the birth of pig crops, swine producers cannot make a major production decision even if the economic variables like hog price or feed cost change. Pig crops reach to marketable weight in 5-6 months. Therefore, inventory of final barrow and gilt harvested directly depends on pig crop on present and previous quarters. Barrow and gilt harvested inventory was thus modeled as a function of pig crops in the present and lagged quarters. In our analysis, lagged pig crops inventory (PC_{t-1}, PC_{t-2}, and PC_{t-3}) yield positive and statistically significant results. The fitness of model was examined using residual plotting and Box-Ljung Q statistics against the chi-square distribution. Results show no problem of heteroscedasticity or serial correlation. Since the estimate procedure converged and the diagnosis appears satisfactory, we can be reasonably confident that we have estimated a consistent model.

Swine Supply Forecasting

Analysis of both econometric and STSM yield expected signs, goodness of fit statistics, and magnitudes of estimated coefficients. The residual analysis and other diagnostic tests also show the validity of the both econometric and STSM models. However, in order to compare the robustness of models and assess the structural integrity of econometric and STSM models, we have examined the in-sample and out-of-sample forecasting accuracy of the models. Exogenous variables necessary to forecast the out-of-sample value for econometric models were obtained by using ARIMA model. We chose 2000-2002 as in-sample and 2003-2005 as out-of-sample forecasting period. The forecasting accuracy of the econometric and STSM were evaluated by comparing the forecasted values with true values of the corresponding endogenous variables.

The measures of root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE) were used to compare the robustness of econometric and STSM models. RMSE is the square root of the average of the set of squared differences between real and forecasted or predicted values, while mean absolute percentage error (MAPE) represents the average value of the absolute values of errors express in percentage terms. These were calculated as:

$$\text{RMSPE}=\{\frac{1}{T}\sum_{t=1}^{T}\left[\frac{Y_t^p - Y_t^q}{Y_t^a}\right]^2\}^{1/2} \text{ and MAPE}=\{\frac{1}{T}\sum_{t=1}^{T}\left[\frac{Y_t^p - Y_t^q}{Y_t^a}\right]^2\}$$

Where T = the number of forecasts

Y_t^P = the predicted value of Y, and

Y_t^a = the corresponding actual value.

Both RMSPE and MAPE measure the absolute mean prediction error of an endogenous variable. The use of percentage measures facilitate comparison among the in-sample, econometric forecast, and time series forecasting values.

Table 5.10 and Table 5.11 report RMSPE and MAPE values of real in-sample data, econometric forecast, and structural time series forecasts for all phases of swine production. As expected, in both cases RMSPE ad MAPE in-sample values were smaller than corresponding values obtained from the econometric and structural time series forecasts. However, in all equations of gilt production, such as breeding herd, gilt farrowing, pig crops, and barrow and gilt harvested, RMSPE and MAPE values of structural time series forecasts were smaller than corresponding RMSPE and MAPE values of econometric forecasts, confirming robustness of structural time series model over econometric model. The RMSPE and MAPE value clearly shows that structural time series model performed superior to the econometric model in forecasting the number of swine and thereby swine water demand.

Swine Water Demand Forecasting

The Alabama-Coosa-Tallapoosa (ACT) and Apalachicola-Chattahoochee-Flint (ACF) river basin study conducted by USDA Natural Resource Conservation Service in 1995 forecasts swine water demand for selected counties of Georgia. ACT/ACF study is considered as the most in-depth and detailed water use study of the region. The ACT/ACF study offers aggregate data and benchmark information for the selected counties of Georgia. However, it carries many flaws by not adopting scientific modeling approaches and econometric techniques to predict present and future water demand. The ACT/ACF study report states that "The current perception among experts is that swine number by the year 2050 will be similar to 1992 number." (Page 283, ACT/ACF study, 1995). In our study, we consider ACT/ACF study as base information of physical livestock water forecasting model.

In Georgia, the number of hogs and pigs has decreased gradually every year since 1992. Therefore, the above citation clearly shows the blemish of ACT/ACF study. Table 5.12 and Table 5.13 present in-sample and out-of-sample forecasting of total number of breeding herd and barrow and gilt harvested in Georgia using econometric and STSM analysis. The combined number of breeding herd and barrow and gilt harvested gives total hogs and pigs in Georgia (Table 5.14). Also present in Table 5.14 is total number of all hogs and swine based on ACT/ACF study. We use the number of total hogs and pigs available from the econometric and structural STSM analysis and water use coefficients available from USGS (2.5 gallons per hog per day) to forecast the amount of water demand for all hogs and pigs in Georgia up to year 2007. Table 5.14 presents the total hogs and pigs and total water demand by all hogs and pigs in Georgia for both econometric and STSM.

The analysis shows that, given the existing conditions remain unchanged, the number of total hogs and pigs will decrease further in Georgia. Econometric analysis shows that total demand of water will decrease from 992.5 thousands in 2003 gallons per day to 866.2 thousands gallons per day in 2006 for all hogs and pigs in Georgia. Similarly, results of STSM show that total demand water by in Georgia water would be

1087.5 thousands gallons per day in 2003 and 863.5 thousands gallon per day in 2006. However, physical model estimates the 1866.75 thousand gallons per day of water demand for any period from 1992 to 2050. Physical model overestimates water demand by nearly 94% in comparison to STSM. As both RMSPE and MAPE values of STSM were smaller than for the econometric model for all swine production equations, we recommend the use of STSM for forecasting of all hogs and pigs and thereby the swine water demand in Georgia.

Conclusions

In this study we adopt a systematic analytical approach based on the economic principle of supply response functions to forecast the number of total hogs and pigs in Georgia. Our study adopts a profit maximization framework given technology constraints for theoretical justification of the study. Swine supply modeling approaches focus on developing a dynamic econometric model capturing the biological features of swine production and a structural time series model assuming stochastic seasonal dummies and time components. In our analysis, all economic variables yield expected signs and demonstrate statistically significant results. RSMPE and MAPE values show the robustness of STSM over econometric model, reflecting the importance of incorporating stochastic seasonal and trend components while forecasting the number of all hogs and pigs and thereby future water demand. In our analysis, physical model overestimates swine water demand by nearly 94% by assuming no change in swine inventory from 1992 to 2050.

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Table 5. 1. Parameter Estimates of Breeding Herd and Elasticities at Mean, 1974-1999

Variables	Coefficients	Standard Errors	P-Value	Elasticity
Intercept	21.283	54.998	0.699	
BH_{t-1}	0.320	0.100	0.001	
BH_{t-2}	0.457	0.103	0.001	
CP_{t-2}	-6522	2817	0.022	-94.351
CP_{t-4}	-2757	1272	0.032	-39.782
HP_{t-3}	389.591	203.057	0.058	11.297
D_1	-9.503	5.087	0.064	
R^2	0.964			
Adjusted R^2	0.954			
DW	2.072			

Table 5. 2. Parameter Estimates of Gilt Farrowing and Elasticities at Mean, 1974-1999

Variables	Coefficients	SE	P-Value	Elasticity
Intercept	8.290	1.246	0.001	
HP_{t-3}	11.286	3.237	0.007	8.701
CP_{t-2}	-75.786	20.473	0.003	-3.008
CP_{t-4}	-78.758	21.995	0.005	-3.118
T	0.030	0.007	0.001	
BH_{t-1}	0.013	0.002	0.001	
BH_{t-2}	0.009	0.003	0.017	
D_2	0.305	0.113	0.023	
R^2	0.956			
Adj R^2	0.963			
Pr > Chi-Square*	0.103			

*Chi-square test for heteroscedasticity

Table 5. 3. Parameter Estimates of Pig Crop and Elasticities at Means, 1974-1999

Variables	Coefficients	SE	P-Value
Intercept	15.953	27.605	0.564
BH_t	0.626	0.199	0.002
BH_t*D_3	0.210	0.130	0.109
BH_t*T	0.013	0.002	0.001
BH_t*T* D_1	-0.010	0.003	0.012
D_1	69.757	39.638	1.761
R^2	0.947		
Adj R^2	0.942		
Pr > Chi-Square*	0.084		

*Chi-square test for heteroscedasticity

Table 5. 4. Parameter Estimates of Barrow and Gilt harvested and Elasticities at Means, 1974-1999

Variables	Coefficients	SE	P-Value
Intercept	6.279	0.130	0.001
PC_{t-1}	0.0008849	0.000331	0.008
PC_{t-2}	0.0008011	0.000384	0.039
T	0.006	0.008	0.039
R^2	0.906		
Adj R^2	0.900		
Pr > Chi-Square*	0.004		

*Chi-square test for heteroscedasticity

Table 5. 5. Estimated Relative Variance (Q) of Breeding Herd, Gilt Farrowing, Pig Crops, and Barrow and Gilt harvested

Variables	The Relative Ration (Q)
Breeding Herd	
Level	0.3400
Slope	0.0188
Seasonal	0.0002
Gilt Farrowing	
Level	1.0000
Slope	0.0012
Seasonal	0.0125
Pig Corps	
Level	1.0000
Slope	0.0023
Seasonal	0.0129
Barrow and Gilt Harvested	
Level	0.5550
Slope	0.0031
Seasonal	0.0009

Table 5. 6. Parameter Estimates of Breeding Herd, Using Structural Time Series Model, 1974-1999

Variables	Coefficients	RMSE	T-Value	P-Value
BH_{t-1}	0.172	0.013	1.647	0.096
BH_{t-2}	0.237	0.102	2.321	0.022
BH_{t-4}	0.213	0.100	2.116	0.036
HP_{t-3}	203.115	110.734	1.834	0.069
DW	2.041			
Q (9,7)*	9.11 2			
	(0.244)			
R^2_S	0.481			

*Box-Ljung Q test for residual serial correlation against chi-square distribution

Table 5. 7. Parameter Estimates of Gilt Farrowing, Using Structural Time Series Model, 1974-1999

Variables	Coefficients	RMSE	T-Value	P-Value
BH_{t}	0.177	0.027	6.415	0.000
BH_{t-1}	0.136	0.027	4.918	0.000
BH_{t-3}	1.708	0.027	1.708	0.090
HP_{t}	67.566	28.532	2.368	0.019
HP_{t-2}	66.210	1.701	1.701	0.015
DW	1.531			
Q (9,7)*	9.213			
	(0.162)			
RS^2	0.502			

*Box-Ljung Q test for residual serial correlation against chi-square distribution

Table 5. 8. Parameter Estimates of Pig Crops, Using Structural Time Series Model, 1974-1999

Variables	Coefficients	RMSE	T-Value	P-Value
BH_t	1.067	0.213	5.010	0.000
BH_{t-1}	1.008	0.215	4.674	0.000
BH_{t-3}	0.402	0.204	1.966	0.051
DW	1.374			
Q (9,7)*	10.290			
	(0.116)			
RS^2	0.493			

*Box-Ljung Q test for residual serial correlation against chi-square distribution

Table 5. 9. Parameter Estimates of Barrow and Gilt harvested Using Structural Time Series Model, 1974-1999

Variables	Coefficients	RMSE	T-Value	P-Value
PC_{t-1}	0.993	0.189	5.254	0.000
PC_{t-2}	0.838	0.213	3.918	0.000
PC_{t-3}	0.240	0.113	2.121	0.103
DW	2.123			
Q (9,7)*	10.893			
	(0.123)			
RS^2	0.481			

*Box-Ljung Q test for residual serial correlation against chi-square distribution

Table 5. 10. Root Mean Square Percentage Error (RMSPE) for the In-Sample Econometric Forecast and Time Series Forecast Values

Equations	In-sample Forecast	Econometrics Forecast	Time Series Forecast
Breeding Herd	0.125	0.144	0.134
Gilt Farrowing	0.030	0.057	0.038
Pig Crops	0.109	0.121	0.095
Barrow and Gilt Harvested	0.150	0.286	0.163

Table 5. 11. Mean Absolute Percentage Error (MAPE) for the In-Sample, Econometric Forecast and Time Series Forecast values

Equations	In-sample Forecast	Econometric Forecast	Time Series Forecast
Breeding Herd	0.0039	0.0728	0.0645
Gilt Farrowing	0.0456	0.0114	0.0048
Pig Crops	0.0640	0.0947	0.0048
Barrow and Gilt Harvested	0.0964	0.2671	0.2561

Table 5. 12. In-Sample Forecasting of Total Number of Breeding Herd (BH) and Barrow and Gilt Harvested (BSS) in Thousands Using Econometric and STSM (2000-2002), Georgia

Year	Breeding Herd			Barrow and Gilt Harvested		
	Actual	Econometric	STSM	Actual	Econometric	STSM
2000-1	60	59	57	420	417	425
2000-2	70	69	54	420	416	420
2000-3	70	68	61	440	423	405
2000-4	65	64	55	425	424	399
2001-1	66	68	56	420	427	410
2001-2	65	67	69	420	401	434
2001-3	64	61	70	415	384	442
2001-4	63	65	68	412	379	447
2002-1	54	57	59	323	384	434
2002-2	54	60	60	320	373	420
2002-3	53	67	62	318	329	393
2002-4	53	61	56	315	340	389

Table 5. 13. Quarterly Out-of-Sample Forecasts of Breeding Herd and Barrow and Gilt Harvested Using Econometric and Structural Time Series Model (2003-2006), Georgia (in thousands)

	Breeding Herd		Barrow and Gilt Harvested	
Year	Econometric	STSM	Econometric	STSM
2003-1	50	49	347	386
2003-2	48	48	362	366
2003-3	57	53	339	363
2003-4	53	48	344	360
2004-1	45	39	353	374
2004-2	43	44	341	367
2004-3	54	53	308	364
2004-4	50	49	316	361
2005-1	41	41	324	360
2005-2	41	45	326	340
2005-3	51	50	294	337
2005-4	47	46	302	334
2006-1	38	34	310	335
2006-2	37	39	312	317
2006-3	37	40	310	309
2006-4	34	38	308	302

Table 5. 14 Water Demand for All Hogs and Pigs Using Econometric, Structural Time Series Model, and Physical Model, 2003-2006 (thousands gallons per day)

Year	Econometric		Structural Time Series Model		Physical Model	
	All Hogs and Pigs	Water Demand	All Hogs and Pigs	Water Demand	All Hogs and Pigs	Water Demand
2003-1	397	992.5	435	1087.5	700	1750
2003-2	410	1025	414	1035	790	1975
2003-3	396	990	416	1040	770	1925
2003-4	397	992.5	408	1020	730	1825
2004-1	398	995	413	1032.5	700	1750
2004-2	384	960	411	1027.5	790	1975
2004-3	362	905	417	1042.5	770	1925
2004-4	366	915	410	1025	730	1825
2005-1	365	912.5	401	1002.5	700	1750
2005-2	367	917.5	385	962.5	790	1975
2005-3	345	862.5	387	967.5	770	1925
2005-4	349	872.5	380	950	730	1825
2006-1	348	870	369	922.5	700	1750
2006-2	349	872.5	356	890	790	1975
2006-3	347	867.5	349	872.5	770	1925
2006-4	342	855	340	850	730	1825

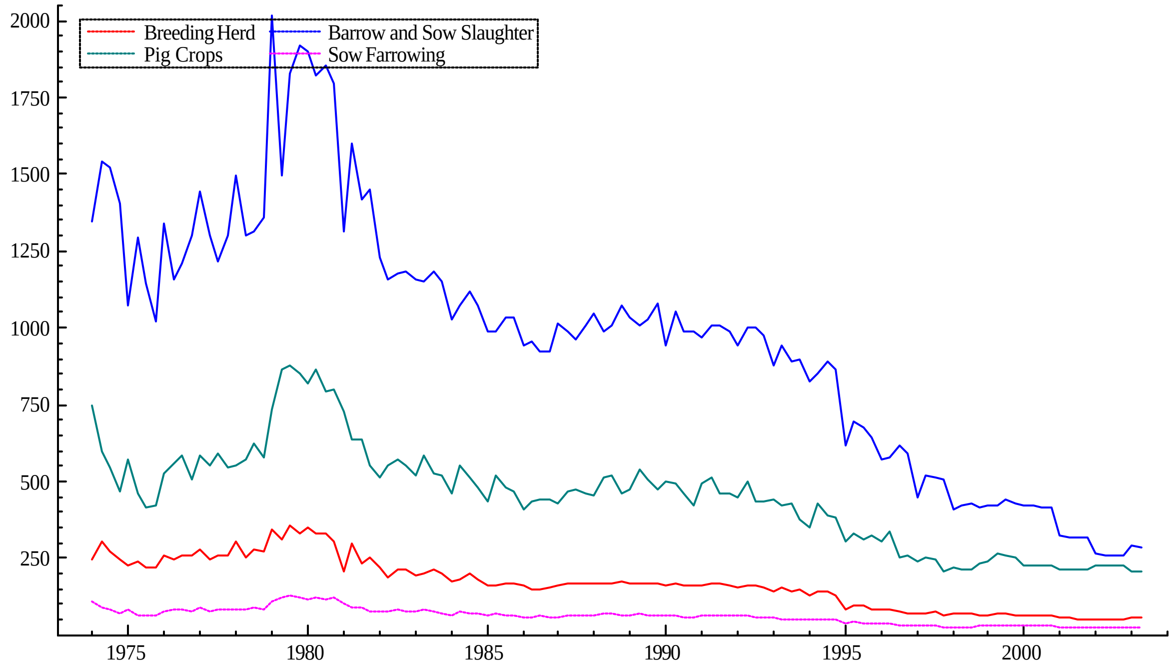

Figure 5. 1. Time Series Plotting of Breeding Herd Inventory, Gilt Farrowing, Pig Corps, and Barrow and Gilt Harvested, Georgia (1973-2002)

CHAPTER SIX

DAIRY CATTLE WATER DEMAND FORECASTING UNDER STOCHASTIC TREND AND SEASONALITY

Introduction

In the last few years, Georgia has suffered a severe water shortage. The causes of the crisis are both natural and man-made. The increase in water demand for domestic uses caused by population growth, rising standards of living, together with climate variations and droughts, resulted in an increasing water shortage in different sectors of Georgia. The growing population, expanding urban areas, and increasing competition among the different sectors of water use likely will increase the water scarcity problem in the coming years, making water a critical local issue which cannot be easily addressed. The water issue has become more critical since Georgia, Florida, and Alabama have failed to reach an agreement in their negotiations to achieve an equitable allocation of water for their shared river systems.

The lack of credible information about present and future water demand by different sectors of water use creates an obstacle for adequate action leading to efficient allocation of water. In many cases, the policy makers and water managers are constrained by the lack of accurate information about present and future trends of water use by different sectors of water use, including animal agriculture in their attempts to develop strategic management and planning of future water withdrawals and allocation. In the absence of this information, policy proposals, and decisions regarding water management are made under incomplete and potentially inaccurate information. Animal water use covers water used for livestock watering, feedlots, dairy operation, catfish farms, poultry, horses, cattle, and hogs. Though small in total demand in comparison to other sectors of water use, information about precise present and future water demand by livestock can contribute to efficiently managing limited water in the critical hour of allocation decision.

Given the dearth of past research and systematic records of water use data, it is very difficult to find accurate information about the present and future water use for animal agriculture. To data, the aggregate animal water use data published by the United States Geological Survey (USGS) and the ACT/ACF study report remain the main sources of animal water use information in the USA. However, the estimates of USGS and ACT/ACF water demand are based on a static physical model, in which future water demand is a function of temperature, daylight, and physiological conditions of animals, or based on expert opinion. The USGS and ACT/ACF water demand models carry the limitations of other physical models by failing to capture the livestock supply behavior of farmers, where by the number of livestock, and thus livestock water demand, varies with changes in economic and institutional variables. These shortcomings make the USGS and ACT/ACF model inappropriate for water demand forecasting purposes.

The accurate estimation of present and future animal water demand is only possible if researchers are able to precisely predict the present and future number of livestock by developing sound animal supply response models. Production of livestock is an economic decision, which is driven by variables such as expected profits, costs of inputs, and government policies. Therefore, our study first aims to develop a dairy cattle supply response model incorporating key economic variables. The information available from the analysis of dairy cattle supply response models and animal water use coefficients available from the USGS and ACT/ACF study will then be used to forecast the future animal water demand. Finally, a comparison between a selected dairy cattle supply model and ACT/ACF physical model will be made to evaluate the slippage in dairy cattle water demand forecasting between structural time series and physical models.

Dairy and Beef Cattle Supply Model

Many researchers have analyzed the supply response function of US dairy cattle industry. These studies differ in specific products, geographic areas, explanatory factors, modeling approaches, and method of analysis. The size and complexity of the market justify the different modeling approaches, research efforts, and diversity of analyses. The primary purposes of analyzing dairy cattle supply response include: forecasting future supplies, identifying the dynamic structure which best describes the observed aggregate data, and identifying the response to price levels (Foster, 1990). For example, Maki (1963), Kulshreshthan and Wilson (1972), Tyfos (974), Freebairn and Rausser (1975), Martin and Haack (1977), Arzac and Wilkinson (1979), Rucker et al. (1984), Sun (1994), and Kaiser et al. (1994) have analyzed the dairy and beef cattle supply response behaviors of farmers.

Traditionally, dairy and cattle supply responses have been modeled as a function of feed cost, market price of animal, interest rate, institutional variables, and lagged dependent variables. Some of the above studies have also incorporated trend and seasonal dummy variables to capture of the impacts of technological progress and seasonal variations on dairy supply. One of the severe limitations of above studies was to assume deterministic trend and seasonality components in the dairy supply model, implying that a model with a constant intercept, a time trend, and deterministic seasonal component is correctly specified. In this paper, we argue that assuming seasonality and trend as deterministic while it is actually stochastic might lead to a mis-specified model and false inferences.

A deterministic seasonality and trend may or may not be correct, but it should not be assumed *a priori* while developing a supply model for the dairy industry. Therefore, the main objective of our article is to develop a correctly specified dairy cattle supply response model, especially incorporating and testing seasonality and trend as stochastic components. We begin our study by selecting a basic dairy cattle supply model as proposed by Sun, 1994, and by Kaiser et al, 1994. The selected model was further extended by assuming different scenarios of fixed and stochastic seasonality and trend variables. To find a correctly specified model, four versions of dairy cattle supply response were hypothesized:

I. Deterministic trend and deterministic seasonality (DTDS),

II. Deterministic trend and stochastic seasonality (DTSS),

III. Stochastic trend and deterministic seasonality (STDS), and

IV. Stochastic trend and stochastic seasonality (STSS).

The structural time series model (STSM) proposed by Harvey (1989), offers the modeling tools for the methodological development in this study. STAMP 6.0 offers options to estimate the proposed versions of dairy cattle supply response models (Harvey, 1989).

Rationale

The US dairy industry has undergone a dramatic restructuring in the last 50 years. During the period from 1940 to 1997, the numbers of dairy farms decreased by 69 percent. From 1950 to 1975, the average number of milk cows on dairy farms declined by over 49 percent from almost 22 million to just over 11.1 million. The average number of milk cow further decreased by 18 percent from 1975 to 2000, making the dairy industry an increasingly concentrated livestock production system. In the meantime, the number of specialized dairy farms increased from 53 to 72 percent (Blayney, 2002).

However, there exists an opposite trend in the case of milk production. Almost 167.7 billion pounds of milk was produced in the US in 2000, 45 percent more than in 1975, and milk production per cow nearly doubled from 1950 to 1975 (95 percent greater), with an additional growth of 76 percent from 1975 to 2000 (Blayney, 2002). Changes in production systems and innovational profits remain the major factors of structural change in the dairy industry. Innovational profits mostly arise from technological advances in the areas of nutrition, health, breeding, and genetics (Blayney, 2002).

While analyzing dairy supply responses, the ideal condition would be to include all variables of technological progress. However, it is not possible to measure the impacts of all these variables separately using different proxies. Therefore, most studies of dairy supply response capture the ongoing technological improvements by using a deterministic trend variable, which basically assumes an unchanged rate of technological improvement throughout the sample period. We hypothesize that technological improvements evolve at changing rates over time and that assuming it to be a deterministic component misspecifies the dairy supply response model. Similarly, seasonal aspects of dairy farmers' decisions on culling and replacement of dairy cows might evolve over time. Therefore, we also suggest against assuming a deterministic seasonal component *a priori* while the developing dairy supply models.

Structural Time Series Model

First proposed by Harvey in 1989, the STSM allows the unobservable trend and seasonal components to change stochastically over time. The STSM is generally developed directly in terms of components of interest, such as trend, seasonal, cyclical, and residual or irregular components. The STSM relates to regression models in both technical formulation and model selection methodology. The Kalman filter, which is a simple statistical algorithm, and a state-space model play fundamental roles in analyzing structural time series models (Gonzalez and Moral, 1995). In STSM, the exogenous variables enter into the model along side with the unobserved components. Unlike traditional ARIMA models, STSM explicitly consists of unobserved stochastic trend and seasonality components. The STSM model reverts to a standard regression model in the absence of unobservable components (Harvey, 1989). Consider the following STSM quarterly dairy supply model:

$$DS_t = \mu_t + ?_t + Z'_t d + e_t \qquad (1)$$

Where,

DS_t = quarterly dairy supply

μ_t = the trend component

$?_t$ = the seasonal component

Z'_t = a vector of explanatory variables (milk feed price ratio, price of harvested cow, etc.)

d = k*1 vector of unknown parameters, and

e_t = random white noise disturbance term.

With deterministic trend and seasonality variables, the model coefficients of μ_t and $?_t$ in equation 1 are assumed to be constant. If these coefficients are statistically significant, the dairy supply response will be driven by deterministic trend and seasonality. However, this would be a highly restrictive assumption. Technical and genetic progress may lead to changes in the values of these coefficients over time. Changes in the values of μ_t and $?_t$ may take different forms, leading to either structural break or a smoothly changing stochastic trend. Therefore, there exist possibilities of mis-specification of the model and false inferences, if we incorporate the seasonality and trend as strictly deterministic components. The proposed STSM allows specifying a possible alternative of the above problem by incorporating a test for deterministic trend and seasonality against a stochastic trend and seasonality alternative. The stochastic trend, which represents the long term movement in the series, can be represented by

$$\mu_t = \mu_{t-1} + ß_{t-1} + ?_t \qquad (2)$$

$$ß_t = ß_{t-1} + ?_t \qquad (3)$$

Where $?_t \sim NID(0, s_?^2)$ and $?_t \sim NID(0, s_?^2)$

Equations (2) and (3) represent the level and the slope of the trend, respectively. Here, μ_{t-1} is a random walk with a drift factor, $ß_t$, which follows a first-order autoregressive process as represented by equation 3. A stochastic trend variable (μ_t) captures the technological progress and structural change in dairy and beef cattle industry in over time. The exact form of the trend depends upon whether the variances, $s_?^2$ and $s_?^2$ (also known as the hyper parameters) are zero or not. If either $s_?^2$ and $s_?^2$ are non-zero, then the trend is said to be stochastic. If both are zero, then the trend is linear and the model reverts to a deterministic linear trend model, as follows:

$$DS_t = a + ?_t + ß_t + Z'_t\, d + e_t \qquad (4)$$

A trigonometric specification was hypothesized to model the stochastic seasonality. This seasonal component, $?_{t,}$ was modeled in terms of sine-cosine waves at the seasonal frequencies, as suggested by Harvey, 1989:

$$?_t = \sum_{j=1}^{s/2} g_{jt}$$

$$\begin{bmatrix} g_{jt} \\ g^{*}_{jt} \end{bmatrix} = \begin{bmatrix} \cos l_j & \sin l_j \\ -\sin l_j & \cos l_j \end{bmatrix} \begin{bmatrix} g_{jt-1} \\ g^{*}_{jt-1} \end{bmatrix} + \begin{bmatrix} w_{jt} \\ w^{*}_{jt} \end{bmatrix}, \quad j = 1,\ldots\ldots\ldots.(s/2)-1 \qquad (5)$$

$?_{jt} = \cos ?_j\, ?_{j,\,t-1} + w_{jt},$

$j=s/2;$

where $?_j = 2p\, j/s_j = 1, 2, \ldots, s/2$, are the seasonal frequencies, w_{jt} and w^*_{jt} are normal errors with zero means and equal variance, $?^2_{w}$, and s is the number of seasons of the year. Seasonality changes slowly by means of a mechanism that guarantees that the sum of the seasonal factors over any s consecutive time periods has an expected value of zero and a variance that remains constant over time. The smaller the variance, the more stable the component (Gonzalez and Moral, 1995).

Economic Model Specification for Dairy Cattle Supply

Following Foster (1990), Rucker et al. (1984), Sun (1994), and Kaiser et al. (1994), the structural time series dairy supply response model is specified as:

$$DS_t = µ_t + ?_t + ß_1 DS_{t-1} + ß_2 DS_{t-2} + ß_3 DS_{t-3} + ß_4 MFPR_t + ß_5 DPSC_t + e_t \qquad (6)$$

where

DS_t = the dairy cattle inventory in current quarter in thousands in Georgia

μ_t = the trend component

$?_t$ = the seasonal components

DS_{t-1} = the dairy cattle inventory in previous quarter in thousands in Georgia

DS_{t-2} = the dairy cattle inventory in two lagged quarters in thousands in Georgia

DS_{t-3} = the dairy cattle inventory in three lagged quarters in thousands in Georgia

$MFPR_t$ = milk feed price ratio

$DPSC_t$ = price of harvested cow deflated by CPI (1982-84= 100) in cents per pound

e_t = Random white noise disturbance term

If $s_?^2 = s_?^2 = s_w^2 = 0$, equation 6 collapses to a standard regression model having a linear deterministic time trend and seasonal component and explanatory variables. Therefore, the STSM with explanatory variables in equation 6 is a generalization of the classical linear regression model.

Data

To carry out the objectives of the study, inventory data (1985-2002) of dairy cows in Georgia were collected from National Agricultural Statistics Services (NASS) of United States Department of Agriculture (USDA) and Georgia Agricultural Facts. Information about the milk feed price ratio, consumer price index, and price of cow harvested were collected from the Economic Research Service (ERS) of United State Department of Agriculture (USDA)'s publications. The price of cow harvested was deflated by consumer price index (all urban consumer, US city) average (1982-84=100). we consider quarterly observations. In this model, dummy variables for first, second and third quarters capture the effects of seasonality and a trend variable is used to model the impacts of technological progress in the dairy industry over the time period.

Results and Discussion

First, the variance-covariance matrices of each time series component, $O_?$ for the levels of the trends, O_s for the slopes of trend, O_d for seasonal dummies, and O_e for the random components, were estimated. The assumptions of DTDS, DTSS, STDS, and STSS were obtained by imposing restriction of variance-covariance matrices as:

DTDS iff ($O_?$ = 0, O_s =0, O_d = 0),

STDS iff ($O_?$? 0, O_s ? 0, O_d = 0),

DTSS iff ($O_?$ = 0, O_s = 0, O_d ? 0), and

STSS iff ($O_?$? 0, O_s ? 0, O_d ? 0)

Structural Time Series Analyzer, Modeller, and Predictor (STAMP) version as suggested by Harvey 1989 was used for the analysis purposes. STAMP allows options to run different versions (DTDS, DTSS, STDS, and STSS) of the dairy supply model. Table 6.1 reports estimates of trend, season, and explanatory variables for four different models of dairy supply. Also included in Table 6.1 are measures of diagnostic and goodness-of-fit of the model, such as Durbin-Watson (DW) test, Ljung-Box Q statistic, Jarque and Bera normality statistic, standard error of the estimated equation (s'), Aikake information criterian (AIC), and Bayes information criterian (BIC). The conventional R^2 is not very useful to measure the goodness of fit in our model due to the use of quarterly time series model. Therefore, we report R^2_S, an adjusted coefficient of determination, suggested by Harvey (1989).

The time-varying parameter estimates of table 6.1 are related to the final state vector when the information in the full sample has been utilized. The trend variable (μ_t) and the slope of the trend ($ß_t$) in table 6.1 are equivalent to the constant and coefficient of trend variable, respectively, in the standard regression equation. Variables $?_{1,}$ $?_{2,}$ and $?_3$ represent the first, second, and third quarter seasonal dummy of the classical regression model, respectively.

Excepting DTDS, the remaining dairy supply models (DTSS, STDS, and STSS) show a strong convergence, reflecting successful maximum likelihood estimation by the numerical optimization procedure. The N value in Table 6.1 is the Jarque and Bera normality test, which follows asymptotically a $?^2$ distribution with two degrees of freedom under the null hypothesis (Gujarati, 1995). At the 5% critical level, $?^2_{(2)}$ yields a value of 5.99. Excepting the DTDS (N= 9.46), the other dairy supply models, DTSS (N= 4.66), STDS (N=0.82), and STSS (N= 5.60), fail to reject the null hypothesis of the presence of non-normality. Therefore, the diagnosis shows that excepting the DTDS model, there is no indication of non-normality in the residual. The residuals and QQ plot (Figure 6.2) also support the results.

The Box-Ljung Q statistic, Q (p,q), is a test for serial correlation, which is based on the first 'p' residual autocorrelations and should be tested against a chi-square distribution with 'q' degree of freedom (Table 6.1). In our analysis DTDS, DTSS, STDS, and STSS dairy supply models' p-values of 0.1406, 0.77, 0.83, and 0.63, respectively, fail to reject the null hypothesis of no serial correlation in the model. The Durbin-Watson d statistic tests for the presence of serial correlation in the model. In our analysis, the DTDS, DTSS, STDS, and STSS dairy supply models yield DW d values of 2.08, 1.83, 1.84, and 1.92, respectively. With the sample size of 68 and 5 explanatory variables, the critical d_L and d_U values range from 1.446 to 2.232. All of the DW d values of our dairy supply models fall between these critical d_L and d_U values, and therefore, fail to reject the null hypothesis of no autocorrelation. The results suggest that there is no autocorrelation in the disturbances.

H(g) is a test for heteroscedasticity, and the 1% critical values of F(g,g), for DTDS, DTSS, STDS, and STSS dairy supply models are 2.05, 2.23, 2.19, and 2.03, respectively. These values fail to reject the null hypothesis of presence of heteroscedasticity in the residuals. In our analysis, the estimation procedures converge and the results of diagnostic tests appear satisfactory for the different models of dairy supply response, suggesting that DTDS, DTSS, STDS, and STSS dairy supply models are appropriately specified.

Structural Time Series Analysis with Explanatory Variables

After confirming the validity of the models using different diagnostic tests, we further analyze the four dairy supply models by using explanatory variables as proposed by Harvey 1989. The parameter estimates of dairy supply models and hyper parameters are given in Table 6.1. The study results show a positive and statistically significant role of one quarter lagged dairy cow inventory in all dairy supply models. However, in DTDS and DTSS model, two quarter lagged cow inventory also show significant but negative results, a result consistent with the finding of Kaiser et al 1994.

As expected, all dairy supply models show a statistically significant and inverse relationship between milk feed price ration ($MFPR_t$) and dairy cow supply. This finding is consistent with those of Kaiser et al., 1994. An increase of milk feed price ratio by 1 percent decreases the supply of dairy cows by 0.0421, 0.0433, 0.0341, and 0.0416 percent, respectively, in DTDS, DTSS, STDS, and STSS dairy supply models. Excepting DTSS, the remaining dairy supply models show a significant and positive impact of harvested cow price on supply of dairy cows. This finding demonstrates that an increase in price of harvested cow by 1 percent increases the supply of dairy cows by 0.025, 0.0667, and 0.064 percent, respectively, in DTDS, STDS, and STSS dairy supply models.

The ‘Best’ Model and Supply Forecasts

The main goal of our analysis was to correctly specify a dairy supply response model. The values of AIC, BIC and R^2_S were considered the main criteria of the ‘best model’ specifications. In our analysis, DTSS dairy supply model yields the smallest AIC and BIC values of 0.784 and 1.098, respectively (Table 6.1). The DTSS model also yields the highest R^2_S value of 0. 452 (Table 6.1). These statistics are significantly different from remaining dairy supply models, especially the STDS and STSS, making the DTSS a superior model specification of dairy supply. The study results reject the classical concept of incorporating deterministic seasonal variables in the dairy supply model a priori.

We further analyze the forecasting performance of DTDS, DTSS, STDS, and STSS dairy supply model using out-of-sample predictions (Table 6.2). Forecasts are made for all dairy supply models for the period from the first quarter of 2004 to the fourth quarter of 2005. The forecasting performance of the model is evaluated by comparing these forecasts with the true values of corresponding variables for the 2000-2003 periods. A root mean square error (RMSE) criterion is used to evaluate the forecasting ability of the model. The forecasts, together with their estimated root mean square errors and actual dairy supplies, are reported in table 6.2. With small RMSE values, DTDS and DTSS dairy supply models lead to more accurate forecasts in comparison to the STDS and STSS dairy supply model. However, the smallest RMSE value clearly shows that the DTSS model is superior in forecasting performance. Forecast and actual values of the dairy cow supply in figure 6.3 demonstrates that a directional change was also correctly forecast in the 2004-2005 period by the DTSS model.

To further assess the robustness, structural integrity, and forecasting accuracy, and thereby to confirm the superior dairy supply model, we also use the measures of root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE). RMSE is the squared root of the average of the set of squared differences between real and forecasted or predicted values, while mean absolute percentage error (MAPE) represents the average value of the absolute values of errors expressed in percentage terms. These were calculated as:

$$\text{RMSPE} = \{\frac{1}{T}\sum_{t=1}^{T}\left[\frac{Y_t^{p} - Y_t^{q}}{Y_t^{a}}\right]^2\}^{1/2}$$

$$\text{MAPE} = \{\frac{1}{T}\sum_{t=1}^{T}\left[\frac{Y_t^{p} - Y_t^{q}}{Y_t^{a}}\right]^2\}$$

Where T = the number of forecasts

Y_t^{P} = the predicted value of Y, and

Y_t^{a} = the corresponding actual value.

Both RMSPE and MAPE measure the absolute mean prediction error of an endogenous variable. The use of percentage measures facilitates comparison of different dairy supply model specifications. Table 6.3 reports RMSPE and MAPE values of real in-sample data and structural time series forecasts for all dairy supply models. As expected, in both cases RMSPE and MAPE in-sample test statistics values for the DTSS dairy supply model were smaller than corresponding values obtained from the remaining DTDS, STDS, and STSS dairy supply models. The RMSPE value of 0.0957 (in-sample forecast) and 0.16991 (out-of-sample forecast) are clearly smaller than RMSPE values of remaining dairy supply models. The small MAPE values of 0.0059 (in-sample forecast) and 0.0028 (out-of-sample forecast) also support the robustness of DTSS models in comparison to the other models of dairy supply response.

Water Demand Forecasting

After selecting the 'best model' of dairy cattle supply response, we forecast the dairy water demand in Georgia by using the dairy water use coefficients reported by ACT/ACF study and dairy supply herd forecasts available from the DTSS dairy supply response model. ACT/ACF study reports approximately 35 gallon of water use per day per dairy cattle in 2000. Excepting, ACT/ACF study reports, there exists no other study of dairy water use in Georgia. Therefore, we consider ACT/ACF study data as baseline information.

Using the educated guess of an expert for heard size, the ACT/ACF study forecasts an increase of dairy cattle inventory in Georgia from 37,717 in 2000 to 38,933 in 2010 in the Georgia study area (not the total state). The report further forecasts an increase of dairy water demand from1.32 million gallon per day in 2000 to 1.37 million gallon per day in 2010 (ACT/ACF River Basin Study, 1995). The ACF/ACT study shows an annual growth of dairy cattle by 0.003224 percent in Georgia. Although the ACT/ACF study is confined to 16 selected counties of Georgia, we assume the same rate of growth of dairy industry under the physical model for Georgia. Table 6.4 reports the forecasts of dairy cattle and corresponding water demand assuming an annual growth rate of 0.00324 in dairy cattle industry in Georgia. Also reported in Table 6.4 are the forecasts of dairy cattle and water demand of dairy cattle under the selected DTSS dairy supply model.

Analysis of dairy water demand forecasting using structural time series model and the physical model yield mixed results. The contradictory results arise because of flaws of the ACT/ACF study-based physical model, which forecasts an expansion of dairy cattle industry by 0.0164 percent between 1995 to 2000 and further expansion of dairy industry by 0.0322 percent between 2000 to 2010 (ACT/ACF study report, 1995). Indeed, the number of dairy cattle has decreased from 100,000 head in 1995 to 85,000 in 2003 (USDA, 2003), a reduction of nearly 15 percent in Georgia. The results clearly show the failure of the ACT/ACF physical based model and questions its validity for forecasting purposes.

In our analysis, DTSS dairy supply model forecasts 85.33 and 84.84 thousand head (in average) of dairy cattle in 2004 and 2005, respectively in Georgia. Given the 35 gallon per animal per day dairy water use, the DTSS dairy supply model forecasts 2.986 and 2.969 million gallons of water (on average) per day in 2004 and 2005, respectively, in Georgia. Dairy cattle and dairy water demand forecasts of structural time series model contradicts the strictly physical model, which forecasts 85.96 and 86.23 thousand head (on average) of dairy cattle and 3.008 and 3.019 mgd (on average) per day in 2004 and 2005, respectively. The physical variable model overestimates dairy water demand by 28,637 gallons per day in 2004 and 49,225 gallons per day in 2005. On average, the physical model overestimates the dairy cattle water demand by 38,931 gallons per day. As the physical model failed to capture the real changes in the dairy cow inventory by forecasting expansion of dairy cattle in Georgia, we suggest against using a restrictive physical model for water demand forecasting purposes.

Conclusions

Our analysis aims to forecast the dairy cattle water demand in Georgia by developing a sound supply response model having an excellent forecasting accuracy. We first extend the existing dairy supply model by incorporating stochastic trend and seasonality components. Four versions of dairy supply models having different assumptions on deterministic and stochastic trend and seasonality were developed to select the 'best' dairy supply model. Contrary to the classical concept of using a deterministic seasonal variable in the dairy supply model, our results demonstrate that a dairy supply model incorporating stochastic seasonality (DTSS) yields a better specification. We demonstrate that the out-of-sample forecasting power of the correctly specified model is superior. In our analysis, all economic variables were statistically significant, showing the importance of incorporating economic variables while forecasting dairy cattle inventory and thereby future dairy water demand. Water demand forecasting comparing the DTSS dairy supply model and the physical model shows a slippage of 38,931 gallons per day (on average) of dairy water demand in Georgia.

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Table 6. 1. Estimation Results of Dairy Supply Response Model under Different Assumptions of Trend and Seasonality Variable

Parameter	Deterministic Time/Deterministic Seasonality	Deterministic Time/Stochastic Seasonality	Stochastic Time/Deterministic Seasonality	Stochastic Time/Stochastic Seasonality
μ_t	15.630**	13.888**	42.817**	42.817**
ß$_t$	-0.0231	-0.041**	-0.027	-0.275
?$_1$	0.831**	0.6176**	1.103**	0.993**
?$_2$	0.0741	-0.0404	-0.047	0.061
?$_3$	0.101	-0.463	-0.884**	0.109
DS_{t-1}	1.324**	1.383**	0.591**	0.591**
DS_{t-2}	-0.652**	-0.676**	-0.193	-0.193
DS_{t-3}	0.171	0.147	0.067	0.067
MFPR	-1.357**	-0.952**	-1.712**	-1.712**
$_t$	(-0.0421)	(-0.0433)	(-0.0341)	(-0.0416)
	9.213**	4.678	25.031**	25.031**
$DPSC_t$	(0.0253)	(0.0251)	(0.0667)	(0.06404)
	1.327	1.290	1.440	1.761
s’	2.085	1.836	1.844	1.927
DW	9.640	4.029	2.777	4.288
Q	0.420	0.452	0.419	0.132
R^2_S	0952	0.784	1.123	1.558
AIC	1.332	1.098	1.539	2.008
BIC	9.46	4.66	0.82	5.60
N	2.05	2.23	2.19	2.03
H(g)				

Note: ** shows variables statistically significant at 10 percent level. The number in the parenthesis shows corresponding elasticity

Table 6. 2. Dairy Supply Forecasts (in thousands) and Root Mean Square Error (RMSE) under Different Models

		DTDS		DTSS		STDS		STSS	
Period	Real	Forecast	RMSE	Forecast	RMSE	Forecast	RMSE	Forecast	RMSE
2002. 1	85.31	86.36	1.54	86.36	1.51	82.53	3.66	82.53	3.67
2002. 2	85.56	84.77	1.54	84.77	1.51	81.47	4.04	81.47	4.06
2002. 3	85.59	86.60	1.54	85.60	1.51	83.14	4.39	83.14	4.41
2002. 4	85.44	86.84	1.55	85.84	1.51	82.53	4.73	82.53	4.73
2003. 1	85.81	86.43	1.55	86.43	1.52	82.45	5.06	82.45	5.07
2003. 2	85.73	86.15	1.55	86.15	1.52	82.30	5.37	82.30	5.38
2003. 3	85.43	85.56	1.55	85.56	1.52	80.96	5.67	80.96	5.68
2003. 4	84.22	87.11	1.56	85.11	1.53	83.56	5.96	83.56	5.96
2004. 1		86.21	1.57	86.21	1.53	82.37	6.25	82.37	6.26
2004. 2		85.57	1.57	85.57	1.53	81.49	6.53	81.49	6.54
2004. 3		86.19	1.57	85.19	1.54	82.17	6.81	82.17	6.82
2004. 4		87.36	1.57	84.36	1.54	83.40	7.08	83.40	7.08
2005. 1		86.47	1.58	84.47	1.54	82.22	7.34	82.22	7.35
2005. 2		85.83	1.58	85.83	1.55	81.34	7.60	81.34	7.62
2005. 3		86.45	1.58	84.45	1.55	82.02	7.86	82.02	7.87
2005. 4		87.62	1.58	84.62	1.55	83.25	8.12	83.25	8.12

Table 6. 3. Mean Absolute Percentage Error (MAPE) and Root Mean Square Percentage Error (RMSPE) for the In-Sample and Out-of-Sample Forecast Periods

Models	RMSPE		MAPE	
	In-Sample Forecasts	Out-of-Sample Forecasts	In-Sample Forecasts	Out-of-Sample Forecasts
DTDS	0.1446	0.3137	0.00201	0.0981
DTSS	0.09579	0.16991	0.00059	0.0028
STDS	0.38706	0.25875	0.01498	0.0067
STSS	0.38706	0.25875	0.01498	0.0149

Table 6. 4 Forecasting of Dairy Supply Herd Response and Dairy Water Demand under Structural Time Series Model (STSM) and Physical Model in Georgia.

Year	STSM		Physical Model		Difference
	Dairy Inventory (000)	Water Demand (MGD)	Dairy Inventory (000)	Water Demand (MGD)	(MGD)
2002.1	86.36	3.022	85.31	2.988	-0.036
2002.2	84.77	2.966	85.37	2.987	0.021
2002.3	85.60	2.996	85.44	2.990	-0.005
2002.4	85.84	3.004	85.51	2.992	-0.011
2003.1	86.43	3.025	85.58	2.995	-0.029
2003.2	86.15	3.015	85.65	2.997	-0.017
2003.3	85.56	2.994	85.72	3.000	0.006
2003.4	85.11	2.978	85.79	3.002	0.024
2004.1	86.21	3.017	85.86	3.005	0.011
2004.2	85.57	2.994	85.93	3.007	0.013
2004.3	85.19	2.981	86.00	3.011	0.029
2004.4	84.36	2.952	86.06	3.012	0.060
2005.1	84.47	2.956	86.13	3.014	0.058
2005.2	85.83	3.004	86.20	3.017	0.013
2005.3	84.45	2.955	86.27	3.019	0.064
2005.4	84.62	2.961	86.34	3.029	0.060

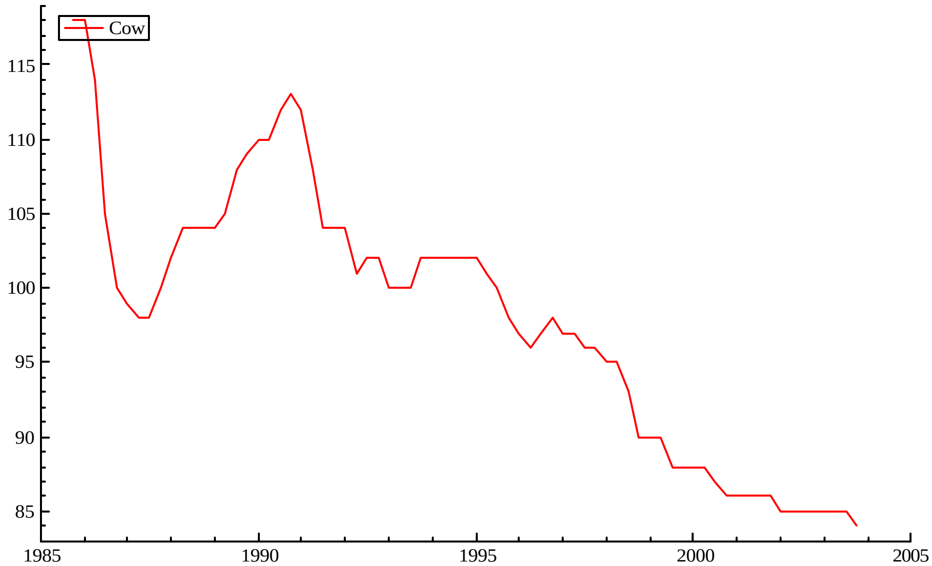
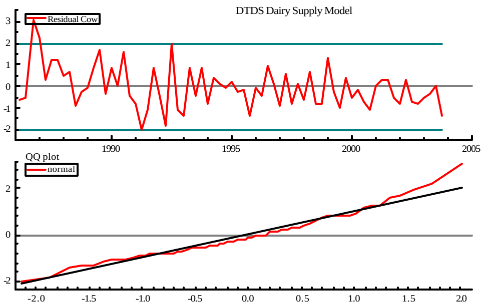
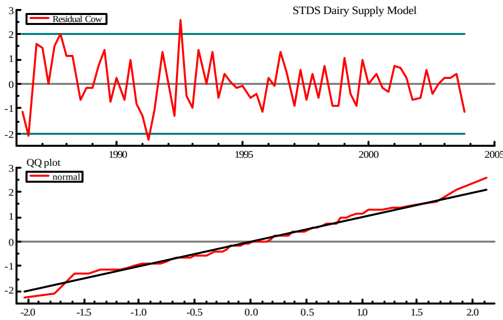


Figure 6. 1. Time Series Plotting of Dairy Cow Inventory in Georgia (1985-2003)



DTDS)



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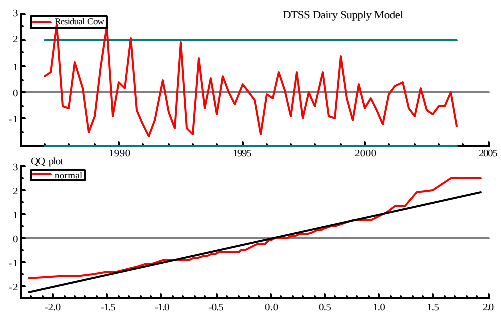

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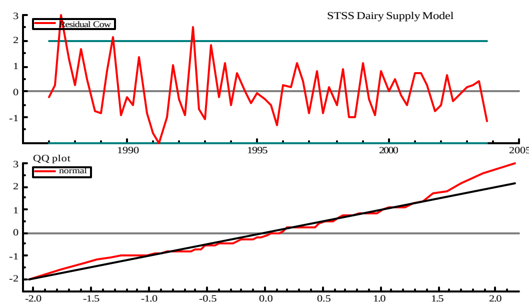
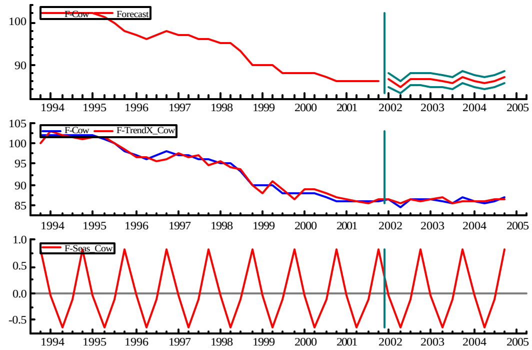


STSS

Figure 6. 2. Residual and QQ Plotting of Different Dairy Supply Models

DTDS



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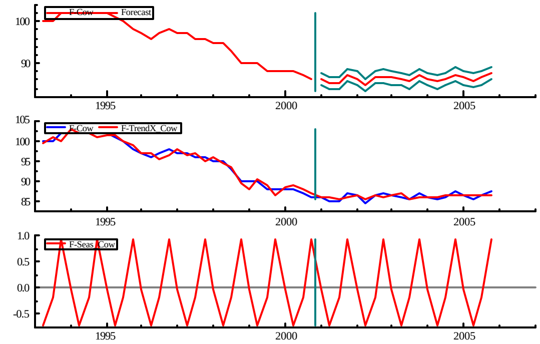
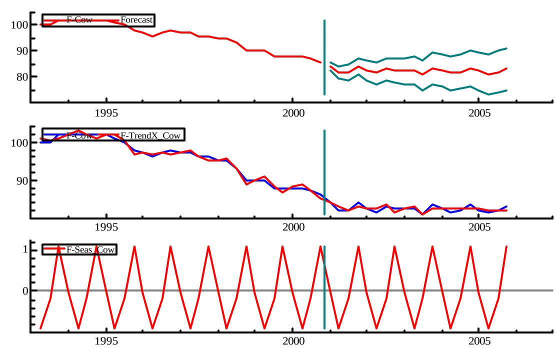


STDS



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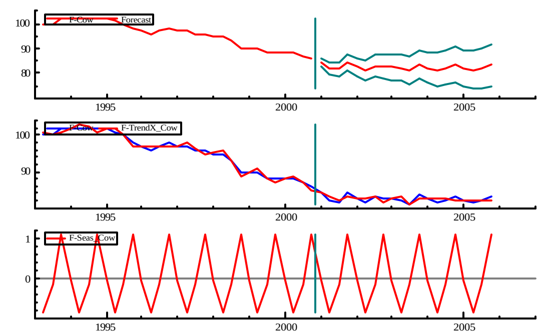

Figure 6. 3. Forecasting Accuracy and Component Graphic of Different Dairy Supply Model

CHAPTER SEVEN

BEEF CATTLE WATER DEMAND FORECASTING

Introduction

In the last few decades, cow-calf and stocker farms have become fewer and larger and few efforts to co-ordinate the segment of the industry from breeding to the consumer have evolved. The rate of structural changes was very slow in comparison to the poultry and pork industries (Gillespie and Schupp, 2000). The rapid technological progress in poultry and swine resulted in to rapid structural change and highly coordinated supply chain structure. However, In the case of beef cattle production, the economics of size have not developed to the level of the poultry and swine industries because of lack of technological improvements. The slow rate of technological development in the beef industry has resulted in the continued existence of small and independent beef operations and a poorly coordinated supply chain structure (Gillespie and Schupp, 2000).

Therefore, researchers commonly ignore the role of technological changes in beef cattle supply response models. Unlike poultry and swine supply response models, researchers rarely use trend variable as a proxy of technological advancements while modeling the beef cattle supply response (Tyfos, 1974; Freebairn and Rausser, 1975; Martin and Haack. 1977; Aadland and Bailey, 2001). Although slow, technological change might affect the beef supply decision of farmers, and assuming no technological effect on beef cattle supply a priori might lead to model misspecification. Therefore, our study aims to further expand the existing beef cattle supply response models by assessing the impacts of technological changes in beef cattle supply response. In order to examine the impacts of technological changes in beef cattle industry and to select a correctly specified beef cattle supply response model, we consider three different versions of technological changes, namely: no trend effect, fixed trend effect, and stochastic trend effect. The beef cattle supply forecasts available from the specified beef cattle model and beef water use coefficients available from the ACT/ACF study are then used to forecast the beef cattle water demand in Georgia.

In the case of beef cattle supply response, we ignore the role of seasonality. No seasonality was assumed because of the unavailability of quarterly data and existing pattern of beef cattle production in Georgia, which shows little or no seasonal impacts on beef cattle supply. We improve the beef cattle supply response model proposed by Rucker et al. (1984) and Foster (1990) by incorporating trend as deterministic and stochastic variables. Three versions of beef cattle supply response were developed separately for breeding herd and all cattle and calves:

i. No trend and no seasonality (NTNS)
ii. Deterministic trend and no seasonality (DTNS)
iii. Stochastic trend and no seasonality (STNS)

NTNS represents the basic beef cattle supply model, where role of trend and seasonality is ignored. STAMP offers options to run the proposed versions of dairy and beef cattle supply response models. Structural time series methodology discussed in the dairy cattle supply response model (previous chapter) provides the theoretical justification needed for the study.

Economic Model Specification for Beef Cattle

The beef cattle supply models proposed by the Rucker et al. (1984) and Foster (1990) provide a starting place for the estimation of the breeding herd and all cattle and cattle supply behavior of cattle producers in Georgia. The structural time series models of breeding herd and all cattle and calves with explanatory variables were developed as specified below:

$$BH_t = \mu_t + ß_1 DCP_{t-1} + ß_2 DBP_{t-2} + ß_3 DBP_{t-3} + ß_4 BH_{t-1} + ß_4 BH_{t-2} + e_t \quad (1)$$

$$AC\&C_t = \mu_t + ß_1 DCP_{t-1} + ß_2 DBP_{t-1} + ß_3 DBP_{t-2} + ß_4 BH_{t-1} + ß_4 BH_{t-2} + e_t \quad (2)$$

Where;

BH_t = the breeding herd inventory in January 1 in year 'T' in thousands in Georgia.

$AC\&C_t$ = all cattle and calves inventory in January 1 in year 'T' in thousands in Georgia

μ_t = the trend component,

BH_{t-1} = the breeding herd inventory in January 1 in previous year in thousands in Georgia,

BH_{t-2} = the breeding herd inventory in January 1 in two lagged years in thousands in Georgia,

DCP_{t-1} = price of no 2 grade yellow corn deflated by CPI (1982-84= 100) in dollars per bushel in Omaha,

DBP_{t-1} = price of steer harvested, choice 2-4 Nebraska direct 1100-1300 lbs deflated by CPI (1982-84 = 100), in previous year in cents per lbs,

DBP_{t-2} = price of steer harvested, choice 2-4 Nebraska direct 1100-1300 lbs deflated by CPI (1982-84= 100), in lagged two years in cents per lbs, and

e_t = random white noise disturbance term

Data

To carry out the objectives of the study, inventory data (1972-2003) of breeding herd and all cattle & Calves of Georgia were collected from National Agricultural Statistics Services (NASS) of United States Department of Agriculture (USDA) and Georgia Agricultural Facts. Information about the consumer price index, corn price, and price of steer harvested were collected from the Economic Research Service (ERS) of United State Department of Agriculture (USDA) publications. The price of steer harvested and corn price were deflated by using consumer price index (all urban consumer, US city) average (1982-84=100). In the beef cattle supply response model, breeding herd inventory comprises of cows and heifers that calved plus heifer replacement (beef) over 500 lbs., while all cattle and calves inventory consists of cow and heifers that calved, bulls over 500 lbs, heifers over 500 lbs (both beef and milk replacement), heifers over 500 lbs (other), steers over 500 lbs, and calves less than 500 lbs.

Results and Discussion

Structural Time Series Analyzer, Modeller, and Predictor (STAMP) 6.0 version was used to estimate the different versions (NTNS, DTNS, and STNS) of breeding herd and all cattle & calves supply models. The estimates of trend and explanatory variables, along with measures of diagnostic and goodness-of-fit of the model such as Durbin-Watson (DW) test, Ljung-Box Q statistic, Jarque and Bera normality statistic, standard error of the estimated equation (s'), Aikake information criterian (AIC), and Bayes information criterion (BIC) for all models of breeding herd and all cattle & calves supply are presented in Table 7.1 and Table 7.5 respectively.

In our analysis, all supply models (NTNS, DTNS, and STNS) of breeding herd and all cattle & calves show a strong convergence. Analysis shows successful maximum likelihood estimation by the numerical optimization procedure of STAMP. The N value in Table 7.1 represents the Jarque and Bera normality test, which follows asymptotically a $?^2$ distribution with two degree of freedom under the null hypothesis (Gaujrati, 1995). At 5% critical level, $?^2_{(2)}$ yields a value of 5.99. In our analysis of breeding herd and all cattle & calves supply response models, Jarque and Bera N values range from 0.39 to 2.72 and fail to reject the null hypothesis of presence of non-normality. Presence of non-normality in all models of breeding herd and all cattle & calves mode is further confirmed by QQ plots (Figure 7.1 and Figure 7.2)

The Durbin-Watson d statistic examines the presence of serial correlation in the model. In our analysis, the NTNS, DTNS, and STNS breeding herd supply models yield DW d values of 2.31, 2.40, and 2.14, respectively. Similarly, NTNS, DTNS, and STNS all cattle & calves supply models yield DW d values of 2.33, 2.43, and 2.46, respectively. DW d values of both beef cattle supply response models fail to reject the null hypothesis of no autocorrelation. The results suggest that there is no autocorrelation in the disturbances. Further diagnostic analysis using residual plotting (Figure 7.1 and Figure 7.2) for all supply models of breeding herd and all cattle & calves show no specific pattern and confirm there is no violation of assumption of homoscedasticity. Strong conversion of all supply models of breeding herd and all cattle & calves and satisfactory diagnostic tests suggest that both breeding herd and all cattle & calves supply models are appropriately specified.

Structural Time Series Analysis with Explanatory Variables

We further analyze all supply models (NTNS, DTNS, and STNS) of breeding herd and all cattle & calves, using structural time series model with explanatory variables as proposed by Harvey (1989). The parameter estimates of all supply models of breeding herd and all cattle & are given in Table 7.1 and Table 7.5 for breeding herd supply model and all calves & cattle supply models, respectively. Our analysis shows a positive and statistically significant role of one year lagged breeding herd inventory in all supply models of breeding herd and all cattle & calves. However, the impact of two-year lagged breeding herd was mixed. The two -year lagged breeding herd inventory had no significant impacts on all supply response models of any cattle & calves. However, in all breeding herd supply response models, the two - lagged breeding herd inventory had a negative and significant impact. These results are consistent with the findings of Foster (1990).

Except NTNS model of all cattle & calves supply, remaining breeding herd and all cattle & calves supply models show a statistically significant and inverse relationship between corn price and beef cattle supply, a finding consistent with Rucker et al. 1988. The elasticity with respect to corn price ranges from -0.0096 to -0.0127 for breeding herd supply response models. The all cattle & calves supply models also show a similarly inelastic range of corn price elasticity (-0.0050 to -0.0897). Analysis of beef price shows mixed results. excepting STNS, one -year lagged beef price failed to show a significant impact on breeding herd supply decision. However, in the case of all cattle & calves supply response models, one-year lagged beef price had a significant and positive impact. Further analysis of elasticity of beef price shows estimated elasticities of 0.023, 0.029, and 0.024 respectively for NTNS, DTNS, and STNS cattle and calves supply model.

The ‘Best ’ Model and Supply Forecasts

In order to select the ‘best’ model and thereby precisely forecast the beef cattle water demand in Georgia, we consider the values of AIC, BIC and R^2_d as the main criteria of model selection. In our analysis, DTNS breeding herd supply model yields the smallest AIC and BIC values of 7.38 and 7.76 respectively (Table 7.1). The DTNS breeding herd supply model also yields highest R^2_d value of 0. 79 (Table 7.1). The AIC, BIC, and R^2_d statistics are substantially different from NTNS and STNS breeding herd supply models, making DTNS a superior and more correctly specified model of breeding herd supply.

Analysis also shows a similar result for the all cattle & calves supply models. In our analysis, all cattle & calves supply model (DTNS) yields the highest R^2_d of 0.85, and the smallest AIC and BIC values of 8.418 and 8.802 respectively (Table 7.2) making it a superior model in comparison to NTNS and STNS all cattle and calves supply response models. The results show a significant impact of fixed trend effect on both breeding herd and all cattle & calves supply models and reject the classical idea of not incorporating trend variables in the beef cattle supply response model as a priori. Our analysis suggests that the best specification of beef cattle supply response model can be achieved by incorporating the variable of technological progress. However, study results provide evidence opposing the idea of incorporating a stochastic trend variable in beef cattle supply response models.

After selecting the best model of breeding herd and all cattle & calves supply response, the forecasting performance of NTNS, DTNS, and STNS breeding herd and all cattle & calves supply models were evaluated using both in-sample and out-of-sample predictions. The supply forecasts of breeding herd supply models and all cattle & calves supply models are presented in Table 7.3 and Table 7.4, respectively. The forecasting accuracy of the breeding herd and all cattle and calves supply models were then evaluated using root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE).

Table 7.5 and Table 7.6 report the RMSPE and MAPE values of in-sample data and structural time series forecasts for breeding herd and all cattle & calves supply models, respectively. As expected, in both cases RMSPE (0.0937) and MAPE (0.0893) in-sample values of DTNS breeding herd supply model were smaller than corresponding RMSPE and MAPE values of remaining breeding herd supply models. Similar results exist for all cattle and calves supply models. The RMSPE value of 0.0885 (in-sample forecast) and 0.0478 (out-of-sample forecast) of DTNS all cattle & calves model are clearly smaller than corresponding in-sample and out-of-sample RMSPE values of remaining all cattle and calves models. The smaller MAPE values for in-sample forecast (0.0863) and out-of-sample forecast (0.0450) also confirm the robustness of DTNS all cattle & calves dairy supply model in term of forecasting accuracy.

Beef Cattle Water Demand Forecasting

Beef cattle water requirements were mostly for drinking purposes, although some flushing of the waste in confined areas and washing of cattle for sanitation does occur.

While estimating the beef cattle water demand, the major problem arises from the contradictory information about the amount of water use by beef cattle for the drinking and sanitation purposes. The USGS reports per day beef cattle water use of 8 gallons. However, the ACT/ACF study reports nearly 12 gallons of water use by beef cattle in the Georgia study area. As our study aims to forecast the water demand for beef cattle in Georgia, we consider 12 gallons per day water use for both breeding herd and all cattle & calves.

Without separating it in to breeding herd and all cattle & calves, the ACT/ACF study forecasts a decrease of beef cattle inventory from 503,100 in 2000 to 502,259 in 2010 in the Georgia study area(not all of Georgia), an annual decrease of 0.000508 percent (ACT/ACF, River Basin Study, 1995). The ACT/ACF report also forecasts a decrease in beef cattle water demand from 6.04 mgd per day in 2000 to 6.01 mgd per day in 2010. While forecasting water demand for beef cattle in Georgia, we assume the ACT/ACF study as baseline information. Table 7.7 and Table 7.8 report the water demand forecasting and slippage in water demand between structural time series model and ACT/ACF physical model.

In our analysis, structural time series model forecasts the 8.313, 8.359, 8.405, 8.451, and 8.497 mgd of water demand in 2004, 2005, 2006, 2007, and 2008, respectively for breeding herd cattle in Georgia. Water demand coefficients of structural time series model substantially depart from the corresponding coefficients of breeding herd cattle water demand of physical model, which reports 9.511, 9.506, 9.501, 9.496, and 9.492 mgd of water demand in 2004, 2005, 2006, 2007, and 2008, respectively. Analysis clearly shows that the physical model overestimates the breeding herd water demand by approximately 8.6 percent (Table 7.7). A similar situation of slippage in water demand forecasting exists between structural time series model and ACT/ACF based physical model in the case of all cattle & calves supply model. The structural time series model of all cattle & calves predicts 13.321, 13.141, 12.958, 12.777, and 12.742 mgd of water demand in 2004, 2005, 2006, 2007, and 2008, respectively for all cattle & calves (Table 7.8) in Georgia. The physical model forecasts 15.560, 15.553, 15.545, 15.537, and 15.529 mgd of water demand in 2004, 2005, 2006, 2007, and 2008, respectively, for all cattle & calves in Georgia. The analysis shows an overestimation of 2.239, 2.412, 2.587, 2.760, and 2.787 mgd of water demand by physical model, in 2004, 2005, 2006, 2007, and 2008, respectively, an average of approximately 14.7 percent.

The main reason of over-estimation of water demand by the physical model appears to be the lack of its prediction ability. ACT/ACF physical model is mostly based on the educated guess of experts and completely ignores the role of economic variables in animal supply response models. In the case of beef cattle, ACT/ACF study forecasts a decrease of beef cattle inventory by 0.000508 per cent (on average) per year. However, USDA reports show that the breeding herd inventory has decreased from by 0.01486 percent (on average) from 1995 to 2003. A similar note of decreasing inventory trend exists for all cattle & calves (Figure 7.3) in Georgia. The results demonstrate the flaws of the physical model and consequences of ignoring economic variables and systematic modeling approaches in animal supply response function.

Conclusions

We forecast water demand for beef breeding herd and all calves & cattle in Georgia using the structural time series model and an ACT/ACF- based physical model. The existing beef cattle supply model was improved by incorporating deterministic and stochastic trend components. We develop three versions of breeding herd and all cattle & calves supply models by assuming no trend, deterministic trend, and stochastic trend. In our analysis, breeding herd and all cattle & calves models with deterministic trend components emerge as the best model as measured by the AIC, BIC, and R^2_d criteria. The selected breeding herd and all cattle & calves models with deterministic trend components yield superior forecasting accuracy. In our analysis, all economic variables were statistically significant, showing the importance of incorporating economic variables while forecasting breeding herd and all cattle & calves supply models. Further analysis of water demand forecasting shows that the physical model over-estimates the water demand forecast by 8.6 percent and 14.7 percent (on average) for breeding herd and all cattle and calves supply models over structural time series model. Though small in amount, this slippage in water demand would be very critical to make efficient water allocation decisions in crucial hours.

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Table 7. 1. Estimation Results of Breeding Herd (Cattle) Supply Response Model under Different Assumptions of Trend

Parameter	NTNS	DTNS	STNS
μ_t		414.671**	397.490**
BH_{t-1}	0.831**	0.7113**	0.787**
BH_{t-2}	-0.228**	-0.403**	-0.439**
DCP_{t-1}	-473.71**	-2003.5**	-2419.7**
	(-0.003)	(-0.013)	(-0.010)
DBP_{t-1}	60.556	223.89	191.45*
	(0.121)	(0.120)	(0.108)
DBP_{t-2}	664.92	536.88	559.95
	(0.260)	(0.298)	(0.355)
s'	31.514	29.345	30.100
DW	2.31	2.40	2.15
Q	5.58	4.22	6.06
R^2_d	0.76	0.79	0.79
AIC	8.29	7.39	7.55
BIC	8.53	7.77	8.03
N	2.13	0.39	1.66
H(g)	0.94	0.68	2.21

Note: ** and * show variables statistically significant at 5 and 10 percent levels, respectively. The number in the parenthesis shows corresponding elasticity.

Table 7.2. Estimation Results of All Calves and Cattle Supply Response Model under Different Assumptions of Trend

Parameter	NTNS	DTNS	STNS
μ_t		-206.07	145.52
BH_{t-1}	1.443**	1.669**	1.392**
BH_{t-2}	-0.308	-0.255	-0.317
DCP_{t-1}	-1982.1	-953.46*	-218.47*
	(-0.005)	(-0.023)	(-0.090)
DBP_{t-1}	439.28**	522.62**	644.70**
	(0.023)	(0.029)	(0.024)
DBP_{t-2}	1383.1**	1295.6**	1361.9**
	(0.031)	(0.04)	(0.044)
s'	55.966	50.039	50.174
DW	2.33	2.44	2.46
Q	4.084	5.47	5.04
R^2_d	0.81	0.86	0.85
AIC	8.49	8.42	8.57
BIC	8.78	8.80	9.05
N	2.72	1.46	2.23
H(g)	0.51	2.08	2.46

Note: ** and * shows variables statistically significant at 5 and 10 percent level, respectively.
The number in the parenthesis shows corresponding elasticity

Table 7. 3. Breeding Herd Forecasts (in thousands) under Different Assumptions of Trend Variable

Year	Real	NTNS Forecasts	DTNS Forecasts	STNS Forecasts
1999	795	785.10	737.30	770.64
2000	795	756.98	715.65	738.80
2001	778	770.29	733.42	744.30
2002	767	739.11	706.87	709.52
2003	800	491.44	688.93	499.08
2004		462.83	692.76	469.64
2005		434.26	696.60	440.56
2006		405.67	700.43	411.77
2007		377.09	704.26	383.21
2008		348.51	708.09	354.82

Table 7.4 All Calves and Cattle Forecasts (in thousands) under Different Models

Year	Real Inventory	NTNS Forecasts	DTNS Forecasts	STNS Forecasts
1999	1300	1254.0	1206.9	1214.9
2000	1310	1194.5	1210.8	1213.6
2001	1270	1239.5	1175.5	1219.2
2002	1240	1198.9	1140.2	1180.7
2003	1290	1003.7	1125.2	1147.7
2004		996.55	1110.1	987.7
2005		988.43	1095.0	971.7
2006		979.64	1079.9	967.7
2007		960.78	1064.8	961.8
2008		950.95	1061.9	953.8
2007		960.78	1064.8	961.8
2008		950.95	1061.9	953.8

Table 7.5. Mean Absolute Percentage Error (MAPE) and Root Mean Square Percentage Error (RMSPE) of all Breeding Herd Supply Models

Models	RMSPE		MAPE	
	In-sample Forecast	Out-of Sample Forecast	In-sample Forecast	Out-of Sample Forecast
NTNS	0.1747	0.5311	0.0984	0.4265
DTNS	0.0937	0.0478	0.0893	0.0106
STNS	0.1760	0.4221	0.1191	0.4309

Table 7.6. Mean Absolute Percentage Error (MAPE) and Root Mean Square Percentage Error (RMSPE) of all Cattle and Calves Supply Models

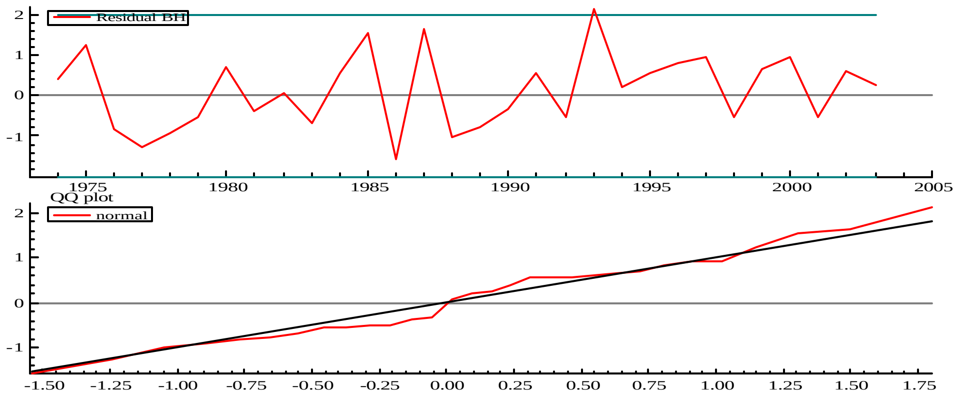
Models	RMSPE		MAPE	
	In-Sample Forecast	Out- of Sample Forecast	In-Sample Forecast	Out-of Sample Forecast
NTNS	0.1095	0.1403	0.0805	0.1394
DTNS	0.0885	0.0478	0.0863	0.0450
STNS	0.0917	0.1464	0.0974	0.1452

Table 7.7. Forecasting of Breeding Herd Water Demand under Structural Time Series Model (STSM) and Physical Model in Georgia

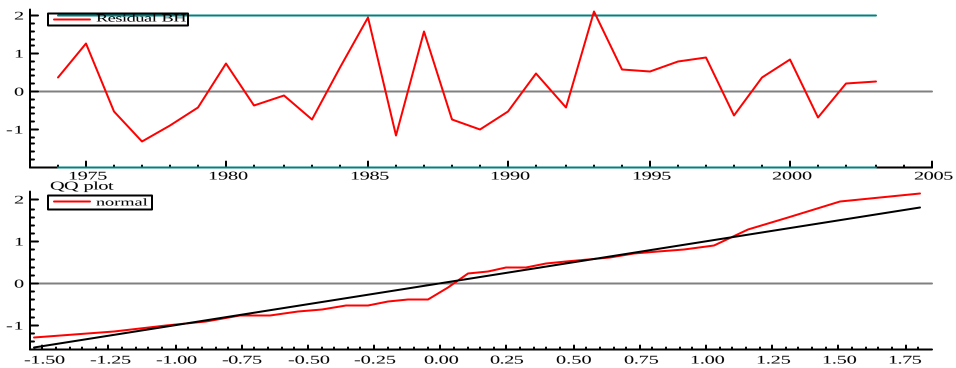
	STSM		Physical Model		Difference
Year	Inventory	Water Demand (MGD)	Inventory	Water Demand (MGD)	(MGD)
1999	737300	8.847	794.596	9.535	0.688
2000	715650	8.587	794.192	9.530	0.943
2001	733420	8.801	793.789	9.525	0.724
2002	706870	8.482	793.386	9.521	1.039
2003	688930	8.267	792.983	9.516	1.249
2004	692760	8.313	792.580	9.511	1.198
2005	696600	8.359	792.177	9.506	1.147
2006	700430	8.405	791.775	9.501	1.096
2007	704260	8.451	791.373	9.496	1.045
2008	708090	8.497	790.971	9.492	0.995

Table 7.8. Forecasting of All Cattle and Calves Water Demand under Structural Time Series Model (STSM) and Physical Model in Georgia (in Million Gallons per Day)

Year	STSM Inventory	STSM Water Demand (MGD)	Physical Model Inventory	Physical Model Water Demand (MGD)	Difference (MGD)
1999	1206900	14.482	1300000	15.600	1.118
2000	1210800	14.529	1299340	15.592	1.063
2001	1175500	14.106	1298680	15.584	1.478
2002	1140200	13.682	1298020	15.576	1.894
2003	1125200	13.502	1297360	15.568	2.066
2004	1110100	13.321	1296701	15.560	2.239
2005	1095000	13.141	1296043	15.553	2.412
2006	1079900	12.958	1295384	15.545	2.587
2007	1064800	12.777	1294726	15.537	2.760
2008	1061900	12.742	1294068	15.529	2.787



DTNS



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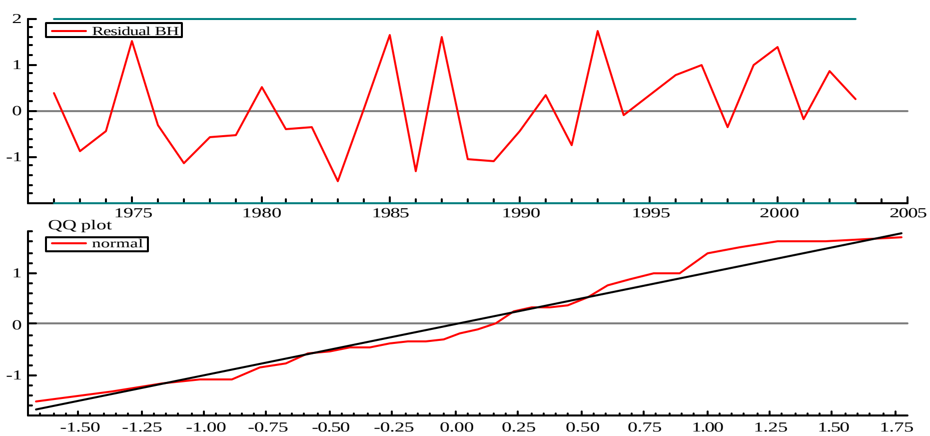

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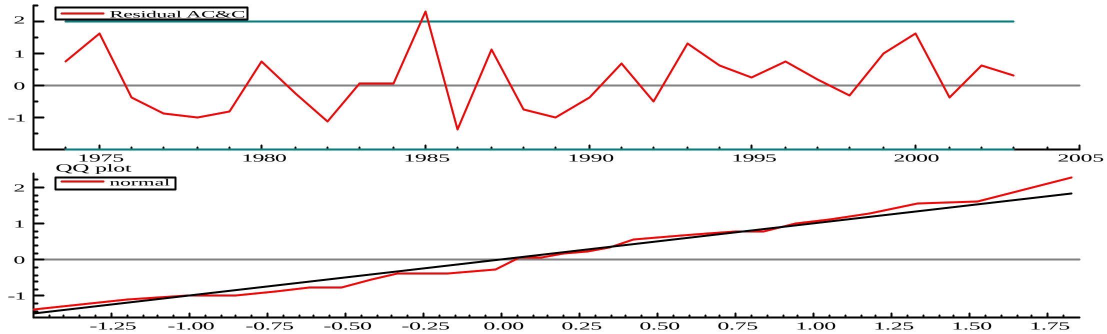
Figure 7. 1. Residual and QQ Plotting of All Breeding Herd Supply



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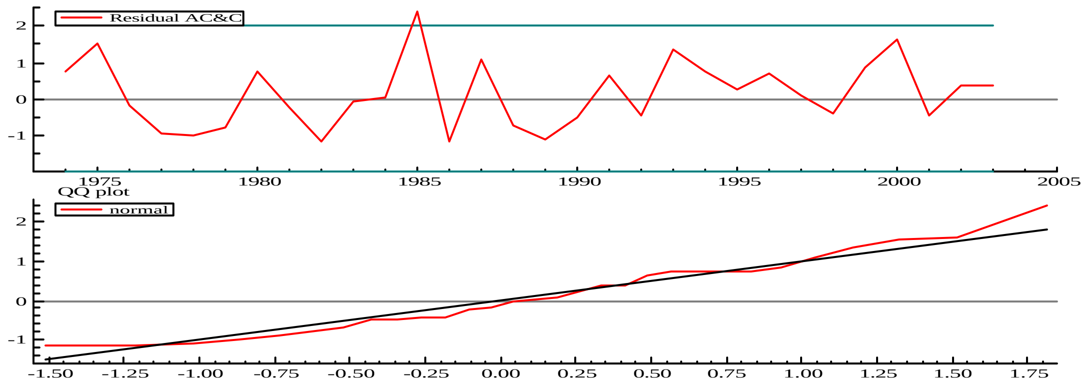

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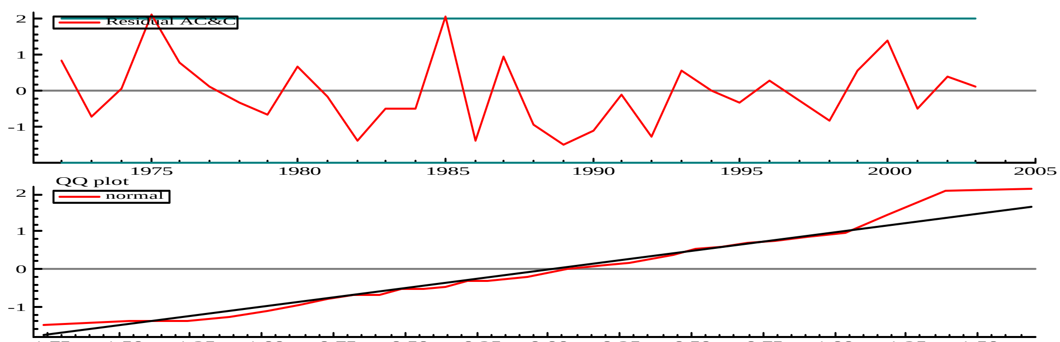

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Figure 7. 2. Residual and QQ Plotting of All Cattle and Calves Supply Response Model

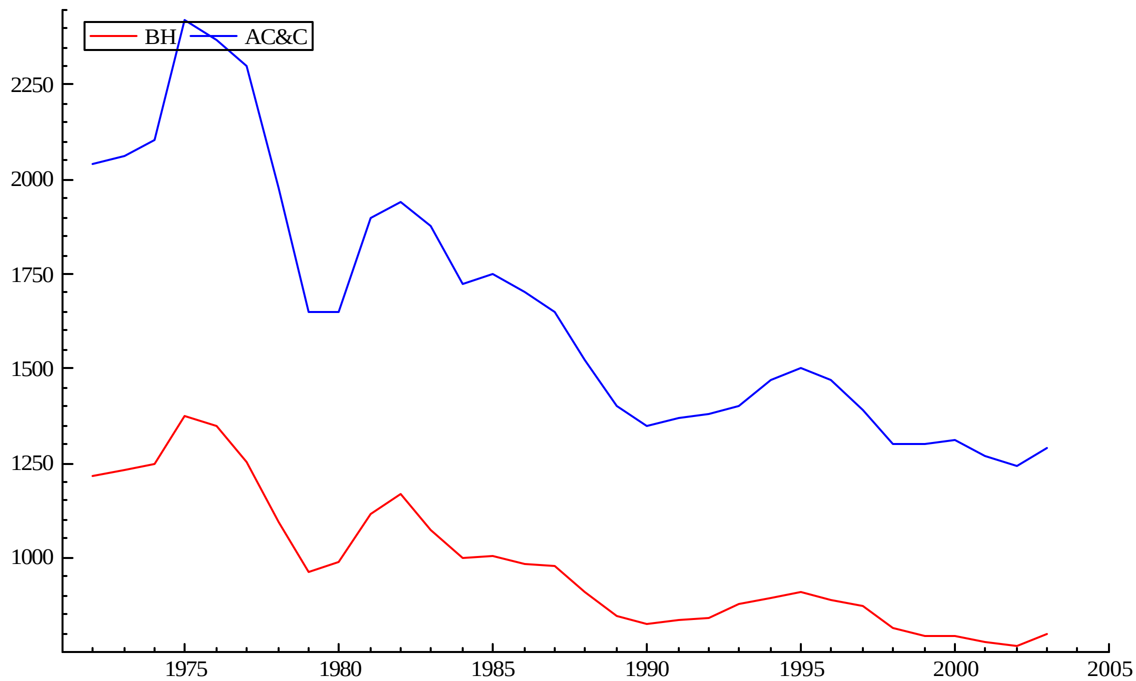

Figure 7.3. Time Series Plotting of Breeding Herd and All Calves and Cattle in Georgia (1972-2003)

CHAPTER EIGHT

SUMMARY, CONCLUSIONS AND IMPLICATIONS

Summary

With 1.25 billion broilers, 1.24 million dairy and beef cattle, and 0.31 million hogs, animal agriculture represents an important sector of water users in Georgia. The animal agriculture sector is also critical in Georgia, as much of the rural economy of Georgia is based on animal agriculture. Out of the 6.22 billion dollars annual farm income, nearly 3.73 billion dollars arises from the livestock poultry sector. In spite of its importance in income generation and water use, the precise present and future water demand by different sectors of animal agriculture is unknown. Apart from USGS and ACT/ACF aggregate livestock water use information, there exists little to no water use information about different sectors of livestock water use.

In the absence of water demand for a particular animal type, such as broilers, swine, dairy, and beef cattle, policy proposals and decisions regarding animal water demand are made under incomplete and inaccurate information. Furthermore, USGS livestock water use coefficients carry the general limitation of physical models by considering animal water use as a function only of temperature, rainfall, and other climatic variables. The ACT/ACT study is also constrained by the use of only an expert's educated guess to forecast livestock water demand for selected counties in Georgia.

Lack of systematic water demand prediction approaches and ignorance of the role of economic decision variables in livestock water demand are the major limitations of USGS and ACT/ACF water demand model. However, livestock water demand is directly related to supply of livestock, which in turn depends on the livestock supply response behavior of farmers. Supply of farm animal by farmers is an economic decision, which is highly affected by the economic variables such as expected prices and costs of production and can be modeled by using profit maximization or cost minimization theory. Therefore, our study addresses the four major problems associated with estimating precise present and future livestock water demand namely: aggregate water use data, lack of livestock water demand models, absence of linkage between econometric and time series water demand model with the USGS or ATC/ACT water demand models, and the water demand gap due to the differences in the physical, econometric, and time series models.

To carry out the stated objectives, the present analysis develops a method of livestock water demand forecasting for broiler, swine, dairy cattle, and beef cattle. Accurately estimating present and future livestock water use directly depends on developing a sound animal supply response model. Therefore, especial efforts have been made to improve the existing livestock supply response models and their forecasting accuracy. In the case of broiler production, a dynamic broiler supply response model was developed by considering the underlying biological and economic decision-making features of broiler production. Our representative broiler model comprises three successive stages of production namely: placement, hatching, and broiler production. At each stage, the broiler growers or integrators make an economic decision related to the investment and some form of capital is transformed into a different form of capital. Forecasting accuracy of the structural broiler supply model was further assessed by developing an autoregressive integrated moving average model (ARIMA).

Swine supply response models basically follow the theoretical model development approach of broiler production. Our representative swine supply response model comprises of three sequential stages of production, namely: Gilt farrowing, pig corps, and barrow and gilt harvest. The representative swine supply response was modeled as a function of feed cost, expected market price of barrow and gilt, trend variable, and seasonal dummies. Using forecasting theory developed by Harvey (1989), we extend the existing swine supply model by introducing stochastic trend and seasonality. The introduction of stochastic trend and seasonality components in swine supply model adds a new research frontier to the existing classical swine supply research, which basically assumes fixed underlying trend and seasonality effects in swine supply response.

The dairy supply response function follows a structural time series model with explanatory variables. In our dairy supply response model, we argue against assuming seasonality and trend as deterministic components. A deterministic seasonality and trend may or may not be correct, but it should not be assumed a priori while developing supply models for dairy cattle. In our analysis of dairy supply response, we select a basic dairy cattle model as proposed by Kaiser et al. (1994). The selected model was extended by hypothesizing four different scenarios of fixed or stochastic trend and or seasonality components.

The beef cattle supply response model basically follows the dairy supply response model. However, we assume no seasonality in the beef cattle equation because of the unavailability of quarterly inventory for beef cattle. Because of the slow rate of technological progress in the beef cattle industry in comparison to poultry and swine, many researchers reject the role of trend or technological progress in beef cattle supply. Though slow, technological changes might affect the beef cattle supply response. Therefore, contrary to existing beef cattle supply models, we develop two alternative beef cattle supply models, hypothesizing deterministic and stochastic trend components by modifying the beef cattle supply response model proposed by Rucker et al.(1984). The beef cattle supply response was assessed by examining breeding herd and all cattle & calves sectors separately.

Ordinary least squares regression analysis (OLS) is based on several statistical assumptions, including independence of the stochastic error terms. However, with the use of time series data, the errors terms might be correlated over time, violating that assumption. The problem of autocorrelation can arise in the broiler and swine autoregressive models where one or more lagged values of the dependent variable serve as explanatory variables. In order to overcome the problem of autocorrelation, SAS autoreg procedure was used. The autoreg procedure of SAS solves the problem of autocorrelation by augmenting autoregressive model and simultaneously estimating regression coefficients.

The dairy and beef cattle supply response models were analyzed by using STAMP, which uses maximum likelihood estimation by the numerical optimization procedure. The Kalman filter, which is a simple statistical algorithm, and a state-space model play fundamental roles in analyzing structural time series models.

Even though different modeling approaches and theoretical considerations were given while developing supply response models for different animal types, all supply response models in our study incorporate economic variables, such as expected profits and costs of production in the analysis. The overall goodness of fit of broiler and swine supply response models was considered by examining the F- test statistic and the co-efficient of determination, R^2. In the case of dairy and beef supply response models, we consider different measures of diagnostics and goodness-of-fit, such as Durbin-Watson (DW) test, Ljung-Box Q statistic, Jarque and Bera normality statistics, standard error of the estimated equation, AIC, and BIC. The conventional R^2 is not very useful to measure the goodness-of-fit in time series models. Therefore, we consider R_s^2 , a coefficient of determination suggested by Harvey. The forecasting accuracy of different dairy and beef cattle supply response models was examined by using mean square percentage error (MAPE) and root mean square percentage error (RMSPE) criteria for both in-sample and out –of- sample forecast values.

Conclusions

In our analysis of broiler supply response model, all economic variables yield expected signs and were significant at 90 percent level of significance, reflecting the informational importance of economic variables in forecasting numbers of broilers and thereby the broiler water demand. Further analysis of broiler water demand forecasting by using physical, structural and ARIMA time series model reveals that the ACT/ACF physical model underestimates water demand by approximately 11 percent in comparison to structural and time series models. The analysis also shows no substantive difference between the structural and time series forecast models.

In the swine supply response model, the F statistic rejects the null hypothesis that all parameters except the intercept are zero for all equations. In all equations, economic variables, such as hog price and corn price, yield parameter estimates that are statistically significant, but the findings were inconsistent with the results of Holt and Johnson (1988). Analysis of the swine supply response model using structural time series with exogenous variables yields similar results to those obtained by using the econometric or structural, model. Further analysis of forecasting accuracy of the econometric model and STSM using RMSPE and MAPE supports the robustness of STSM over the econometric model for predictive purposes. In our analysis, the econometric model forecasts decrease of swine water demand from 992.5 thousand gallons per day in 2003 to 866.2 thousand gallons per day in 2006. Meanwhile, the STSM forecasts a decrease of water demand from 1087 thousand gallons per day in 2003 to 863.75 thousand gallons per day in 2006. Assuming no change in all hogs and pigs inventory, the physical model forecasts 1866.7 thousand gallons of swine water demand in Georgia in 2006. Analysis shows that physical model overestimates swine water demand by 94% (on average) in comparison to STSM. As both RMSPE and MAPE values of STSM were smaller than econometric model, we recommend STSM for swine water demand forecasting purposes.

In the case of the dairy supply response model, the measures of diagnostic and goodness-of-fit of the model confirm the specification validity of the DTDS, DTSS, STDS, and STSS dairy supply response models. All economic variables were statistically significant, again showing the importance of incorporating economic information variables while forecasting dairy cattle inventory and thereby future dairy water demand. As expected, all dairy supply models show a statistically significant and inverse relationship between milk feed price ratio and dairy cow supply. Except DTSS, remaining dairy supply models show a significant and positive impact of harvest cow price on the supply of cows.

In order to select the superior model, we consider AIC, BIC, and R_s^2 values as the main criteria. These values support the use of DTSS (seasonal stochasticity) dairy supply model as the 'best' model of dairy supply, clearly rejecting the classical idea of incorporating deterministic seasonal variables in the dairy supply model *a priori*. Further analysis of forecasting performance using MAPE and RMSPE support the robustness of the DTSS dairy supply model in term of forecasting accuracy. Water demand forecasting using DTSS dairy supply model and the physical model shows an overestimation of only 1.21% of dairy water demand by the physical model.

The estimates of trend and explanatory variables, along with measures of diagnostic and goodness-of-fit for all models of breeding herd and all cattle & calves supply support the correctness of the specification of the models. Further analysis of all supply models of breeding herd and all cattle & calves by using a structural time series model with explanatory variables proposed by Harvey (1989) yield expected signs and statistically significant parameter estimates.

Using the highest R_d^2 and the smallest AIC, BIC values to select the breeding herd and all cattle & calves supply models support a deterministic time trend and no seasonality component as the correctly specified models. The smallest RMSPE and MAPE values further support the forecasting accuracy of selected breeding herd and all cattle & calves models. The physical model overestimates the water demand by 8.6

percent and 14.7 percent (on average) for breeding herd and all cattle and calves, respectively, over the structural time series model.

Implications and Future Research

Thus far, there exist no systematic efforts to estimate and forecast livestock water demand by using a statistically valid modeling approach. A major contribution of this research is to develop econometric and time series livestock water demand forecasting models incorporating economic variables. Analysis shows the importance of systematic modeling approaches and econometric/time series analysis for valid results. Our analysis shows that, ignoring economic variables, a restrictive physical model failed to capture the ongoing changes in the livestock sector in Georgia. Furthermore, ignoring economic variables, the physical models underestimate broiler water demand (15%), but they overestimate swine water demand (94%), dairy cattle (1.2%), breeding herd (8.6%), and all cattle and calves (14.7%) in Georgia. In our study, efforts mostly center around improving the existing livestock supply response models and accompanying forecasting accuracies. However, precise forecasting of livestock water demand is a difficult task in the light of variations in the factors that affect the livestock water uses.

Livestock water use comprises of water consumed by animals and water used in different management practices. Water in-take of poultry, swine, dairy cattle, and beef cattle is relatively well understood and is known to be influenced by the feed intake, temperature, production stage of the animal and some factors related directly to the water, such as salinity or components contributing to its palatability. However, how changes in these factors affect the livestock water demand is not understood. Still, researchers and policy makers use the water use coefficients reported by USGS without considering variations in these factors.

Furthermore, a major portion of livestock water demand is used for livestock management activities, such as waste management, washing, and other sanitation practices, including cleaning of watering devices. In the last few decades, technological progress brought drastic changes in many of these livestock management practices. The changes in livestock management practices ultimately affect livestock water demand. However, how recent developments in the livestock management practices affect livestock water demand is ignored in the empirical research. Accurate estimation and forecasting of livestock water requires a complete understanding of the impacts all livestock water demand affective factors. Therefore, future research should consider breaking down existing USGS livestock total water use coefficients into consumptive water use and management water use, study them separately, and update them periodically.