THESIS
2
1999

MICHIGAN STATE LIBRARIES
3 1293 01834 2075

LIBRARY
Michigan State
University

This is to certify that the

dissertation entitled

Predicting the Path of Grain Prices With Limited Data: A Case Study From Mali

presented by

Kimberly M. Aldridge

has been accepted towards fulfillment
of the requirements for

Ph.D. degree in **Agricultural Economics**

Major professor

Date **May 13, 1999**

MSU is an Affirmative Action/Equal Opportunity Institution

O-12771

PLACE IN RETURN BOX to remove this checkout from your record.
TO AVOID FINES return on or before date due.
MAY BE RECALLED with earlier due date if requested.

DATE DUE	DATE DUE	DATE DUE
MAR 1 8 2000		
MAR 1 7 2001 022101		

PREDICTING THE PATH OF GRAIN PRICES WITH LIMITED DATA: A CASE STUDY FROM MALI

By

Kimberly M. Aldridge

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics

1999

ABSTRACT

PREDICTING THE PATH OF GRAIN PRICES WITH LIMITED DATA: A CASE STUDY FROM MALI

By

Kimberly M. Aldridge

The late 1980s witnessed a surge of agricultural market reform efforts in the developing world, including Africa. Many of these efforts were accompanied by the implementation of market news services, which sought to encourage the competitive growth of the private sector by improving market transparency. One result of market reform in Mali has been the increased demand for improved outlook information on the likely evolution of grain prices. Such information is essential for making, *inter alia*, better marketing store/sell decisions.

This purpose of this research is twofold. The first is methodological in nature and focuses on developing and evaluating alternative methods of forecasting short-term agricultural prices with limited data, using the grain markets from Mali as a case study. In fiscally austere environments, publicly-funded market information systems must continually show evidence of their social/economic value, thus, the second objective is to demonstrate that investing scarce resources in improved forecasting methods can be economically valuable.

Monthly grain price data from the Malian market information system, from September 1982 to September 1998, are used to build univariate and multi-variate time-series models of rice, sorghum and maize prices. The models which have errors that

approximate a white noise process, a necessary condition for efficient forecasting, are entered into a forecast competition and out-of-sample forecasts are generated for 1, 2 and 3-steps ahead. The forecast contenders are statistically evaluated and scored using root mean squared error and turning point error criteria. The competitor with the lowest score emerged as the winner. For sorghum, the results of the forecasting competition indicated that the ARIMA with second-order harmonic specification of seasonality was the most accurate for forecasting sorghum price changes 2, and 3 months ahead, while the vector error correction model had the lowest root mean squared error for predicting 1 month ahead.

To demonstrate the value of investing in improved price forecasting techniques, model-generated store/sell strategies of a sorghum producer in the Zangasso region of Mali, were compared to marketing strategies generated from a random walk model. The criteria used to evaluate the models included mean net price received (net of storage cost) and percentage of correct decisions. The model with the highest mean net price and highest percentage of correct decisions was declared the winner. The results indicate that relative to the random walk, marketing strategies based on improved forecast models, generate a higher mean net price received, thus, without accounting for risk preferences and capacity to respond, such models can indeed be economically valuable.

Copyright by

Kimberly M. Aldridge

1999

DEDICATION

for my Imani

ACKNOWLEDGMENTS

The completion of this dissertation is a product of fierce determination and a staunch belief in myself. I can make that claim because despite the fact that dissertations assume lives of their own, the cycle of our own life does continue. The challenge lies in striking an appropriate balance between investing time in theories of time-varying volatility and a 3 year old's dance recital. Although, the path has been long and often painful, my growth academically, professionally and personally indicate that it is well worth the struggle.

I had help. Many thanks to my guidance committee: To John Staatz, my major professor and thesis coordinator, who skillfully, but gently nudged me along, yet again. Since completing my masters program under your guidance, my profound gratitude to you has only deepened. Your continued support and standard of excellence was the impetus that encouraged me to work harder and to not succumb to the trials and tribulations of just living life. Somehow, if you could believe, then I could as well. I look forward to years of collaboration and friendship. To Bob Myers from whom I gleaned the intricacies of time-series econometrics (well, I tried anyway!). Dr. Myers patiently (usually) spent many hours trying to convince me that "it's not rocket science"! Fortunately, "it" turned out okay, although I remain skeptical about its unrocketscienceness! To Tom Reardon, your energy and enthusiasm during our initial brainstorming sessions made conceptualizing enjoyable and the potential exciting. To John Strauss, many thanks for your support over the years. And finally, to Al Schmid who insists that high exclusion cost and non-appropriability both add up to the marginal cost of an additional user being zero! Al, I only wish I had time to learn more.

I must also thank Nango Dembele and Jim Tefft, both who work or have worked at the market information system in Mali, for sending data and helping me to understand the stories behind the numbers.

Financial support for this research was critical to its completion and was provided by the Food Security II Cooperative Agreement between USAID and Michigan State University, Department of Agricultural Economics, for which I am most grateful. I would also like to thank the food security project and the Department for its institutional and infra structural support, including Chris, Carol and Elizabeth of computer services, Janet and Josie of the business office, Roxie Damer, and the folks in the reference room, and many others. I would also like to express my gratitude to the Minority Competitive Doctoral Fellowship program and the ALANA fellowship program which both provided support during the early years of my doctoral studies.

To my family, and the many friends and colleagues whom I've met along this journey and who in numerous ways contributed to its successful completion, thank you all for your unwavering support and belief in me. Special thanks go to my mom, Cheryl Danley and Raymond Familusi. Finally, thanks to my daughter, Imani, my faith, my peace, for enduring the many hours at the babysitter so Dr. mommy could finish her big book!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION AND RESEARCH CONTEXT

1.0 Introduction

The future is uncertain, and thus the full impact of decisions taken today is often not realized until later. To reduce some of this uncertainty and improve the efficiency of the decision making process, many economic decisions require forecasts of the future behavior of key economic variables. The more accurate the predictions, the better able are decision makers to make accurate and timely decisions (Holden 1990).

Agricultural management decisions in a market-oriented economy involve considerable uncertainty. Indeed, the special position of food production in a nation's security, coupled with the public-good characteristics of information, have led most developed countries to institute national statistical and analytical organizations which regularly disseminate market news and outlook information on the agricultural sector. Forecast information is used to inform policy decisions such as the provision of market support to producers, as well as provides private decision makers information with which to plan and strategize. These projections are typically made with conventional econometric methods, with time-series approaches occupying minor roles (Allen 1994).

The late 1980s witnessed a surge of agricultural market reform efforts in the developing world, including Africa. Many of these efforts were accompanied by the implementation of market news services, which sought to encourage the competitive growth of the private sector by improving market transparency. As expected, liberalization altered the operating and decision environments facing economic agents. One result has been the increased demand for improved outlook information on the likely evolution of cereals and related markets. Such information is essential for making better storage/sales decisions, for production planning and acquiring stock for processing, as well as for planning trade operations and for better public policy decisions.

To the degree that they are undertaken systematically in newly liberalizing economies, forecasts of key economic decision variables are largely subjective, i.e., based on guesses, experience or intuition without an explicit structure or method for processing information[1]. And the forecasts that are derived from explicit or model-based procedures (formal relationships between variables) are usually based on simple smoothing or trend extrapolation methods. Because these methods often fail to capture turning point errors (Tomek & Robinson, 1990), more sophisticated models that account for such turning point errors can theoretically ameliorate forecast accuracy and increase the value of outlook information to the economic agent and society as a whole.

Most market information systems (MISs) in the developing world are primarily price reporting services which are publicly supported with substantial reliance on external/donor financing. However, as donor support is increasingly withdrawn, the sustainability of market information systems is challenged as they are forced to survive on very fragile governmental budgets. The value of market information and information services is often poorly understood by policymakers, making market information systems

---

[1]Subjective forecasting techniques are not necessarily less accurate than model-based forecasting, but these methods usually preclude any quantitative measure of confidence in the resulting forecasts.

prime candidates for budget cuts and possible elimination. Indeed, despite the well known public good arguments of non-appropriability and high exclusion costs, even the developed world debates the necessity of public investment in market news services[2]. Nonetheless, these services in industrial countries continue to receive public support by delivering information products that are in demand from the business, policy-making and research sectors. Analogously, market information systems in the developing world are under pressure to demonstrate that they are a worthwhile public investment by creating a constituency to lobby for political support by strengthening and adding value to their current product profile. Meeting the demand for improved outlook information such as short-run forecasts on the future path of prices, is one such effort to induce constituents to contribute financially to maintaining market information systems.

1.1 Problem Statement and Research Objectives

The cereals market information system in Mali, known until recently as the SIM, has regularly disseminated price information on various grains in various markets throughout the country since 1989[3]. Currently the SIM is fighting to sustain itself financially by *inter alia* meeting the revealed demand for price outlook information. Using the SIM price data, this research develops and evaluates statistically and economically short-term price forecasting models. The specific objectives are to:

---

[2]For instance, see Bonnen 1977, 1996.

[3]In late 1998, the SIM was restructured (broadening its mandate) and renamed the Observatoire des Marches Agricoles (OMA).

- develop alternative models for sorghum, maize and rice prices in Mali that can be used for short-term forecasting in the context of sparse data.
- evaluate the forecasting ability of the alternative price models based on statistical criteria.

One way to improve outlook information is to develop "better" forecasting models, where better implies an increase in value to an end-user and/or society[4]. Once an appropriate forecast model is developed, in the context of grain marketing strategies, the value of improved price forecast information is analyzed. Towards this end, this research

- evaluates the economic value of improved price forecast information to a group of users by evaluating the utility of the alternative price models in a decision-making context and;
- draws lessons on which time-series models produce accurate and economically useful forecasts with limited data.

In order to predict the future path of grain prices, it is first necessary to develop an understanding of the markets in which the prices are formed. The next section therefore sets the research context by identifying important aspects of the sorghum, maize and rice markets in Mali which are relevant for understanding and modeling grain price behavior. It describes the salient characteristics of the these markets which influenced the formation of grain prices during the January 1982 to September 1996 period.

---

[4]The terms "outlook" and "(short-run) forecasts" are used interchangeably.

1.2 Malian Grain Markets

Theoretically, commodity prices are determined by the interaction of supply and demand, which in turn is conditioned by the institutional and climatic environment in which the markets operate. Mali is a landlocked country where about 85% of the total population derives its livelihood from agriculture and livestock. Millet, sorghum and maize are rainfed while a large component of rice production is irrigated. Between the 1984/85 and 1996/97 production campaigns total cereal production increased by almost 50%, led by a significant rise in rice production of 9.8% to 27.9% of total cereals produced. See table 1.1.

Table 1.1: Evolution of Grain Production in metric tons

	1984/85	1990/91	1995/96	1996/97
Sorghum	369,818 (33.2)	531,433 (30.0)	710,275 (21.3)	540,273 (24.5)
Maize	101,440 (9.12)	196,579 (11.0)	264,457 (12.2)	289,761 (13.2)
Rice	109,354 (9.83)	282,236 (16.0)	462,702 (21.3)	613,965 (27.9)
Total	1,111,668	1,769,153	2,172,429	2,200,933

Source: Ministere du Developpement Rural et de L'Eau (March 1998). Recueil des Statistiques du Secteur Rural Malien. (Percent of total cereals in parentheses)[5]

[5]Millet, fonio and wheat are included in the total.

Millet, sorghum, maize and rice are the staple crops produced and consumed in Mali. Smallholders account for the bulk of grain production. Millet and sorghum comprise the largest cultivated areas and are produced throughout the country, while maize is produced in the higher rainfall areas. Irrigated rice is concentrated in the irrigated areas of the Office du Niger zone[6]. See map of the different agricultural zones in figure 1.1. Mais sorgo and riz are the French terms for maize, sorghum and rice respectively.

The structure of millet and sorghum production has changed little over the last twenty years. The technological change that has occurred has come from the introduction of shorter-cycle varieties, which has allowed farmers to manage climatic risk better but has not led to dramatic increases in yield. Maize and rice on the hand have witnessed technological change[7] In general, only farmers engaged in cash crop production such as cotton and rice have access to purchased inputs and labor-saving technologies[8].

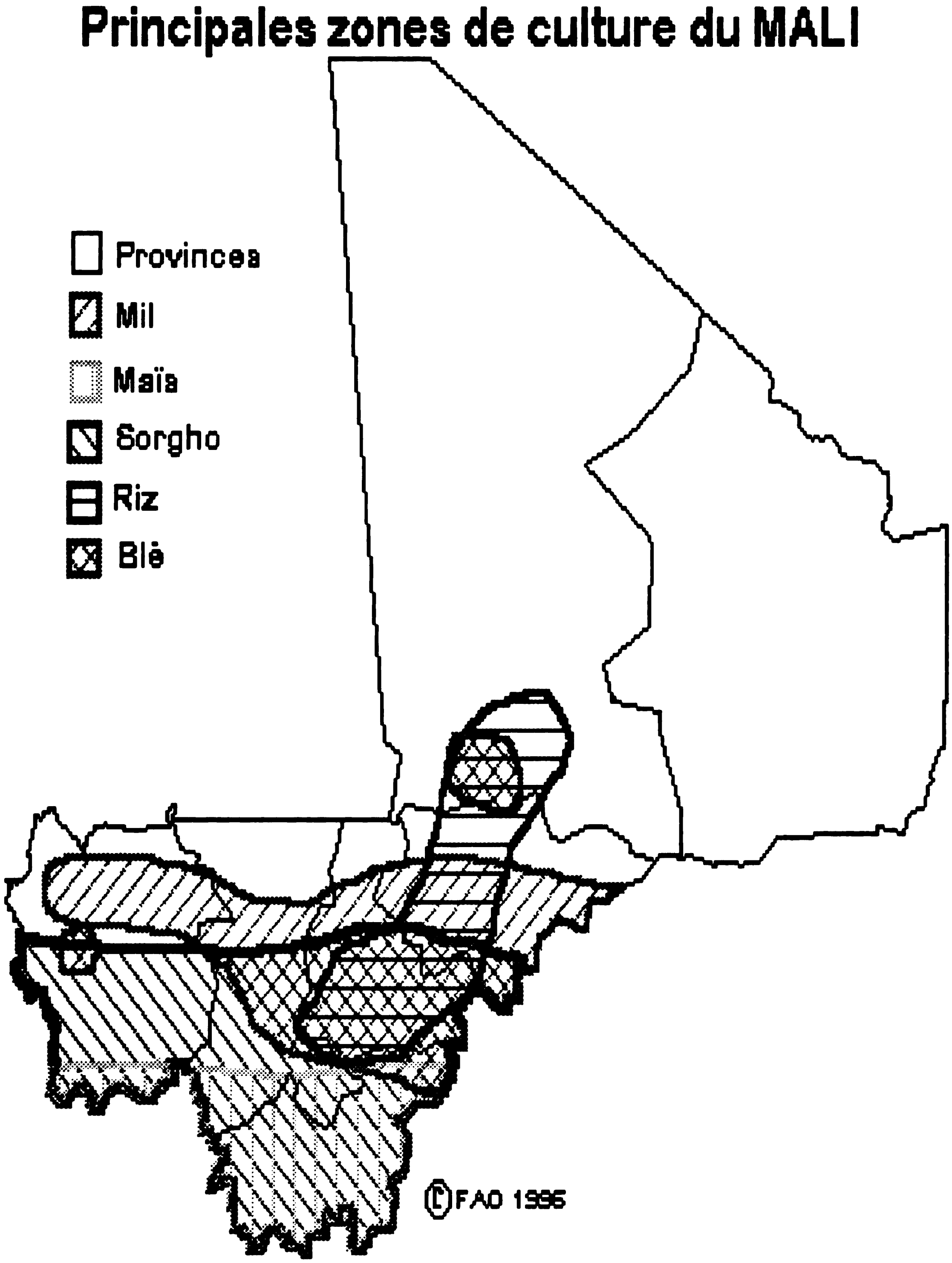
---

[6]The Office du Niger is a parastatal enterprise established in 1932 to provide irrigation in the area surrounding Niono (Diarra 1994).

[7]Although animal traction has become common in the cotton zone of southern Mali, most farmers continue to rely on the traditional hoe to cultivate. See Dimithe (1997), Boughton (1994) and Diarra (1994) for further discussion of technological advances of grain crops in Mali.

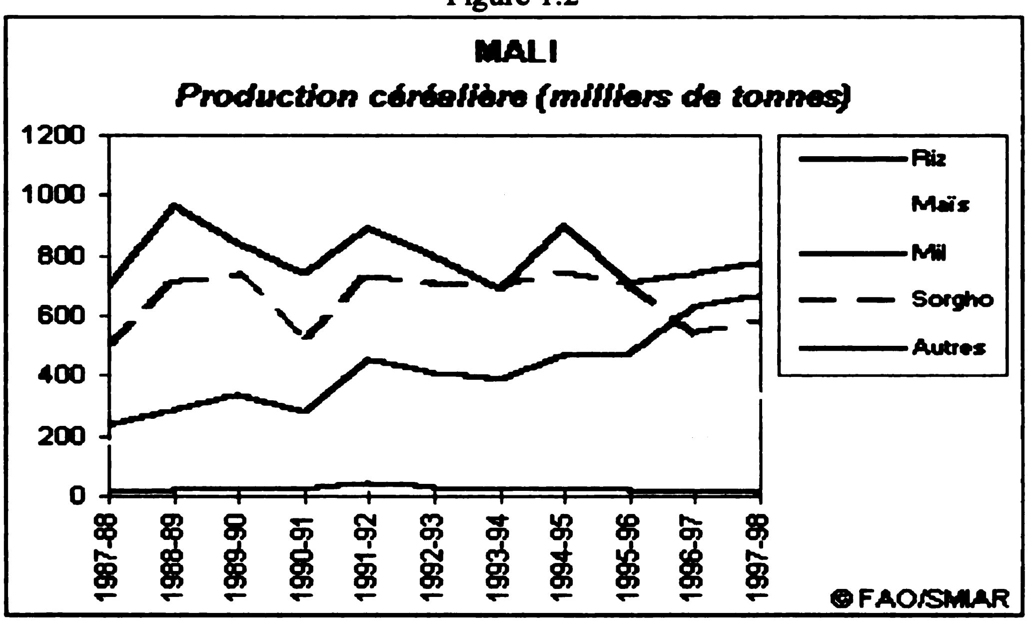
[8]Paddy rice is produced both as a food and cash crop.

Figure 1.1


Principales zones de culture du MALI
Provinces
Mil
Maïs
Sorgho
Riz
Blé
©FAO 1996

Rainfall variability, which in the agricultural zones of central and southern Mali ranges from an average of 700 mm to1300 mm. per year, is the major factor affecting the productivity of smallholders. Grain production fluctuates directly with the variability in rainfall. In figure 1.2, from 1991 to 1998, sorghum production appears relatively stable around 700 thousand tons, increasing towards 800 thousand tons in 1998. From 1987 to 1998, maize production, which is considerably less than both sorghum and rice, increased slowly from about 200 thousand tons to 375 thousand tons. Rice appears to be the most rapidly growing and highly variable grain, increasing from about 250 thousand tons in 1987/88 to almost 700 thousand tons in 1997/98 (FAO website, January 1999).

Figure 1.2



Cereals (millet, sorghum, maize and rice) account for 80% of total calorie intake in rural diets and 70% of urban diets (Badiane et al., 1992 as reported in Dembele 1994). Rural consumers produce most of their grain needs; consequently only about 15% of total grain production reaches the market. Like most developing countries in Africa, the pattern of domestic consumption in Mali has evolved with urbanization, with rice, which is easier and faster to prepare, being the preferred urban grain. Urban consumers devote about 51% of their total expenditures to food, and cereals comprise 48% of household food expenditures (reported in Diarra 1994). Grain prices therefore strongly influence the real incomes of urban consumers.

The coarse grain markets are thin, with maize being the lowest in volume. Rice benefits from the stabilizing effects of irrigation and imports, and thus rice prices appear more stable relative to coarse grains. Variations in marketed surplus are determined largely by variations in climatic conditions. During good rainfall years a higher proportion of total production reaches the market, while during bad years marketed surplus drops sharply. The level of production influences inter-annual variability in marketed surplus, while the marketing strategies of producers determine the seasonal distribution of marketed surplus within years. Another factor that contributes to the volatility of the market is that many farmers go from being net sellers in good years to net buyers in bad years. Hence, both the supply curve and the demand curve are shifting in ways that accentuate price movements.

Furthermore, cash-crop producers store most of their cereals at harvest and spread sales over the season, while the majority of noncash crop producers tend to sell more at harvest (when prices are low) to meet financial obligations (Dione 1994). In general, marketed surplus, which takes place through a network of rural collectors, assemblers, wholesalers and retailers, peaks during harvest and declines progressively over the months, consequently shifting the storage function from producers to traders and/or farmer cooperatives (Mehta 1989; Dembele 1994). It should be noted that some farmer cooperatives support farm prices at harvest by buying and storing grain for sale when prices rise later in the season.

As mentioned above, domestic grain production in a given year is largely determined by the level of rainfall, such that shortfalls in rainfall translate into shortfalls in production. To satisfy the growing demand for cereals, Mali uses cereal imports and food aid to offset the instability in domestic production and stabilize domestic consumption. Thus, when domestic production is low, imports including food aid are high, and when domestic production is high, imports are low and exports rise. Rice and wheat constitute the bulk of imports and food aid. Moreover, since the 1994 devaluation, export demand has increased sharply, as Mali has become more competitive within the CFA zone vis a vis non-franc zone suppliers.

In addition to food aid and imports, the national grain board maintains and manages a national food security stock (NSS) to guard against severe food deficits. At 58,500 tons, the NSS is comprised primarily of millet and sorghum. The replenishment of the NSS creates an additional demand for traders and thus is very politicized. Indeed, under political pressure OPAM distributes its demand across all agricultural zones by way of quotas instead of pursuing more cost effective strategies such as procuring solely from surplus zones[9]. According to Dembele (1994), these quotas inflate prices in deficit zones, later creating pressure for food aid distribution.

The polices governing the grain subsector have varied almost as much as the weather[10]. Nonetheless, governmental policy has consistently stressed self-sufficiency in cereals as a major policy objective. While this goal has remained largely unchanged, the policies used to achieve self-sufficiency have varied. In 1981, the Malian government, in collaboration with several donors, began the process of reforming the grain markets under the Cereals Market Reorganization Project, known by its French acronym, PRMC. The previous agricultural policies which included sanctioning the national grain board (OPAM) as a legal monopoly in cereals marketing and official price fixing, were unproductive, inefficient and financially unsustainable (Steffen 1992). During the early years of the PRMC, when the country faced severe food deficits, the objectives of the PRMC were to:

- legalize and increase the role of the private sector in the grain trade;
- reduce marketing costs through increased competition and better management of OPAM; and
- transfer resources to farmers to enable them to invest in productivity-increasing technologies.

Food aid receipts were used to stabilize and increase market prices for cereals, and the national grain board was assigned a market stabilization role to support official producer and consumer prices (Dembele 1994).

---

[9]Procurement is from local production during surplus years and from imports and food aid during periods of poor harvests.

[10]For a historical perspective of the policies governing the Malian grain markets see Dembele (1994) or Steffen (1992).

These policy instruments were effective until 1986, when the return of normal rainfall patterns resulted in two successive surplus years, making it financially difficult for OPAM to stabilize producer prices through the management of a buffer stock[11]. Grain marketing policies were adjusted in1987; specifically, OPAM's role was reduced to the distribution of food aid, the management of the national security stock, and the collection and diffusion of market information. The determination of producer and consumer prices was left to market forces and instead supported indirectly by credit and export assistance programs. These marketing-facilitating services were financed by the sale of food aid.

Although the process of liberalization began in 1981/82, the above policy adjustments led to the effective liberalization of the coarse grain markets in 1987. However, the paddy rice market, which is more concentrated, strategic and politically sensitive, liberalized at a much slower pace. Indeed, in 1987, the rice marketing parastatal for the main irrigated rice production area, Office du Niger, continued to set a floor price for paddy rice (Diarra 1994). Moreover, relative to the coarse grains, imports and thus import policies play an important role in the rice market. In 1981, as part of the initial reform process and to encourage imports, the government eliminated nearly all rice import duties and taxes. Improved efficiencies in the irrigated rice sector, coupled with good rains, led to significant increases in domestic paddy rice production in the mid-1980s, leading the government to increase import duties from 5 to 32 percent of the border price

---

[11]In 1984/85 the country experienced a drought, and consequently market prices were higher than OPAM's prices. But in 1985/86 and 1986/87 rains were abundant and OPAM's guaranteed producer prices were higher than the market prices, so most merchants attempted to sell to OPAM.

in 1986 (Diarra 1994) in order to protect domestic producers. In 1987, further attempts to protect domestic rice production witnessed the introduction of "twinning", in which private traders wishing to import rice were forced to purchase an equal quantity from the Office du Niger. A low world price and accumulating domestic stocks led the government in October1987 to completely ban all rice imports.

The ban on rice imports resulted in high grain prices until June 1988, when the ban was relaxed. In 1989, "twinning" was abandoned as part of an import reform program imposed by the IMF. In 1990, another import ban was imposed which produced similar results until the ban was lifted in the later part of 1990. From March 1991 to March 1992, the transitional government, in need of financial resources, encouraged rice imports by reducing import tariff rates if importers agreed to pay the import tax in advance of actually importing the rice. This caused rice prices to decline in 1992/1993. More recent import policies include a variable levy. The increased protection for the domestic rice subsector starting in the early 1980s represented an implicit compensation for the increasingly over-valued CFA franc, which hurt the competitiveness of Malian rice. In January 1994, the CFAF, the Malian currency, was devalued by 100 percent, making rice imports and fertilizer more expensive, but making domestic rice production more competitive[12].

As a result of near stagnant production technology for sorghum and millet, uncertain rainfall, relatively low demand for maize, variable sectoral and tariff policies

---

[12]Prior to devaluation in 1994, rice could be obtained more cheaply on the international markets.

which affect rice, the sorghum, maize and rice markets can be largely characterized as thin, low-volume markets. Capturing the dynamic behavior of prices that result from such uncertain markets and making short-term forecasts is the focus of this research and is conceptualized as follows:

Basic conditions

Inter-annual variation	**Intra-annual variation**
Production	Seasonality
Rainfall	Storage
Policies	Marketing strategies

The variation in grain prices is examined under two broad categories: inter-annual variation, where the forces explaining the difference in prices from one year to the next are examined; and intra-annual variation, where determinants of month-to-month variation are identified. In a first-best world, the factors specified above could be measured and quantified and described in an econometric model designed to capture the price determination process and then used to forecast the future path of prices. However, historical data bases in many developing countries are limited, and Mali is no exception. The challenge is to develop reasonably accurate forecast models with limited data on variables other than price.

1.3 Organization of Dissertation

The dissertation is organized into eight chapters. Chapter 2 reviews the forecasting literature and identifies relevant forecast modeling techniques for countries with sparse data sets (i.e., limited in length, quality and number of available measured variables). Having identified a set of forecasting procedures, chapter 3 discusses and analyzes the grain price data for Mali, while chapters 4 and 5 develop univariate and mulitvariate price models, respectively. In chapter 6, the alternative price forecasting models for sorghum, maize and rice are evaluated statistically for forecasting and the "best" models for each commodity are identified. In an effort to analyze the value of improved price forecast information, chapter 7 uses the forecast-decision-support literature and the storage literature to economically evaluate forecasts models of producer prices. Chapter 8 summarizes the study and draws major conclusions for policies and for future research.

CHAPTER 2

ECONOMIC FORECASTING IN AGRICULTURE FOR DEVELOPING COUNTRIES

2.0 Introduction

The nature of agricultural production and the historical relations among different groups of participants in agriculture make agriculture different from most economic activity. Both nature and governmental policy can have a major impact on agricultural production, prices and profits, making agriculture forecasting very difficult. In fact, empirical research has found that the large structural econometric models often do poorly or do no better than simple naive models at forecasting agricultural production and prices. The most likely reason, according to Allen (1994), is the influence of random shocks or unpredictable events such as droughts, floods, and pest attacks. Nonetheless, forecasts of future events must be incorporated into the decision-making process to manage better the impact of these events.

The purpose of this chapter is to discuss the various forecasting techniques and terminology that have been applied to agriculture as well as to justify and outline the methods that are used in this study. It begins by reviewing the conceptual tools that are used throughout the paper, with the majority of this chapter dedicated to the theoretical models and forecast functions upon which the models in chapters 4 and 5 are grounded.

2.1 Conceptual Issues

A forecast is defined as a qualitative or quantitative estimate or set of estimates about the likelihood of future events based on current and past information (Pindyck and Rubenfeld 1991; Holden 1990). In the forecasting literature a distinction is made between short, medium and long-term forecasts. Short-term forecasts, or outlook, generally refer to the next few months to a year. With short-term forecasts, it is usually assumed that there will be little change in recent patterns of behavior, and that the market structure and policy environment will remain the same over the forecast horizon. Medium-term forecasts can range from one to three years, while a forecast horizon of three years or longer is considered as long-term since the economic environment can change dramatically after three years (Holden 1990).

Forecasting can be done *ex ante* or *ex post*. With *ex-post* forecasting techniques, observations on both the endogenous and exogenous variables are known with certainty during the forecast period. This type of forecasting provides a means of evaluating a forecasting model because the forecast can be checked against existing data. *Ex ante* or out-of-sample forecasting predicts values of the dependent variable beyond the period of estimation and is considered to be a true test of a model's forecasting ability.

Forecasting techniques are classified into two broad categories: qualitative (subjective or implicit) and quantitative (model-based or explicit). Subjective or implicit forecasts are based on guesses, experience or intuition without an explicit structure or method for processing information. Explicit or model-based forecasting techniques are based on formal relationships between variables of interest. Explicit model building forces one to think clearly about, and account for, all the important interrelationships involved in a problem, whereas reliance solely on intuition can cause one to ignore or improperly use important relationships. In addition to the forecast itself, a measure of forecast accuracy gives more information to the user with which to plan. Subjective forecasting techniques usually preclude any quantitative measure of confidence in the resulting forecasts. Rather, with qualitative forecasting it is difficult to analyze why a particular forecast is good or bad or learn from past forecast errors.

In practice, most forecasting systems employ both qualitative and quantitative forecasting techniques - the results of explicit forecasting are modified based on qualitative information known by the analyst. In general, quantitative methods are used when the existing data pattern is expected to persist, while qualitative methods are useful when the existing data pattern is expected to change. Moreover, forecasts generated by quantitative methods are subjectively evaluated by the forecast user and may be revised accordingly. Because qualitative forecasting techniques can be very important when historical data is sparse or of dubious quality, the next section discusses a common qualitative forecasting technique. The remainder of this chapter discusses quantitative forecasting techniques, with a focus on the methods employed in this study.

2.2 Qualitative Forecasting Techniques

In practice, qualitative forecasting methods generally use the opinions of experts to subjectively predict the future. Subjective forecasts are formed and based on the experience, intuition and judgement of the forecaster. The goal is to pull expert opinion from those who have insights about a particular future event. The Delphi technique, developed by the RAND Corporation, is a common qualitative forecasting technique. In this method, experts are surveyed independently to forecast a particular event over a specified time period. The results are collected and discussed by the experts. Those with the highest and lowest forecast are asked to justify their opinion, and after further discussion the experts are surveyed again, results are again discussed and this process continues until a consensus forecast emerges. The discussion may take place in a round-table format or in written or computer form where the experts never physically meet.

Combining the opinion of several experts who must justify their forecasts and then iterating until a consensus is reached is considered to be the main advantage of the Delphi method. It is assumed that the consensus forecast will be more accurate than any outlier. The major disadvantage is that experts may be influenced by the opinion and personalities of other experts if anonymity is not preserved. In addition, the Delphi method can be costly to implement and it is possible to end up with a forecast that none of the experts strongly believe in. Moreover, the definition of an "expert" must be agreed upon as well as how much information should be passed on in the iterative stages. According to Holden (1990), the Delphi method is most appropriate for longer-term forecasting and where historical data may be misleading.

2.3 Structural Models for Forecasting

The rest of this chapter discusses quantitative forecasting methods, which are techniques that focus on the analysis of historical data to predict future values. There are two groups of quantitative forecasting methods: causal and noncausal models. This section discusses causal or structural models in which the focus is on explaining the behavior of a variable and using that explanation to predict the future behavior of that variable. According to Holden (1990), the best method for forecasting the future values of a given variable, *ceteris paribus*, is to build a structural (causal) econometric model using time-series data. Once the correct economic theory is employed and a model is specified, the parameters can be estimated from a data base, and by extrapolating the model beyond the estimation period, forecasts of future values of the variable of interest can be made. Single and multi-equation regression models and multi-equation simultaneous models are common structural models used for forecasting.

To illustrate, a simple linear single-equation in which x explains the movement of y is described below:

$$y_t = \alpha + \beta x_t + \epsilon_t \tag{1}$$

The equation is estimated and if it is found acceptable in a statistical sense, then the estimated parameters are used to forecast future values of y conditional on x. Since the model is causal, future values of exogenous or explanatory variables will need to be projected forward or taken from another source. In this model, the forecast information is embodied in a single-equation structural model. The forecast function for a number of periods can be obtained as a series of one-step-ahead forecasts as in equation 2. The

$$\hat{y}_{T+1} = \hat{\alpha} + \hat{\beta} x_{T+1} \tag{2}$$

simple linear model can be expanded and modified to include other regressors, equations or different functional forms if the theory and data availability warrant.

In multi-equation simulation modeling, the variable may be a function of several explanatory variables which are related to each other, as well as to the variable under study through a set of equations. If assumptions are made about the future behavior of explanatory variables, then the model is simulated into the future to obtain forecasts for each of the variables in the model. As simulation models presume to explain individual relationships and interactions among all the relationships of the process under study, the data requirements as well as the time and money for such models can be quite large. These models can provide insight and thus greater understanding of the relationships between variables, which can improve forecast precision.

The major steps involved in constructing a structural model and using it to forecast include: selecting the appropriate endogenous and exogenous variables according to economic theory; writing the theory as an equation or series of equations linking together variables with an appropriate functional form; finding data on the variables; estimating parameters using appropriate econometric techniques; and conditional on the estimated equation parameters, generating predictions of the future value of the exogenous variables to forecast the endogenous variables.

Causal models are useful in that they allow decision makers to evaluate the impact of various alternative policies once the relationship between variables is identified. While structural models attempt to explain behavior by identifying the links between variables, they are complex and difficult to develop. They require more data and time and thus are more costly than non-causal models. Often reliable data is unavailable on the relevant variables that economic theory suggests should be included in the structural model. In other cases, it is not clear what constitutes the appropriate economic theory. As a consequence of the foregoing points, the costs of constructing and estimating a structural model may be greater than the perceived benefits, so a cheaper forecasting technique may be required. But if the costs are justified, structural models by design give more accurate long-term forecasts than noncausal techniques.

2.4 Noncausal Forecasting Techniques

Unlike structural models, noncausal models presume to know nothing about the causal relationships that affect the variable of interest. That is, noncausal modeling techniques focus on identifying a statistical method for projecting or extrapolating the historical data into the future. Smoothing, trend extrapolation and Box-Jenkins or ARIMA models are common classes of univariate noncausal models used for short-term forecasting and are discussed below. Each class of model involves a different degree of complexity and presumes a different level of comprehension about the underlying processes that are being modeled. Smoothing and trend extrapolation are simple forecasting tools which are discussed in the next section, followed by a discussion of the Box-Jenkins method, also referred to as ARIMA or time-series models. Vector autoregression (VAR) is a common mulitvariate noncausal forecasting technique which is also discussed.

2.4.1 Trends and Exponential Smoothing Methods

One class of extrapolation methods is based on trends or the general movement of a time series in a particular direction. In trend extrapolation, the type of trend (linear or nonlinear) observed in past values of a series is identified and then projected into the future. Various polynomial functions of time can be estimated using regression methods or by forming moving averages of the time series. Some common trend extrapolation models include the linear trend, exponential growth curve, the quadratic, autoregressive and logarithmic curves[13]. Trend regression models relate the dependent variable y_t to functions of time and are useful when the parameters describing a time series remain constant over time. The model formulation depends on the forecaster's beliefs about the future growth of the variable of interest. According to the literature, these simple trend models often have larger standard errors than some other models and are better used as a quick and inexpensive way of formulating initial forecasts.

Exponential smoothing is a forecasting method that weights the observed time series values unequally, with more weight given to more recent observations. The weighting scheme is determined by using one or more smoothing constants that are determined by smoothing equations. Simple exponential smoothing methods are most effective when the time series has no discernable trend and the parameters change slowly over time. Double-exponential smoothing methods are useful when the time series displays a slowly changing linear trend. Other smoothing methods incorporate

---

[13]These models will not be used in this study and thus are not described in detail here. See any forecasting textbook for examples.

adjustments for changing trends and seasonal factors[14]. Exponential smoothing methods work well in situations that call for one-step ahead forecast in successive time periods.

2.4.2 Time-series Models

Time-series econometrics is based on the theory of linear stochastic difference equations, where a difference equation expresses the value of a variable as a function of its own lagged values, exogenous variables and a disturbance term (Enders 1995). It is based on two fundamental notions: the idea of unobserved components, and a more probabilistic theory based on parametric models (Nerlove 1995). Time-series analysis can be used to identify the properties of and decompose a series into a trend, a seasonal and an irregular component to forecast the time path of a variable. These predictable components of the series are then extrapolated into the future, uncovering the dynamic path allowed for more accurate forecast. The basic idea is that past patterns in the data series will be repeated in the future and thus predictions about future values can be made by extrapolating from past and current information. For example, since the trend component changes the mean of the series and the seasonal component imparts a regular cyclical pattern, predictions concerning the future path of the variable would include such information.

The challenge is to develop grain price models that capture the essence of the true data generating process, as it is difficult to completely characterize the probability

[14] Holt-Winters two-parameter double exponential smoothing and Winters'method for forecasting seasonal data are common methods and are described in most forecasting books.

distributions for prices. A univariate reduced-form difference equation is expressed solely as a function of its own lags and disturbance terms, and is particularly useful for forecasting because predictions can be made solely on its own current and past observations. For instance, the naive model is a simple deterministic model that predicts future values of a variable to be its current value.

$$y_t = y_{t-1} \tag{3}$$

However, if y_t is not thought to be perfectly predictable (i.e., deterministic), then the naive model can be modified by adding a random term, becoming the random walk model:

$$y_t = y_{t-1} + \epsilon_t \tag{4}$$

The random walk accounts for the probabilistic nature of a time series by including a stochastic term, ϵ_t, such that the change in y is random. The model says that the value in time t is a function of the value in time t-1 plus some random error, where the random error term is assumed to meet the standard requirements (i.e., is white noise).

A one-period ahead forecast of a random walk process is given by:

$$\hat{y}_{T+1} = y_T + E(\epsilon_{T+1}) = y_T \tag{5}$$

where $E(\epsilon_{T+1})=0$. The best prediction of y_t is its previous value. If upon visual inspection of a time series an upward or downward trend is detected, then a drift parameter, (d), can be used to capture the trend, and the random walk becomes a random walk with drift.

$$y_t = y_{t-1} + d + \epsilon_t \tag{6}$$

The *l*-period ahead forecast is given by:

$$\hat{y}_{T+l} = y_T + ld \quad \textbf{(7)}$$

The major advantage of the random walk model is the minimal data requirements, that is, the only information needed is the current value of y_t. Additionally, because the random walk model is stochastic, a standard error of forecast can be computed, which allows forecast confidence intervals to be constructed. Decision makers often need to know the margin of error associated with a particular point forecast, thus confidence intervals are important, useful planning tools.

2.4.2.1 ARIMA Models

In this section, several different types of stochastic processes that are useful in modeling time series are discussed. The random walk model described above is a simple example of a stochastic time-series model. This section discusses a more general class of stochastic time-series models that explain the movement of a time series by relating it to its own past values and/or to a weighted sum of current and lagged random disturbances. models. A linear difference equation is essentially an auto-regressive process and can be described by the following:

$$P_t = a_0 + \sum_{i=1}^{p} a_i P_{t-i} + x_t \quad \textbf{(8)}$$

Equation (8) is a p^{th}-order linear difference equation, equation (9) is a moving average

$$x_t = \sum_{i=0}^{q} \beta_i \epsilon_{t-i} \tag{9}$$

process of order q and equation (10) is an ARMA(p,q) model for P_t. The autoregressive part of the model is the difference equation. The white noise process is the basic building

$$P_t = a_0 + \sum_{i=1}^{p} a_i P_{t-i} + \sum_{i=0}^{q} \beta_i \epsilon_{t-i} \tag{10}$$

block of stochastic time series models and is a necessary condition for forecasting. A sequence $\{\epsilon_t\}$ is a white noise process if each value in the sequence has a mean of zero, a constant variance, and is serially uncorrelated; $E(\epsilon_t)=E(\epsilon_{t-1})= \ldots 0$; $E(\epsilon_t^2)=E(\epsilon_{t-1}^2)= \sigma^2$; and for all j, $E(\epsilon_t\, \epsilon_{t-s})=E(\epsilon_{t-j}\, \epsilon_{t-j-s})=0$ for all s.

Linear forms of the autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and the autoregressive integrated moving average (ARIMA) time-series models were popularized by Box and Jenkins (1976), and are known as Box-Jenkins models. Like all the non-causal models, the Box-Jenkins forecasting techniques assume that past observations can be used to predict future values. These models have been found to give good forecasts in a wide variety of situations and thus are commonly used.

Because of its generality, the Box-Jenkins method is one of the most widely used approaches for the analysis of time-series data. The Box-Jenkins method consists of four stages: 1) identification, 2) estimating the coefficients, 3) checking the adequacy of the fitted model, and 4) using it for forecasting. Identification consists of examining the autocorrelation and partial autocorrelation functions to determine the appropriate order of the AR and MA components. In a time series, adjacent values are often highly correlated and autocorrelation coefficients are used to examine the strength of the relationship among the values at different lags. The autocorrelations are graphed against T/4 lags, where T is the number of observations[15]. For example, a large value of the autocorrelation at the second lag indicates that values two time points away are closely related. The researcher may thus consider including an AR(2) or MA(2) term in the model. The partial autocorrelation coefficients are the result of eliminating (controlling for or netting out) the effect of intervening values. In this way, the pattern of autocorrelations is used for selecting the ARIMA model. There are, however, no clear-cut rules for this identification process, and in fact, some have called it more of an art than a science.

Estimation of these models is commonly accomplished with maximum likelihood methods, which are standard in most time-series software packages. The Akaike information criterion (AIC) and the Schwartz-Bayesian criterion (SBC) are commonly used diagnostic measures to check the goodness of fit of a tentative model to the data.

---

[15]T/4 is standard for determining how many lags to examine (Enders 1995).

The lower the AIC/SBC, the better the fit[16]. Because the marginal cost of adding regressors is greater with the SBC than the AIC, the SBC selects a more parsimonious model than the AIC. A necessary condition for forecasting with ARIMA models is that the residuals approximate white noise; therefore, as part of the diagnostic tests, the residuals are examined for serial correlation. The Box-Pierce Q and the Ljung-Box Q^* are the commonly used statistics for testing for serial correlation. The Q^*-statistic is more appropriate for small samples and is used in this study (Enders 1995). If the model is fitted appropriately, then Q has an asymptotic χ^2 with *m-p-q* degrees of freedom, where p and q are, respectively, the orders of the AR and MA components[17]. Once an appropriate model is identified, estimated and checked, it can then be used for forecasting.

In the **autoregressive process (AR)**, the current observation is assumed to have been generated by a weighted average of its past observations:

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \epsilon_t \tag{11}$$

The above equation describes an AR(2) process in that y_t is described by a weighted average of past observations going back two periods, a constant term, δ, and a random disturbance in the current period, ϵ_t. An AR(p) of order p is given by:

---

[16] $AIC(p) = n \log \hat{\sigma}_p^2 + 2p$, where $\hat{\sigma}_p^2 = RSS/(n-p)$ and p is the total number of parameters estimated. *SBC* is the same except instead of adding *2p*, *pln(n)* is added. RSS is the residual sum of squares.

[17] It should be noted that Maddala (1992) argues that the Q-tests have low power because of the autoregressive components and that a Lagrange-Multiplier (LM) test described in Maddala (p.541) is more appropriate, i.e., has higher power. However, since most software packages do not compute the LM-statistic, the Q-tests continued to be widely used.

$$y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots \phi_p y_{t-p} + \epsilon_t \tag{12}$$

If the time series is assumed to have been generated by a weighted average of random disturbances going back q periods, the process is described as a moving average of order q, MA(q). An MA(q) model is simply a linear combination of white noise error terms.

$$y_t = \mu + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \ldots - \theta_q \epsilon_{t-q} \tag{13}$$

However, many random processes have characteristics of both autoregressive and moving average and thus are modeled as an ARMA of order (p,q). Rather, the time series is expressed as a function of its lagged values and lagged residuals:

$$y_t = \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \delta + \epsilon_t - \theta_1 \epsilon_{t-1} - \ldots - \theta_q \epsilon_{t-q} \tag{14}$$

The AR, MA, and ARMA models described above assume that the underlying random process that generated the time series is invariant with respect to time. That is, the characteristics of the stochastic process remain stationary over time. This is particularly important for forecasting because if the random process is stationary, it can be modeled with an equation with fixed coefficients which can be estimated from past data and used for forecasting future values of the dependent variable. However, in practice many economic time series are nonstationary and the underlying characteristics do change over time. Fortunately, nonstationary processes can be made stationary by differencing the time series and the differenced series is then modeled as a stationary time series. If the differenced series ($\Delta y_t = yt - yt_{-1}$) is modeled as an ARMA(p,q), then the original series y_t is said to be an integrated ARMA or ARIMA(p,d,q) where *d* is the number of times the original series must be differenced to become stationary[18]. Note that the differencing operation used to achieve stationarity involves a loss of potential information about long-run movements. Differencing can remove trends, and seasonal differencing removes seasonal trends.

One of the most difficult aspects of time-series modeling is determining the correct lag length for model specification and indeed can require considerable trial and error. The properties of the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to identify the underlying data-generating process of a time series including the order of the ARIMA process. The ACF indicates how much correlation (interdependency) there is between neighboring data points in a series, where the size of the autocorrelation represents the strength of the pattern between past values of the variables. An analysis of the ACF can help determine the order of the moving average component and for moving average models of order *q*, the autocorrelation should be close to zero for lags greater than *q*. Similarly, the PACF, which indicates the partial or extra effect of adding another lagged variable when one lag is already included, is used to determine the order of the autoregressive component.

Once a time-series model has been estimated and checked, it can be used for forecasting. ARIMA models are commonly used in empirical work since many economic

---

[18] There are several methods available for testing the stationarity of a time series, such as the unit root test. The procedures are discussed in most time series econometric books and are examined in greater detail in chapter 3.

time series are generated by nonstationary processes. Equation (16) describes how computation of a forecast is accomplished. Let w represent a differenced series ($w=\Delta y_t=y_t-y_{t-1}$).

$$w_t = \phi_1 w_{t-1} + \ldots + \phi_p w_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \ldots \theta_q \epsilon_{t-q} + \delta \qquad \textbf{(15)}$$

A one-period ahead forecast involves modifying the above equation by one period:

$$w_{T+1} = \phi_1 w_T + \ldots + \phi_p w_{T-p+1} + \epsilon_{T+1} - \theta_1 \epsilon_T - \ldots \theta_q \epsilon_{T-q+1} + \delta \qquad \textbf{(16)}$$

The forecast is calculated by taking the conditional expected value of w_{T+l}:

$$\hat{w}_T(l) = E(w_{T+1} | w_T, \ldots) = \phi_1 w_T + \ldots + \phi_p w_{T-p+1} - \theta_1 \hat{\epsilon}_T - \ldots - \theta_q \hat{\epsilon}_{T-q+1} + \delta \qquad \textbf{(17)}$$

$\hat{\epsilon}_t$ and $\hat{\epsilon}_{T-1}$ are observed residuals and the expected value of $\epsilon_{T+1} = 0$.

Once the differenced series has been forecasted, a forecast of the original series can be obtained by summing the differenced series d times. An l-period ahead forecast for y when $d=1$ is given by:

$$\hat{y}_T(l) = y_T + \hat{w}_T(1) + \hat{w}_T(2) + \ldots \hat{w}_T(l) \qquad \textbf{(18)}$$

Because they account for the dynamic structure of the time series, Box-Jenkins models (univariate ARIMA) can often forecast quite well compared to econometric or structural models. However, once the temporal structure of the data is accounted for, structural models can perform well. One of the major theoretical limitations of ARIMA models is that they assume linearity and cannot accommodate nonlinear data generating processes. Moreover, this class of models assumes that the underlying structure that generated the time series remains constant. But if structural change does occur, then the ARIMA model estimated and used for forecasting under the old structure may give misleading and even incorrect forecasts for the new structure. It can also be difficult to obtain sufficient observations to identify/specify an appropriate ARIMA model, therefore parameter estimates should be frequently updated as new observations become available (Holden 1990). If the time series exhibits seasonality, then it can be removed by seasonally differencing the time series and specifying a seasonal ARIMA.

In summary, the major advantage of non-causal modeling techniques is that they are cheap and relatively simple, while the major disadvantage is that they assume the future will be like the past and are unable to explain behavior. However, shift variables (e.g., dummies) can be added to ARIMA models to capture structural and other exogenous changes greatly improving the utility of non-causal modeling techniques.

2.5 Vector Autoregression Models

The above methods focus on the time-series analysis of a single time series. The Box-Jenkins methodology can be extended to the simultaneous study of two or more time series. The vector autoregression (VAR) is essentially a multiple-time series or vector generalization of the autoregression model which focuses on the interrelationship between different time series and is a popular forecasting tool. Equations (19) and (20) describe a simple 2-equation system:

$$y_{1t} = \delta + \phi_{11} y_{1,t-1} + \phi_{12} y_{2,t-1} + \epsilon_{1t} \tag{19}$$

In VAR models, the ϵ_{it} terms are called impulses.

$$y_{2t} = \alpha + \phi_{21} y_{1,t-1} + \phi_{22} y_{2,t-1} + \epsilon_{2t} \tag{20}$$

VAR models are nonstructural models where the data specifies the dynamic structure of the models instead of economic theory and thus puts minimal demands on the structure of a model. Indeed, one need only specify the set of variables that are assumed to interact with each other, decide the number of lags needed to capture most of the effects the variables have on each other. However, a major weakness of VAR modeling is over-paramaterization: the tradeoff between having a sufficient number of lags to capture the dynamics of the system with having a sufficient number of free parameters or degrees of freedom. VAR modeling techniques often make good short-term forecasting models because they are simple, and can be estimated using OLS procedures; they avoid some of the restrictiveness of structural model, and the multi-variate representation allows them to overcome some of the limitations of the univariate models.

2.6 Measuring Forecast Accuracy

Regardless of the forecasting technique employed, a forecast is a **prediction** of an outcome and thus is subject to a certain amount of forecast error. Given that different economic agents have different needs, the amount of acceptable forecast error to a particular user differs. For example, decision makers who are less risk averse may be willing to rely on a forecast that has a wider confidence interval than agents who are more risk averse because the economic decisions that are based on those forecasts embody a wider margin of error. Various measures are available for assessing the predictive accuracy of forecasting models. Most are designed to evaluate *ex post* forecasts, that is, forecasts for which the exogenous variables do not have to be forecast. Forecasts based on models made before the values of the exogenous variables are known are called an *ex ante* forecasts and are the true test of a models predictive accuracy.

There are three types of forecasts: point forecasts, prediction intervals of a forecast and forecasts with probability distributions attached. A point forecast is a single number representing the best guess of the variable being forecasted, whereas a prediction interval forecast is a range of numbers calculated such that one is e.g., 95% confident that the actual value is contained in the interval. The third type calculates a probability for each possible point forecast such that there is a 60% chance that the actual value will be x.

If the forecasting technique is appropriate, the forecast errors should be purely random. Mean squared error (MSE) is a common measure of forecast error:

$$MSE = \sum_{t=1}^{n} (y_t - \hat{y}_t)^2 / n \qquad \textbf{(21)}$$

which penalizes a forecasting technique more for larger errors than smaller errors. This is also known as a quadratic loss function, which is simply a summary of how concerned the user is if the forecast is off by a particular amount (Hamilton 1994). The forecast is chosen to minimize the MSE and will be used in this study to assess the performance of alternative price forecasting model.

Choosing an appropriate forecasting method involves consideration of the user's needs in regard to form; for instance, will a point forecast suffice or is an interval prediction required? Further, what is an acceptable margin of error? In some cases, a 10% margin of error is acceptable whereas in other cases it might be disastrous. The length of the forecast horizon can also influence the forecasting technique. In general, the longer the time frame (longer than two years), the more difficult it is to make accurate forecasts with quantitative models, and qualitative techniques become more useful as the forecast horizon lengthens. Data availability is a major factor in deciding which forecasting methods are plausible.

In Mali, developing large structural models for forecasting is not feasible because the current data base cannot support their construction. Structural models also require that large amounts of data be stored. The complexity and operation of the forecasting technique influences the cost of forecasting and must be considered when choosing a forecasting technique. The method should be simple enough to operate and understand for decision-makers to have confidence in the predictions. A balance of cost, complexity and desired accuracy is needed. For these reasons, this study builds forecasting models using time series methods. The next chapter presents the results of the preliminary analysis of the data and discusses the conceptual issues necessary for modeling commodity price series.

CHAPTER 3

PRELIMINARY ANALYSIS OF PRICE LEVEL DATA

3.0 Introduction

Using time-series methods, this study develops and estimates alternative price models for rice, sorghum and maize which can be employed to produce reliable short-term forecasts in representative grain markets in Mali. This chapter will discuss the data, perform some preliminary analysis including statistical descriptives and real price trends, and end with a discussion of the stochastic properties of the time series relevant for modeling commodity prices.

3.1 Data

As in many studies of this nature, the choice of cereals and markets is partly driven by the availability, continuity and quality of data. The cereals price data used in this study were constructed from three sources: the PRMC/OPAM (1982-1984), the MSU/Mali Food Security Project from 1985 to 1989, and the market information system (SIM) from 1989 to September 1998[19]. By design, the SIM data set is considerably more comprehensive and complete than the MSU project data. For example, the SIM reports average weekly cereals prices for 52 markets across the country including six different qualities of rice at various levels in the marketing chain. Since price information was not the primary focus of the MSU project, it collected monthly (and some weekly) average

---

[19]The market information system is known by its French acronym, SIM. It first came into being in 1989, in part as an outgrowth of the MSU/Mali Food Security Project.

prices for key cereals in fewer markets and thus is much more limited in scope.

The analysis undertaken here uses monthly data spanning from January 1982 to September 1998. The last twenty-four observations were excluded from the modeling process to check the accuracy and consistency of the alternative forecasting models. To obtain a complete monthly price series for each cereal, simple averages of the weekly SIM data were computed to obtain monthly observations and then merged with the MSU data[20]. The different levels of aggregation and reporting in the two data sets required that careful consideration be given to ensuring that the variables in the two data sets were consistent. Specifically, the MSU data report an average monthly price for rice in Bamako while the SIM reports an average weekly price for six different qualities of rice in various markets across Bamako. Determining what quality of rice and what market in Bamako the MSU rice price referred was not a trivial task. Based on discussions with MSU project people and given that RM40 (40% broken) is the most commonly consumed and marketed quality of rice in Mali, and Niarela is the most heavily traded market in Bamako, it is assumed here that the MSU rice price referred to RM40 in the Niarela market.

The producer prices were taken from the most actively traded markets for each grain in each region. Consideration was also given to data availability, as an effort was made to construct the longest monthly time series possible. Since the SIM did not become operational until April 1989, the markets covered by the MSU project dictated which

[20]The SIM enumerators were trained by the MSU project and hence the sampling methodologies are consistent.

markets were actually studied[21]. All urban retail prices are studied at the Bamako-Niarela market, resulting in a monthly time series ranging from January 1982 to September 1998. Rural retail and producer prices for rice are studied in the markets of the Office du Niger zone and cover the period from February 1988 to May 1997, while the coarse grains are from the region of Sikasso and cover the period from October 1985 to September 1998. Refer to figure 1.1 in chapter 1 for map of the agricultural zones.

3.2 Missing Data

From January 1982 to September 1998 there are 201 months of potential price observations for urban markets. In the urban retail market (Niarela), the price series for sorghum and maize are complete, with 201 observations each. The price series for rice (RM40), however, has 9 missing values[22]. One common way to deal with missing data is to simply replace the missing values with the series mean or the mean of the values surrounding the missing observations. Close examination and comparison of plots of the actual series with the missing observations and the series completed with the means revealed that these methods appear to seriously under- predict the actual series.

Riz DP, another quality of rice for which data was available in the Niarela market, is a close substitute in consumption to RM40. Correlation analysis revealed that prices for the two varieties were, as expected, highly correlated (correlation coefficient of 0.93).

---

[21]The SIT, transitory information system, actually began in April 1989, while the permanent market information system (SIM) began in October 1989.

[22]Missing February 1995-May 1995 and February 96-June 1996.

Since RM40 and riz DP are closely related, simple linear regressions specified with and without a time trend were estimated to predict RM40 prices conditional on riz DP prices. The mean squared error (MSE) was computed and used to determine which specification best fit the data. This resulted in replacing the 9 missing values for the RM40 series with the predicted values conditional on riz DP and a time trend.

Also at issue is why the observations for RM40 are missing. The SIM defines Rm40 to be imported 35% broken rice or rice produced domestically (riz DP). According to SIM technicians, imported rice was not competitive with local rice during those periods, nor were the industrial mills producing very much, which resulted in literally no RM40 on the market. Rather, the observations are missing because RM40 was truly absent on the market. This study made an effort to work with as long a series as possible and rather than work with 9 less observations, particularly since the correlation between the series was high, it was decided that completing the series was justified.

3.3 Inflation

Inflation plays an important role in understanding price movements. For most of the study period the average rate of inflation remained relatively low and constant. In fact, between 1982 and 1993 inflation as measured by the GDP deflator was an average 2.4% . In 1994, the CFA franc was devalued, and inflation as measured by the annual percentage change in the national consumer price index increased to 32% (Tefft et al. 1997). Prices began to stabilize in 1995, and, as indicated in table 3.1, continue to fall towards their pre-devaluation levels[23].

Table 3.1: Annual percentage change in national consumer price index	
1994	32
1995	9.2
1996	2.8
1997	3.1
Source: Tefft et al. 1997	

If price movements are a function of inflation, then deflating the price series by an appropriate measure of inflation theoretically removes the inflationary effect, making it easier to identify other components like seasonality, cycles and trends. Choosing an appropriate measure of inflation, however, is not a trivial task and often depends on data availability[24]. Ideally, the measure of inflation should reflect the decision environment and opportunity sets within which decision agents operate.

Food products represent the largest weights in the consumer price indices in the CFA countries, including Mali, with cereals representing a large component of the food subgroup (Tefft et al. 1997). Therefore, increases in grain prices directly influence the rate of inflation, which in price analysis can bias coefficient estimates or lead to spurious inferences. It is not uncommon in extension work to use nominal prices to develop models which are created explicitly for the purpose of forecasting. Since the level of

---

[23] For a specific analysis of the effect of devaluation on cereals prices, see Tefft et al. (1997).

[24]See price study by Jayne et al. (1996).

inflation in Mali has been relatively low, and because cereals comprise such as large component of the food subgroup, this study seems justified in using nominal prices.

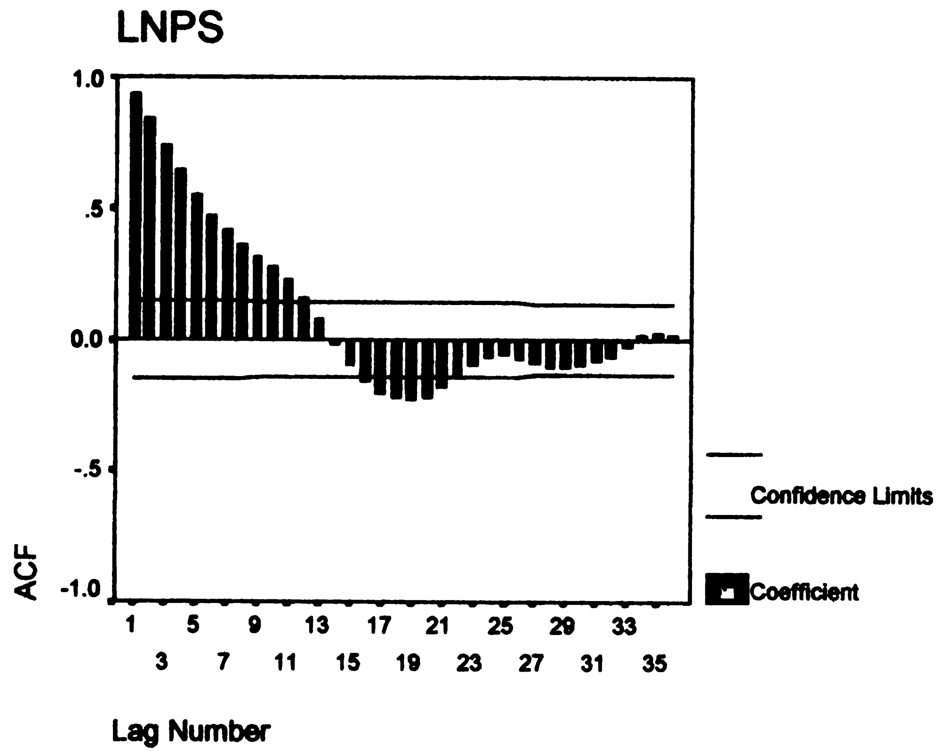
3.4 Seasonal Analysis & Price Trends

The seasonal nature of grain production and market supply in Sub-Saharan Africa, including Mali, suggests that the price series should be investigated for seasonal patterns. In time series, adjacent values are often highly correlated. Autocorrelation coefficients are used to examine the strength of the relationship among the values at different lags. Inspection of the correlogram, which is a graph of the auto and partial autocorrelation functions, of the sorghum and maize series revealed that these series exhibit significant spikes (i.e., correlation coefficients that fall outside the two standard error band) at or near seasonal lags, consistent with *a priori* expectations of rainfed crops. For instance, the partial ACFs in figures 3.3 and 3.4 have spikes at near lags (12-14) which are considered seasonal in monthly data, and the ACFs show an oscillating pattern consistent with theoretical seasonal patterns. That is, prices peak during the hungry season (June-August) and are at their lowest when harvest is complete (November-January). The intra-annual variation of when peaks and troughs occur is influenced by rainfall and the marketing strategies of net sellers.

In figure 3.5, the correlogram of the rice series, it is more difficult to ascertain whether seasonal patterns exist in the rice series because of its imported and food aid components. With the exception of the first lag, the partial autocorrelation coefficients are not statistically different from zero. Close inspection of the time series revealed that in some years, a clear seasonal pattern approximating the peaks and troughs in the coarse grain series exist, whereas in other years no discernible pattern emerges or one contrary to expectations[25]. The fluidity of the import laws and other macro exogenous shocks may help to explain this phenomenon.

[25] For instance, import policies might explain the price peak in December/January in 1989/90, and the low price in June and April, while substantial food aid arrivals in 1988 might explain why the peak price was in July and the low price in January.

Figure 3.3: Correlogram of Sorghum Prices



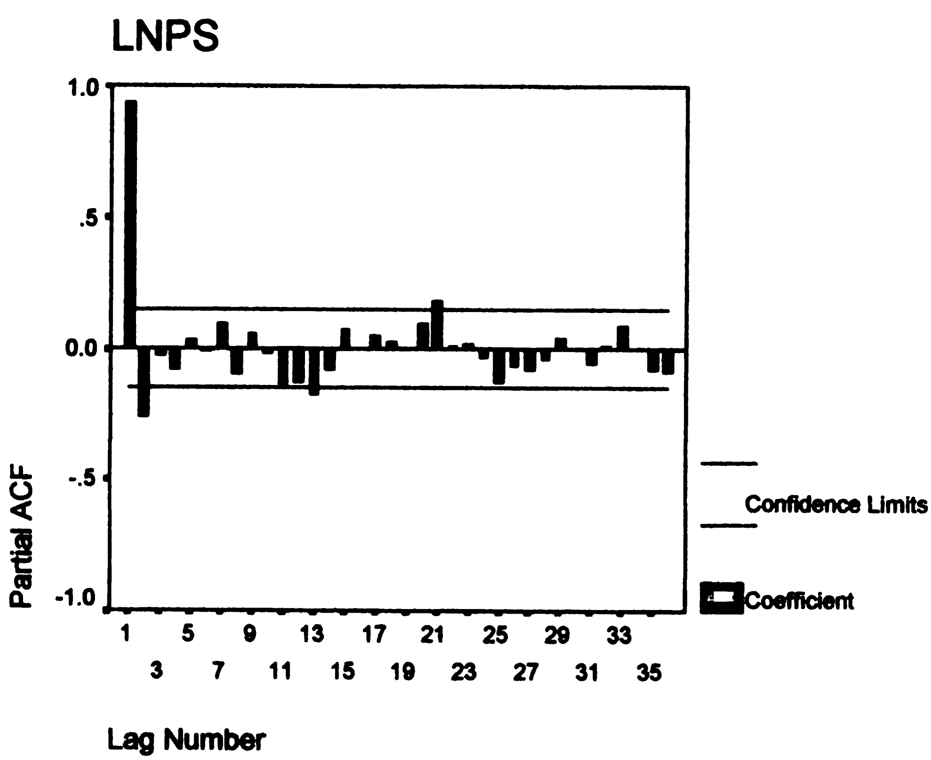
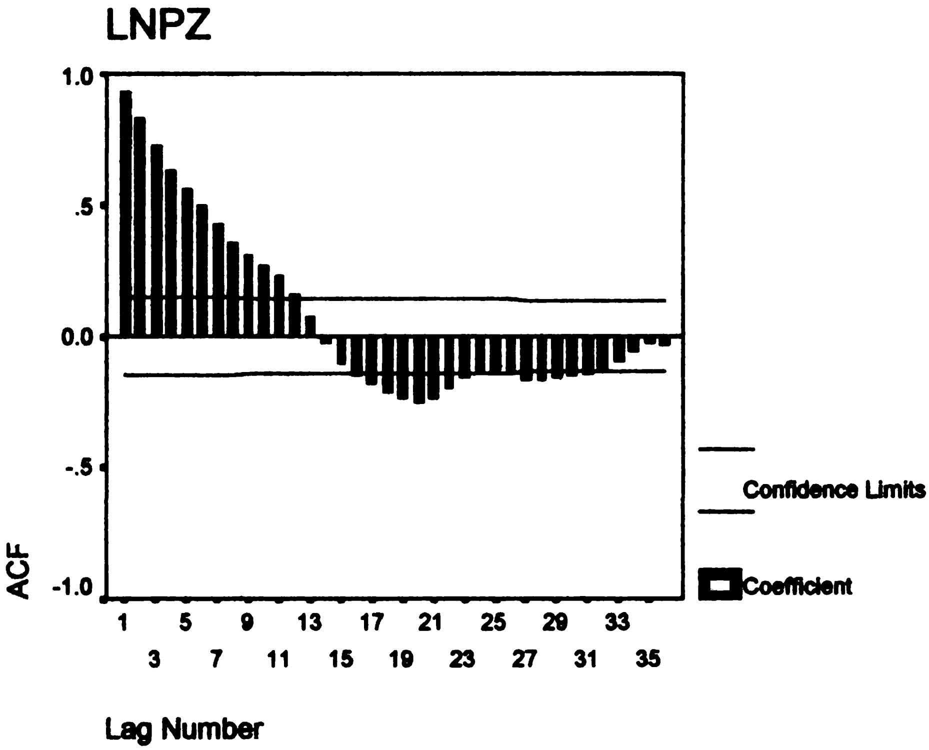


Figure 3.4: Correlogram for Maize



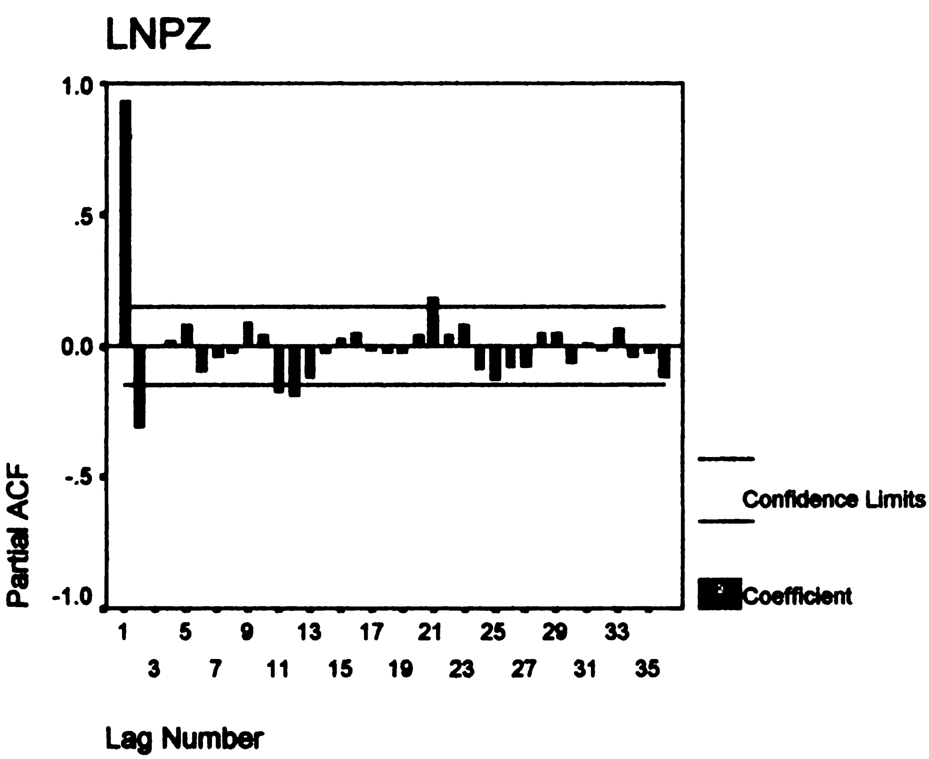
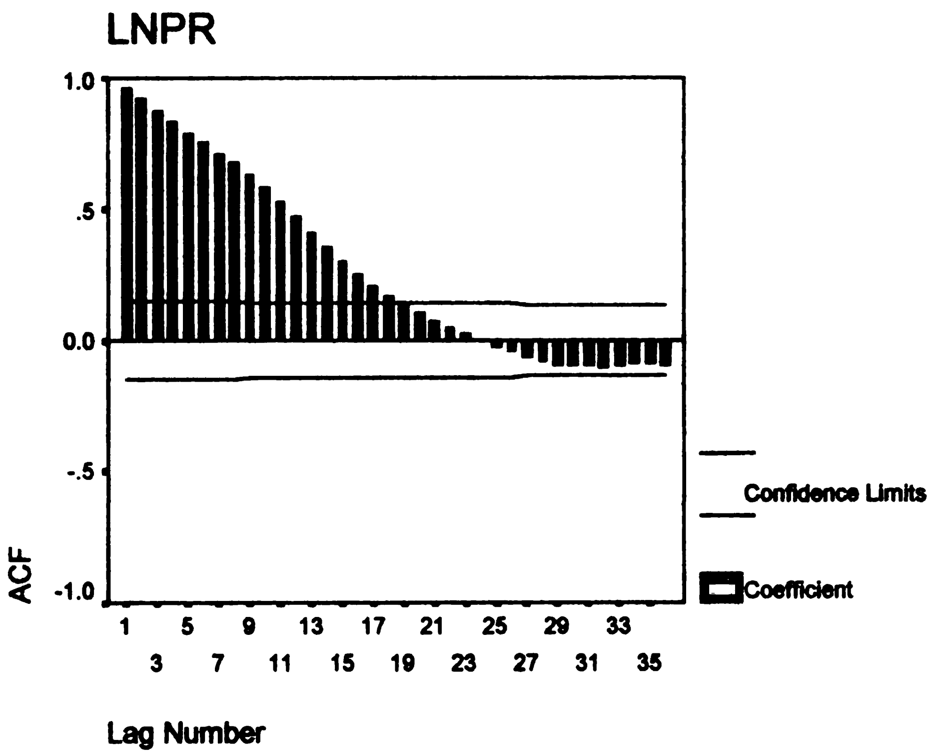
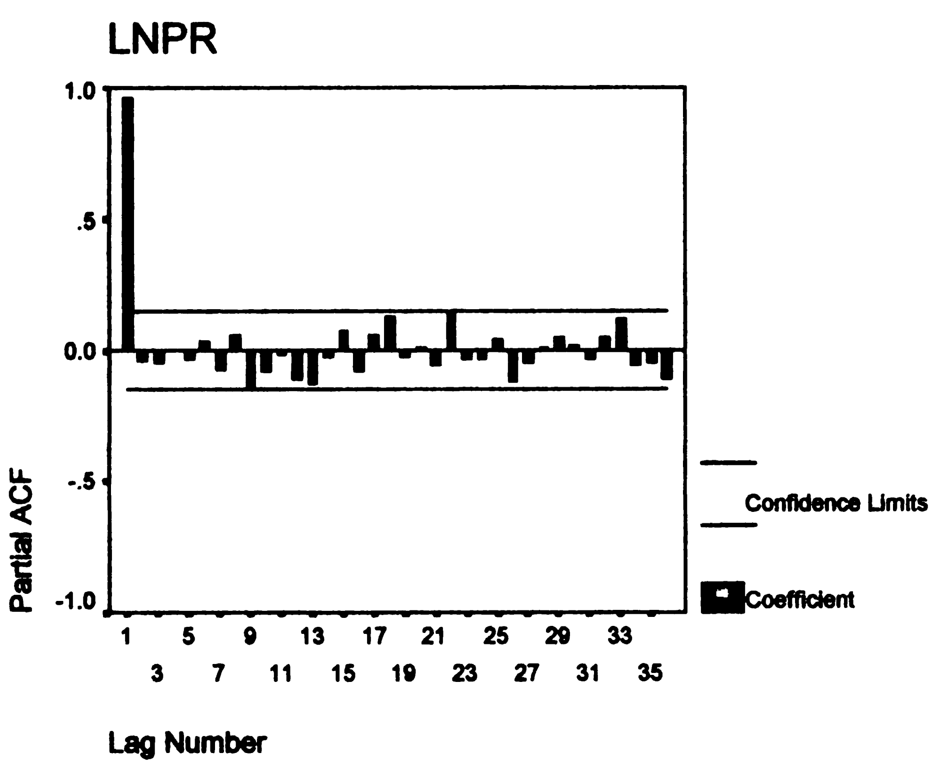


Figure 3.5: Correlogram for Rice





Many economic time series trend over time, and if the underlying data generating process is stationary (i.e., mean reverting), then the series can be broadly characterized by the polynomial trend models discussed in chapter two. The plots of the nominal sorghum and maize series in figure 3.1 were suggestive of a slight trend during the post devaluation period, while the upward trend in the rice series is readily apparent. Simple linear time trends ($P_t = \beta_0 + \beta_1 Time + \epsilon_t$) were fitted to all three series using OLS regression procedures. To examine the effect of the devaluation on prices, two trend lines, pre and post devaluation, were fitted to each series. Tables 3.2-3.5 present several summary statistics for consumer and producer prices in the Bamako-Niarela market and two other important trading markets, Niono and Zangasso.

Note that the CPI is based on an urban consumption basket purchased in Bamako and has a base year of July 1986 to June 1987. Due to the unavailability of a consistent and sufficiently long CPI series for the rural areas, the urban-Bamako CPI was also used to deflate rural prices, which can often lead to misleading results and spurious inferences. For example, urban consumption baskets in developing countries tend to have a higher import content than rural consumption baskets, thus devaluation would have a greater impact on the urban basket than it would the rural basket. Therefore, deflating rural prices by an urban CPI may suggest that real prices in rural areas are falling more than they are, hence the real prices in the Niono and Zangasso markets should be interpreted with caution.

Nonetheless a few observations: In the Niono market, a major rice producing zone, before devaluation nominal consumer and producer prices declined from 1988 to

December 1993, while post devaluation nominal consumer and producer prices have increased 1.5 CFAF/kg and 1.3 CFAF/kg per month respectively. In this same market real prices rice declined both before and after devaluation. The coefficient of variation indicates that producer rice prices in Niono have been more unstable than consumer prices.

In Zangasso, a high rainfall area and major coarse grain producing zone, real producer prices for both maize and sorghum increased both prior to and after the devaluation. The magnitude of the monthly price increase is larger after the devaluation. Relative to rice prices in Niono, maize and sorghum prices in Zangasso are more than twice as volatile. This is consistent with knowledge of the grain markets, as mentioned earlier. Rice is more heavily traded than either sorghum or maize and so the markets are not as thin. Also rice benefits from the potential stabilizing effects of imports and food aid. In the Bamako-Niarela market, a major consuming area, real maize and sorghum prices increased from 1986 to 1997 both during and after devaluation. Nominal prices of these cereals were on a downward trend before devaluation and increased post devaluation. Real rice prices, on the other hand, decreased before and after devaluation, while nominal prices increased 1.76 CFAF/per kg per month after the devaluation. Sorghum prices in the Bamako-Niarela market have been the most volatile, while rice is the most stable.

Table 3.2: Summary Statistics for Niono Consumer and Producer Rice Prices - February 1988 to May 1997

Variable	T	Max	Min	σ^2	$\bar{P}$	trend t1 = pre t2 = post	CV	S.E.
Nominal Consumer	112	280	157.2	1246	208	t1 = -0.68* t2 = 1.50*	0.17	17.3
Real Consumer	112	207	150	169	171	t1 = -0.32* t2 = -0.54*	0.08	11.4
Real Producer	112	166	88.9	210	127	t1 = -0.31* t2 = -0.31*	0.11	13.4
Nominal Producer	112	240.	90.8	1106	156	t1 = -0.58* t2 = 1.28*	0.21	20.5

Table 3.3: Summary Statistics for Sorghum Producer Prices in Zangasso - October 1985 to September 1998

Variable	T	Max	Min	σ^2	$\bar{P}$	trend t1 = pre t2 = post	CV	S.E.
Nominal Producer	156	136.2	24.15	648.2	56.41	t1 = 0.11** t2 = 1.02*	0.45	20.1
Real Producer	132	95.7	23	289	44.5	t1 = 0.16* t2 = 0.56*	0.38	16.2

Table 3.4: Summary Statistics for Maize Producer Prices in Zangasso - October 1985 to September 1998

Variable	T	Max	Min	σ^2	$\bar{P}$	trend t1 = pre t2 = post	CV	S.E.
Nominal Producer	156	118.8	17.3	492.4	47.3	t1 = 0.07 t2 =0.98*	0.47	15.9
Real Producer	132	77	17	18.1	36.6	t1= 0.14* t2 = 0.65*	0.37	12.2

Table 3.5: Summary Statistics for Consumer Grain Prices in Bamako-Niarela-January 1982 to September 1998

Variable	T	Max	Min	σ^2	$\bar{P}$	trend t1 = pre t2 = post	CV	S.E.
Nominal-rice	201	288	157.2	1306	198.6	t1 = -0.06 t2 = 1.76*	0.18	21.2
Nominal-sorghum	201	186.3	57	966.6	97.53	t1 = -0.12* t2 =0.73*	0.32	27
Nominal-maize	201	175	52.9	700	91.2	t1 =-0.09* t2 =0.86*	0.29	20.7
Real-rice	132	207	150	148.8	171	t1 = -0.09* t2 = -0.48*	0.07	11.8
Real-sorghum	132	123	46.8	351.2	74.75	t1 = 0.13* t2 = 0.65*	0.25	18.1
Real-maize	132	110	47.7	219	71.2	t1 = 0.09* t2 = 0.61*	0.21	14.1

where:
σ^2 = variance of the price series
$\bar{P}$ = mean price
Trend = the coefficient of the trend variable in the regression: t1=pre-devaluation and t2= post-devaluation
T = number of observations
CV = coefficient of variation
S.E. = standard error of the regression equation
* = significant at the 5% level
** = significant at the 6% level
Max = maximum value of the series
Min = minimum value of the series

3.5 Marketing Margins

Real marketing margins for coarse grains between Zangasso and Bamako declined slightly between 1986 and 1997. Simple regressions of real marketing margins, defined as the difference between retail prices in Bamako-Niarela and producer prices in Zangasso, on pre and post-devaluation time trends, revealed that relative to 1986/1987, real margins for both sorghum and maize declined significantly before and after the devaluation. Specifically, real sorghum margins fell -0.07 (-2.91) CFAF/kg per month before the devaluation and fell -0.18 (-2.62) after the devaluation[26], while real maize prices fell -0.07 (-2.46) CFAF/kg per month before devaluation and -0.22 (-2.84) during the post devaluation period. Unlike the coarse grains, trends in the real rice marketing margins between Niono and Bamako before the devaluation, were not statistically significant. The post-devaluation margins however, fell by -0.24 (-2.07) CFAF/kg per month.

As mentioned above, the rice market was much slower to liberalize than the coarse grain markets, which could help explain why margins in the rice market did not fall prior to devaluation. Moreover, rice is internationally traded, so domestic prices are linked, albeit imperfectly, to world prices. Historically, sorghum and maize have been largely nontraded goods for Mali, especially in the pre-devaluation era.

3.6 Characteristic Time Series Properties of Commodity Price Data

As reviewed in chapter two, time-series models can be quite useful in capturing information about past patterns in price behavior to generate short-term forecasts. The

---

[26]The t-statistics are in parentheses.

challenge is to develop models that capture the essence of the true data generating mechanism. In addition to seasonality, there are several characteristic time-series properties which many commodity price series seem to share, specifically stochastic trends, excess kurtosis and time-varying volatility in the error term (Myers 1994). In this section, the stochastic properties of the historical price data are examined in the context of the commodity price literature. The discussion serves as the conceptual framework for modeling the underlying data generating mechanism of each grain price.

3.6.1 Stochastic trends

Since time-series analysis focuses on regressing current values on past values, there is a possibility that the resulting forecasts could be divergent (or unstable), causing the forecast error to become larger over time (Ferris, class notes). To minimize this, ARIMA modeling techniques, which focus on analyzing the stochastic properties of economic time series, require that the underlying data generating processes be (covariance) stationary, i.e., not contain stochastic trends or unit roots[27]. Simply put, a time-series is covariance stationary if its mean and all autocovariances are unaffected by a change of time origin, i.e., are time invariant. In a simple example, suppose a price, P_t^1 is described by equation (22) and a price, P_t^2 is described in equation (23):

$$P_t^1 = \mu + \epsilon_t \qquad \textbf{(22)}$$

---

[27] Stochastic trend, nonstationarity and unit root are all synonyms and used interchangeably throughout the paper.

$$P_t^2 = \beta t + \epsilon_t \tag{23}$$

Also suppose that ϵ_t is a Gaussian white noise process, such that $E(\epsilon_t)=0$. Then the mean in equation (22) is given by $E(P_t^1) = \mu + E(\epsilon_t) = \mu$; analogously the mean of equation (23) is given by $E(P_t^2) = \beta t$. Given the definition of stationarity, the process described in equation (22) is stationary, while that described in equation (23) is not, because the mean, βt, is a function of time.

If the series is stationary, then the theoretical mean, variance and autocorrelations of the time series, which are unknown to the researcher, can be approximated by the sample mean, variance and autocorrelations. The sample descriptives can then be used to estimate the parameters of the underlying data generating process. Moreover, stationarity is also required if the usual asymptotic results are to apply (Enders 1995; Hamilton 1994; Myers 1994; Pindyck 1991).

Many economic time series do trend upward over time, *potentially* violating the stationarity assumption. Indeed, several empirical studies of commodity prices find strong evidence of stochastic trends (Baille 1997; Enders 1995; Myers 1994). Moreover, Phillips (1988) argues that a unit root is a theoretical implication of models which postulate the rational use of information available to economic agents, suggesting that we should expect unit roots. The important point is to evaluate the nature of the trend, that is, diagnose whether it is deterministic or stochastic as the type of trend affects long-term forecasts. If stationarity tests revealed that the underlying data generating process of the trending time series was stationary, then the trend is considered to be deterministic and can be captured with a polynomial time trend like the process described above in equation (23). Such a data generating process is often referred to as trend-stationary because it is made stationary by subtracting out the trend. A stochastic trend, on the other hand, is made stationary by differencing and hence, is sometimes called a difference-stationary process. The random walk with drift, i.e., ($P_t = P_{t-1} + \mu + \epsilon_t$), which shows no particular tendency to increase or decrease over time, is the classic example of a stochastic trend.

It is important to model the trend correctly because deterministic and stochastic trends have differing impacts on long-term forecasts. A deterministic trend has a permanent effect on the time series; since the irregular component is stationary (i.e., mean reverting) shocks to this component have a tendency to die out, while the trending elements remain in the long-term forecasts. But if the trend is stochastic, then shocks to the irregular component accumulate (i.e., do not die out), imparting a permanent, albeit random change in the conditional mean. To forecast a trend-stationary process, the known deterministic component is simply added to the forecast of the stationary stochastic component. The forecast of process with a stochastic trend, like the random walk, is given by: $\hat{P}_{t+s|t} = s\mu + P_t$, such that P_t is expected to grow at the constant rate of μ per period from whatever its current value P_t happens to be, where s is the step-ahead horizon.

In summary, the forecasts in both specifications converge to a linear function of the forecast horizon, s, with slope β or μ. The key difference is that the trend-stationary process converges to a line whose intercept is the same regardless of the value of P_t, while the intercept of the limiting forecast for a difference stationary or unit root process is continually changing with each new observation on P. The two processes also differ in their implications for the variance of the forecast error. The mean squared error (MSE) increases with the forecasting horizon if the trend is deterministic, but as the horizon gets larger, the added uncertainty from forecasting over a longer horizon becomes negligible. That is, the MSE reaches a finite bound as the forecast horizon becomes larger. In contrast, for a unit root process, the MSE also gets larger as the forecast horizon increases but eventually grows linearly with the forecast horizon, not reaching a finite bound.

There are several tests available to test the hypothesis of a stochastic trend and evaluate the nature of the nonstationarity, particularly in determining whether the trend is stochastic through the presence of a unit root, or deterministic through the presence of a polynomial time trend (Phillips 1988). These include the Dickey-Fuller (DF), the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests. The tests differ in their specification of the data generating process, i.e., some include a constant, implying a non-zero drift, while others include a time trend and/or autoregressive terms. The ADF test corrects for serially correlated errors, but is unable to eliminate autocorrelation in residuals if the error term has moving average components. The Phillips-Perron tests can be more robust to autocorrelation and hetereogeneity in the distribution of residuals than the Dickey-Fuller tests (Myers 1994). In these standard tests, the stochastic trend is the null hypothesis. It is argued that these tests in general are not very robust and have low power to discriminate between unit root and near unit root processes (Enders 1995). It is important to include the appropriate regressors in the test equations. Because of the low power of all the tests, there is no clear advantage of preferring one test over another. The ADF test is the most common procedure and is used in this paper.

Before beginning, it is common practice in price analysis to transform the series into natural logs to eliminate some of the variability inherent in time series. Inspection of the autocorrelation and partial autocorrelation functions is the first indicator of whether a unit root is present. A slowly decaying ACF is indicative of a nonstationary process. As shown above, the ACFs for the sorghum and maize series are indicative of seasonality, while the rice series decays more slowly. The test procedure for sorghum and maize included estimating a first equation with seasonal dummies, then using the residuals from these equations to essentially deseasonalize the series. The stationarity tests for sorghum and maize are performed on the deseasonalized series. The test equations for rice includes a time trend.

Determining lag length is also an important consideration for testing nonstationarity. Including too many lags further reduces the power of the test to reject a unit root, since the an increased number of lags requires estimating additional parameters, and a loss of degrees of freedom. On the other hand, too few lags will fail to capture the actual error process. Enders (1995) suggests starting with a relatively long lag length and paring down the model by the usual t-test and/or F-test. For example, the ADF equation is estimated using a lag length of n^*. If the t-statistic on lag n^* is insignificant at some specified critical value, then the model is re-estimated using a lag length of n^*-1. This process is repeated until the lag is significantly different from zero. In a pure autoregressive case, if the initial choice of lag length includes the true length, such a procedure will yield the true lag length with an asymptotic probability of unity (Enders 1995, p. 227).

If the data exhibit seasonality, the procedure is modified with the intent to employ a lag length long enough to capture the seasonal pattern. For example, with monthly data, one could start with 3 years of lags (n=36). If the t-statistic on lag 36 is insignificant, and an F-test indicates that lags 25-36 are insignificant then one reduces *n* to 24 and repeats the process until a reasonable lag length has been determined. Once a tentative lag length is found, diagnostic checking of the residuals should reveal them to approximate a white noise process.

This study followed these procedures, and the natural log of all three series were subjected to various specifications of the Dickey-Fuller tests. Equation (24) below assumes there is no serial correlation while equations (25) and (26) correct for serial correlation. Preliminary analyses of the coarse grain data revealed that the errors were indeed serially correlated and therefore the augmented Dickey-Fuller tests were performed. Specifically, the following random walk processes with and without a time trend were fitted by OLS regression to the monthly data and H_0: $\delta=0$ was tested

$$\Delta P_t = \delta P_{t-1} + \epsilon_t \tag{24}$$

$$\Delta P_t = \alpha + \delta P_{t-1} + \beta_1 \Delta P_{t-1} + \beta_2 t + \epsilon_t \tag{25}$$

$$\Delta P_t = \alpha + \delta P_{t-1} + \beta_1 \Delta P_{t-1} + \epsilon_t \tag{26}$$

where P refers to the natural log of the individual price series.

The software package used (EVIEWS) computes the Dickey-Fuller τ-statistic, which is compared to the asymptotic critical values for unit root tests calculated in Davidson and McKinney (1993). A series that is found to be nonstationary is made stationary by differencing. The remainder of this chapter discusses the other time series properties characteristic of commodity price data.

3.6.2 Time-varying Volatility and Excess Kurtosis

In addition to not having a constant mean, many economic time series exhibit phases of relative tranquility followed by periods of high volatility. ARIMA modeling techniques generally assume that ϵ_t is i.i.d. with mean zero and variance σ^2. However, empirical research (Myers 1994; Wang 1996) on commodity prices has shown that time-varying volatility and excess kurtosis (i.e., fat tails) are inherent in commodity price data. Particularly, studies show that while a series of price changes is uncorrelated and thus linearly independent, often in high frequency data, the moments of the price distributions are correlated, implying that the price changes are nonlinearly dependent[28]. That is, the volatility of price changes tends to vary over time, in that large (small) price changes tend to be followed by other larger (smaller) changes.

Temporal instability in the variance of commodity prices leads to autocorrelation patterns in the conditional variance of the price errors, where the variance is conditional

---

[28] Annual data is considered as low frequency and daily data is considered to be high frequency. Since monthly data falls in between it can possess characteristics of both low and high frequency data.

on an information set available at the time the forecasts are being made. This is known as conditional heteroskedasticity, after Engle (1982) who developed the autoregressive conditional heteroskedasticity (ARCH) model to capture such effects. The ARCH model was later generalized by Bollerslev (1986).

Econometric work which ignores conditional heteroskedasticity leads to hypothesis tests which are not asymptotically valid, and/or biased estimates of standard errors. Thus, the models developed in chapter 4 are examined for ARCH effects. The conventional test statistic is: $TR^2 \sim X^2(q)$ where T is the number of observations, q is the number of lags and degrees of freedom, and R^2 is the coefficient of determination from the following OLS regression:

$$\hat{\epsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\epsilon}_{t-1}^2 + \alpha_2 \hat{\epsilon}_{t-2}^2 + \ldots \alpha_q \hat{\epsilon}_{t-q}^2 \tag{27}$$

and $\{\hat{\epsilon}_t\}$ are the residuals from the price model. The null hypothesis is that the errors are normally distributed with mean zero and constant variance σ^2.

In addition to conditional heteroskedasticity, research on empirical distributions of commodity prices indicates that the tails of such distributions are fatter than the generally assumed standard normal distribution, suggesting excess kurtosis in commodity price changes (Myers 1994). The price models are tested for excess kurtosis relative to the standard normal. A kurtosis greater than three indicates excess kurtosis. Most computer software packages compute kurtosis as a descriptive statistic.

3.7 Implications for Forecasting

If nonstationarity is not properly accounted for, then forecasts based on models which assume stationarity when in fact the series is nonstationary are of dubious value. In fact, there are important differences between stationary and nonstationary time series. Shocks to a stationary time series are necessarily temporary. That is, over time the effects of shocks will dissipate and the series will revert to its long-run mean. As such, long-term forecasts of a stationary series will converge to the unconditional mean of the series (Enders 1995).

On the other hand, the presence of a stochastic trend implies that fluctuations in a time series are the result of shocks not only to the transitory or cyclical component but also to the trend component of the time series. That is, the mean and/or variance are time dependent, and thus shocks to such time series will permanently alter their level (Gujariti 1995). Moreover, a variance that changes over time has implications for the validity and efficiency of statistical inferences about the parameters that describe the dynamics of the price level. Changes in variances can also be very important in understanding price movements. Using the standard ARIMA modeling techniques, chapter 4, uses the results of the unit root and ARCH tests, the autocorrelation and partial autocorrelation functions, and the Q-tests to identify price models for each commodity. The best models are then identified as forecast competitors and evaluated in chapters 6.

CHAPTER 4

SPECIFICATION AND ESTIMATION OF ALTERNATIVE PRICE MODELS

4.0 Introduction

In this chapter alternative stochastic models for rice, sorghum and maize prices are specified and estimated for the sample period of January 1982 to September 1996. Because there are insufficient data to build structural models, the price models developed in this chapter use a time-series approach, modeling statistical properties such as serial correlation and temporal dependence of the univariate time series. Information on exogenous forces hypothesized to affect price movements, such as rainfall, are incorporated in the modeling process when data are available. The tentative models are evaluated with standard statistical selection criteria for time-series models, such as the Q-statistic, the Akaike information criterion, the Schwartz-Bayesian criterion, parsimony and tests for conditional heteroskedasticity. The most appropriate models for each commodity are then put forward as forecast competitors and evaluated further for forecasting ability using statistical and economic criteria in chapters 6and 7, respectively.

Due to their simplicity, broad availability in software packages, as well as their limited success in forecasting (Makridakis 1993), exponential smoothing models are examined in section 4.1. Furthermore, since part of this research seeks to identify the benefits of improved price forecasts, the forecasts from the smoothing models are included in the forecast competition, along with the results generated from random walk (naive) models. The interdependent behavior of different grain prices suggests that modeling the commodities as a system, such as a vector autoregression (VAR), might improve the forecasts of the individual grain prices. Therefore, a simple VAR is also developed and evaluated for forecasting in chapter 5.

4.1 Smoothing Models

Exponential smoothing is a method of forecasting which is not based on any formal statistical model or economic theory. It is a simple method of adaptive forecasting in which the forecasts adjust based on past forecast errors (e.g. $P_{t+1} = P_t + \alpha e_t$) where α is an adjustment or smoothing parameter, and e is the forecast error in period t. The past forecast error is used to correct the next forecast in a direction opposite to that of the error (Makridakis 1978). Smoothing methods require only a minimal amount of data and are most effective when the parameters describing the time series change slowly over time (Bowerman 1993).

There are several different smoothing procedures available. Single exponential smoothing is appropriate for a series that moves randomly above and below a constant mean with no trend or seasonal pattern (EViews users guide 1997). However, if the series displays a slowly changing linear trend, then double exponential smoothing which produces forecasts that grow along a trend is more appropriate. And if the trend is nonlinear, then the smoothing model is modified to handle nonlinear trends. Indeed, most statistical packages allow for nonlinear trends such as the exponential (rate faster than a straight line) and damped (rate slower than a straight line).

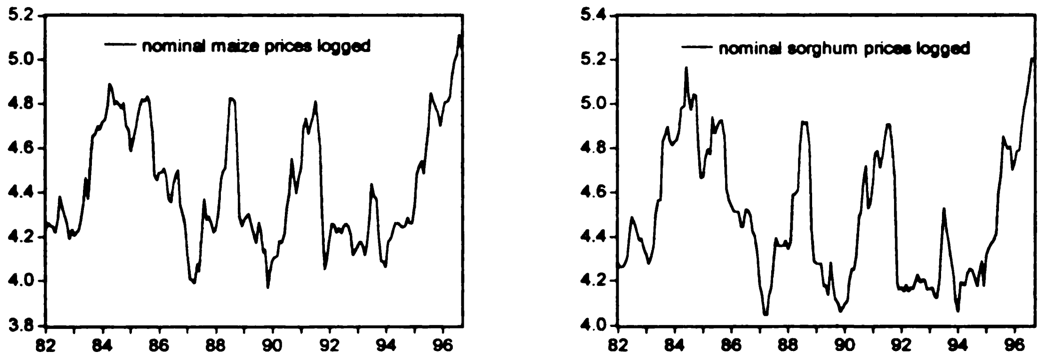
If the time series has a seasonal pattern and a linear trend, then Holt-Winters is a more appropriate exponential smoothing procedure. The Holt-Winters forecasting procedure can accommodate increasing (multiplicative) seasonal variation, i.e., seasonal effects whose magnitudes grow along with the series and constant (additive) seasonal variation. Short-term forecasts for sorghum, maize and rice are produced using the smoothing procedures in EViews.

4.1.1 Smoothing Procedures for Sorghum and Maize

The choice of smoothing procedure is a function of the underlying pattern observed in the time series. The plots of the evolution of logged, nominal sorghum and maize retail prices from January 1982 to September 1996 are shown in figure 4.1. The results in chapter 3 indicated that sorghum and maize prices exhibited seasonal patterns and possessed significant downward trends prior to devaluation, and significant upward trends after devaluation. Therefore, the observed time series were assumed to trend with temporal dependence occurring at or near seasonal lags. Smoothing procedures which capture seasonality and trends were examined.

Holt-Winters is a common exponential smoothing method for forecasting seasonal time series and is standard in most time series software packages. Holt-Winters requires that the seasonal pattern in a time series be identified as either increasing or constant over time. If it is increasing over time, the seasonal pattern is assumed to exhibit increasing seasonal variation and the smoothing equation is multiplicative. If the seasonal pattern is independent of time, it is modeled as additive.

Figure 4.1



As there is no *a priori* reason to believe that the seasonality is increasing in the coarse grain series, it is assumed to be constant and modeled as additive. The smoothed series $\hat{P}_t$ of P_t is computed recursively by: $\hat{P} = a + bk + c_{t+k}$ where P is the nominal price in levels, a is the permanent component or intercept, b is the trend, c_t is the constant seasonal factor and k is the forecast horizon. The coefficients a, b and c are given by equations (28)-(30) and are computed recursively in EViews. α, β, and γ are damping factors which fall between 0 and 1, and s is the seasonal frequency, 12 in this case.

$$a_t = \alpha(P_t - c_{t-s}) + (1-\alpha)a_{t-1} + b_{t-1} \tag{28}$$

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \tag{29}$$

$$c_t = \gamma(P_t - a_t) + (1-\gamma)c_{t-s} \tag{30}$$

The smaller the smoothing parameter the smoother the series. The Holt-Winters procedures in EViews estimates initial values for the damping factors by minimizing the sum of squared errors. Forecasts are given by: $\hat{P}_{t+k} = a_t + b_t K + c_{t+k-s}$. The results of the smoothing procedures (forecasts) for October 1996 to September 1998, starting from the September 1996 prices for sorghum and maize, are reported in table 4.1.

Table 4.1: Forecasts from Holt-Winters Smoothing Procedures

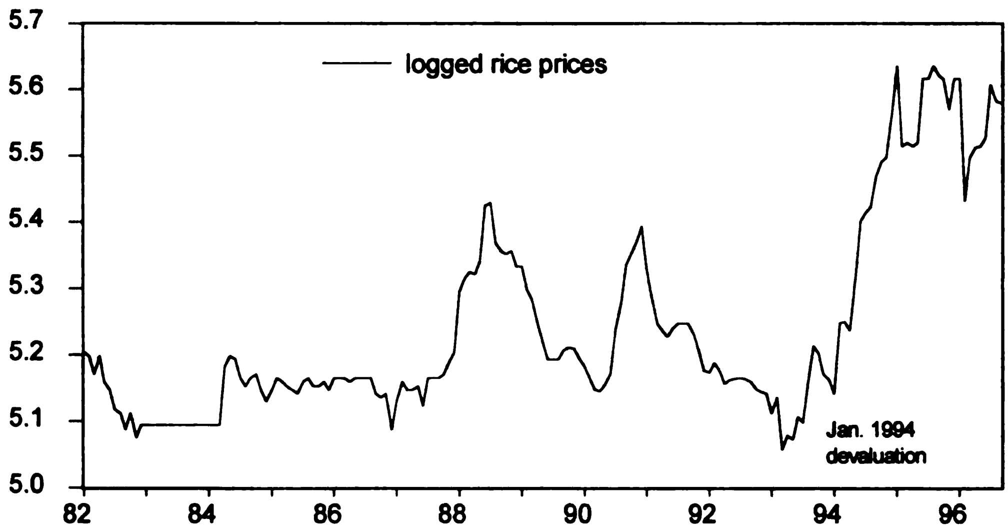
Period Ahead	Sorghum $\alpha=1;\ \beta=\gamma=0$	Actual Sorghum	Maize $\alpha=1;\ \beta=\gamma=0$	Actual Maize
Oct. 1996	176.6	170	150.1	144.4
Dec. 1996	159.4	110	141.6	109
Feb. 1997	160.7	122.5	145.1	122.5
June. 1997	174.2	125	152.3	125
Aug. 1997	181.9	121.3	160.5	121.3
Oct. 1997	178.3	102.5	152.6	102.5
Dec. 1997	161.1	106.7	143.8	105
Mar. 1998	164.8	115	150.2	115
June 1998	175.9	144	154.8	134
Sep. 1998	183.4	177	161.7	152

The mean, a_t, is computed as 168.8 and 148.2 for sorghum and maize respectively, while the trend, b_t is 0.14 and 0.21. The seasonal factors for sorghum range from -3.8 to 12.1, with the negative factors occurring in November through May. The results are similar for maize prices, which range from 1.69 to 10, with the negative factors occurring in the same months as for sorghum. The zero values for β and γ in the table imply that the trend and seasonal components are estimated as fixed and not changing. That is, fixed nonzero trend and seasonal factors are included in the forecasts.

4.1.2 Smoothing Model for Rice

Figure 4.2 shows that the rice series to be trending upward over time, particularly since the January 1994 devaluation of the CFAF. Furthermore, the autocorrelation function does not indicate significant seasonality in the rice series. These characteristics are consistent with rice's role as an imported and food aid commodity. Nonetheless, various specifications with and without seasonality were examined and compared on the

Figure 4.2



basis of the root mean squared errors (RMSEs). The trend in the rice series was best described as linear. The model with the lowest root mean squared error was the Holt-Winters with additive seasonality and is described below in table 4.2.

Table 4:2: Forecasts from Holt-Winters Smoothing Procedures for Rice

Period Ahead	Rice w/o seasonality α=0.99; β=0	Rice w/seasonality α=0.96; β=γ=0	Actual Rice
Oct. 1996	265	265.5	268
Dec. 1996	265.1	264.7	233
Feb. 1997	265.2	266.1	240
June. 1997	265.3	269.2	257.5
Aug. 1997	265.3	271	252.5
Oct. 1997	265.5	272.8	235
Dec. 1997	265.5	272.1	240
Mar. 1998	265.6	271.1	246
June 1998	265.6	276.5	257
Sep. 1998	265.7	279.8	288
RMSE	7.47	7.33	

Smoothing methods assume that the parameters describing the time series are changing slowly over time. However, the estimates of the damping parameter, α, which minimized the sum of the squared residuals, is equal to one in both the coarse grain models and nearly one (0.99 and 0.96) in the rice models. This indicates that the parameters are not changing slowly. In fact, the large value of the smoothing constant suggests that the series are essentially random walks in which case the best forecast gives high weight (in this case 100%), to the most recent observation and little weight to past observations. Bowerman (1993) suggest that if the smoothing parameter that minimizes the sum of the squared errors is greater than 0.3, then smoothing is probably not the best forecast method.

In summary, although smoothing procedures are simple and inexpensive, the results of the smoothing procedures for each of the commodity prices generates smoothing constants considerably greater than 0.3. This indicates that forecasting performance may be improved with other forecasting techniques. Structural analysis in which prices are related to other variables such as quantity produced can lead to improved forecasts. But since data is limited in the Malian case, time-series modeling techniques are used to forecast the commodity prices. In section 4.2, the price series are fitted with various univariate ARIMA models.

4.2 ARIMA Models

Recall that a univariate ARIMA (p,d,q) model is a stochastic or probabilistic description of the outcome of a process operating through time (Enders 1995). As discussed in chapter 3, ARIMA models describe time series where the statistical properties are independent of time, i.e., are covariance or weakly stationary. If the time series is stationary, then the sample mean, variance and autocorrelations can be used to estimate the parameters of the underlying data generating process. And if the process can be described with a stationary statistical model, the model can be used to predict the time path of prices. Therefore, the starting point for building ARIMA models is to test for stationarity to determine whether first-differencing is needed to achieve stationarity or if the models should be developed using levels.

The results of the preliminary analyses in chapter 3 suggested that each series had a tendency to trend upwards after the devaluation. Structural change can complicate the unit root test by making an otherwise stationary series appear nonstationary. Since the Dickey-Fuller tests are biased towards the nonrejection of a unit root in the presence of structural change, Perron (1989) developed a formal procedure to test for unit roots in this context and is described below in equation (31):

$$P_t = a_0 + a_2 t + \mu_2 D_L + \sum_{i=1}^{k} \beta_i \Delta P_{t-i} + \epsilon_t \tag{31}$$

where P_t is logged price, t is a deterministic time trend, and D_L is similar to the devaluation dummy variable described above, equal to 0 before devaluation and 1 after the devaluation. Since the autocorrelation functions indicated that sorghum and maize price series had strong seasonal patterns, 11 seasonal dummies were added to equation (31). The augmented form is used to correct for serial correlation. The model is estimated and H_0: $a_1=1$ is tested and compared to the critical values in Perron (1989)[29].

It should be noted that there is a substantial literature concerning the appropriateness of the various Dickey-Fuller and Perron test statistics, where it is argued

---

[29]The distribution of a_1 depends on the proportion of observations occurring prior to the break, which in this case is 0.82 (λ=144/177). The critical values are identical to the Dickey-Fuller statistics when λ=0 or 1. Note that Perron's critical values do not account for seasonal dummies. This is believed not to have a significant effect on the results.

that these tests have low power to distinguish between unit roots and near unit root processes. However, for forecasting, borderline cases have nearly identical forecasting performance and one-step ahead forecasts from a differenced model are usually superior to forecasts from a stationary model (Enders 1995). Furthermore, the tests are confounded by the presence of deterministic regressors like trends, intercepts and seasonal dummies. Too many or too few deterministic regressors reduce the power of the tests. Nonetheless, each of the price series was subjected to the unit root test described by equation (31) and each were found to have unit roots. So the models are built on the first differences of the logged prices multiplied by 100, thus in effect modeling the percent change in prices. Table 4.3 reports the t-statistics. Further tests indicated that the first-differenced series were indeed stationary.

Table 4.3: Results of Unit Root tests - T-statistics for H_0: a_1=1

Sorghum	Maize	Rice	Critical value @ 5%
-0.54	-0.67	-1.33	-3.5

Using the Box-Jenkins methodology outlined above in chapter 2, this section further examines the time-series properties of the first-differences of each series to identify tentative models of the underlying data generating processes. The focus is not identifying precisely the forces that actually determine prices, but to develop models that capture the essence of the true data generating process. The models are estimated by OLS in EViews using White's covariance estimator instead of the standard OLS formula[30]. White's heteroskedasticity-consistent covariance corrects estimates of the coefficient covariance when the form of the heteroskedasticity is unknown. This is used because many economic series exhibit time-varying volatility (a time dependent variance). The models are estimated for January 1982 to September 1996 and include 177 monthly observations.

The specification search proceeds as follows: beginning with sorghum, followed by maize and then rice, the correlogram of the percentage change of each price is plotted and the sample autocorrelation and partial autocorrelation coefficients are used to identify tentative models. The correlogram of the model residuals is then casually investigated for serial correlation and formally tested using the Ljung-Box Q-statistic. The correlogram of the squared residuals is examined and formally tested for conditional heteroskedasticity. The specification search continues until the model residuals approximate a white noise process. Further validation is accomplished with the Akaike Information Criterion and the Schwartz-Bayesian Criterion. The models that emerge from the diagnostic tests as statistically adequate representations of the true data generating process are put forward as forecast competitors. In chapter 5, vector autoregression representations of the price series are developed and evaluated. The predictive performance of the univariate and mulitvariate forecast competitors is further evaluated using statistical criteria, such as root mean squared error and turning point errors in chapter 6, and economically evaluated in chapter 7.

---

[30]The White covariance matrix is given by: $\hat{\Sigma}_W = \frac{T}{T-k}(X'X)^{-1}(\Sigma u_t^2 x_t x_t')(X'X)^{-1}$, where T is the number of observations, k is the number of regressors, and u_t is the least squares residual.

4.2.1 ARIMA MODELS FOR SORGHUM

Figure 4.3 is a graph of the percentage change in sorghum prices, which clearly fluctuates around a constant mean of zero, and is indeed stationary.

Figure 4.3

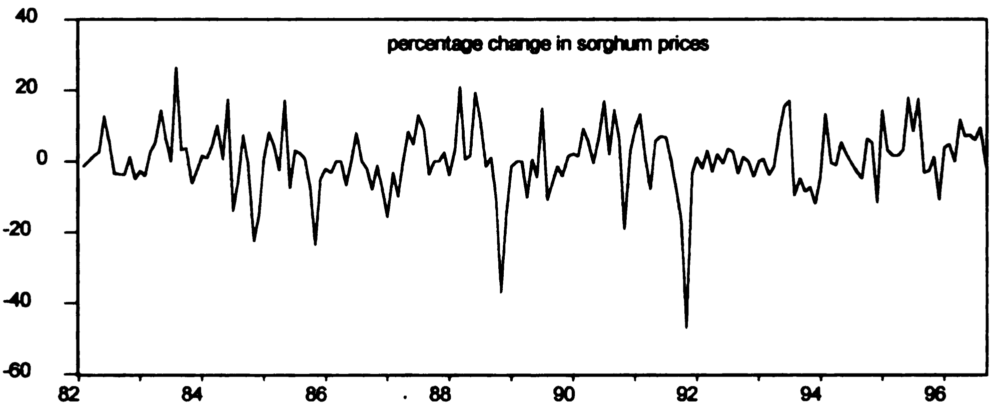
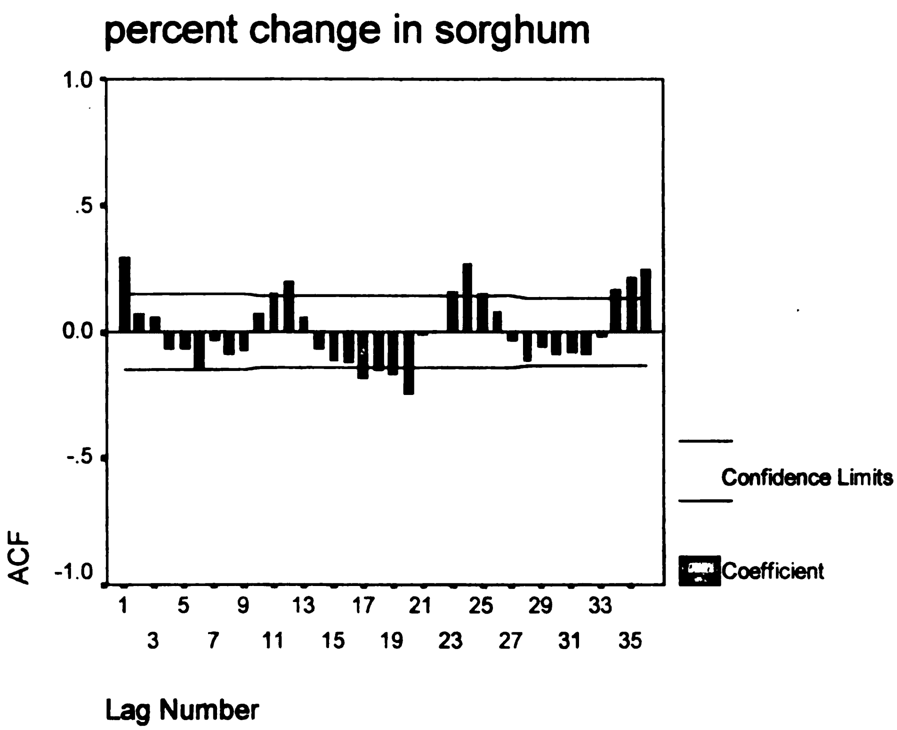
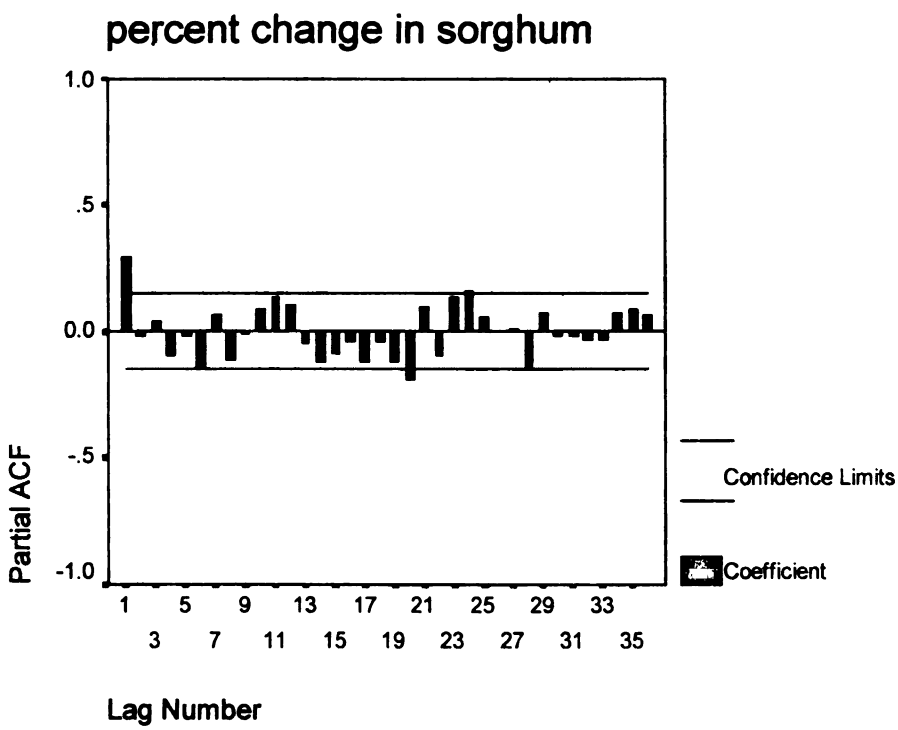


Figure 4.4 graphs the autocorrelation and partial autocorrelation functions of the series depicted in figure 4.3. Consistent with *a priori* expectations of rainfed crops in Mali, the correlogram for 36 lags displayed in figure 4.4 reveals a cyclical pattern and indicates that at a 5% level of significance there is significant autocorrelation at or near seasonal lags.

Figure 4.4: Correlogram of the Percent Change in Sorghum Prices





The Q-statistic at lag 36 is 135 and with a p-value of 0.0 rejects the null hypothesis of zero serial correlation.

In general, there are two major ways of handling seasonality in a time series using ARIMA models: deseasonalize/seasonally adjust the time series, or model the seasonality. Recent literature on time series econometrics argues against deseasonalizing, maintaining that seasonal and ARMA coefficients are best identified and estimated jointly (Enders 1995; Davidson & Mckinnon 1993). Therefore, this study models the seasonal pattern in the time series using typical methods, such as seasonal dummy variables, harmonic functions and seasonal ARIMAs. The next section discusses the results of the alternative representations of seasonal pattern fitted to various ARIMA structures of the sorghum price series.

4.2.1.1 Specification Search for Seasonality in Sorghum Prices

Harmonic functions and seasonal dummy variables are common methods of describing deterministic seasonality in a time series. Seasonality is defined as any cyclical or periodic fluctuation in a time series that recurs at the same phase of the cycle or period. Due to their flexibility in capturing periodic fluctuations, harmonic functions have been successful in describing the deterministic seasonal component of a time series and are examined here. When the seasonal variation is believed to be constant over time, seasonal dummy variables can also be an effective means of capturing seasonal patterns. *A priori* expectations coupled with visual examination of the correlogram in figure 4.4, and the plot of the nominal series did not indicate that the seasonal pattern in the sorghum series was increasing or decreasing over time. Hence, the seasonal variation is assumed to be constant. Excluding December from the analysis, the seasonal dummies equal one for the current month and zero otherwise. The seasonal parameters are interpreted relative to the harvest month of December. There are two significant spikes in the PACF in figure 4.4, one at lag 1 and the other at lag 20. Several low-order ARIMA models with seasonal dummies or harmonic frequencies with first and second order seasonality were estimated and evaluated. The results of the most statistically adequate models are presented in table 4.4.

Beginning with the seasonal dummy specification of the seasonality, the true process that generated the sorghum realizations could be characterized as an ARIMA (1,1,1). The ARIMA structure was significant at the conventional level. The seasonal dummies were all significant at the 5% level except for October and November. All the seasonal dummies were positive, except November. The negative sign on November is valid if abundant rainfall leads to an early harvest. The parameter estimates indicate that in the Bamako-Niarela market, the average percentage increase in sorghum prices is greatest in June (13%) and smallest in October (3.1%). This is consistent with knowledge of the sorghum market. The constant is significant and negative. The Q-tests for lags 1-12 and 1-36 indicates that the residuals are not serially correlated, and Q-tests of the squared residuals indicates that there are also no ARCH (i.e., the variance is constant).

Table 4.4: ARIMA Models for Sorghum with Seasonal Dummies and Harmonic Functions

Dependent variable: percent change in sorghum prices

	ARIMA (1,1,1) w/seasonal dummies	ARIMA (1,1,(1,13)) harmonic	ARIMA ((1,24),1,(1,24))
Constant	-6.1 (-3.5)	0.06 (0.31)	0.68 (0.50)
January	6.3 (2.7)		
February	8.7 (4.2)		
March	8.4 (3.7)		
April	6.8 (3.1)		
May	10.8 (4.8)		
June	13.1 (5.1)		
July	12.9 (4.8)		
August	8.5 (2.9)		
September	5.2 (2.4)		
October	3.1 (1.4)		
November	-5.3 (-1.3)		
Sin $(2\pi t/12)$		2.0 (2.4)	-0.09 (-4.76)
Cos $(2\pi t/12)$		-5.6 (-6.9)	-0.07 (-3.55)
Sin $(2\pi t/6)$		3.1 (3.0)	0.01 (2.05)
Cos $(2\pi t/6)$		-0.03 (-0.03)	-0.03 (-2.96)
AR (1)	0.78 (3.7)	0.74 (8.6)	1.05 (26.34)
AR (24)			0.68 (13.7)
MA (1)	-0.70 (-2.6)	-0.71 (-10.5)	0.20 (3.3)
MA (13)		-0.25 (-3.8)	
MA (24)			-0.62 (-1164.8)
Log Likelihood	-605.6	-604.3	-534.5
AIC/SBC	7.08 / 7.33	6.99 / 7.14	7.09 / 7.16
Q(12) / Q(36)	0.48 / 0.47	0.24 / 0.59	0.65 / .18
$Q^2(12)$ / $Q^2(36)$	0.60 / 0.16	0.86 / 0.23	0.90 / 0.15

T-statistics are in parentheses and the Q() statistics are the probability values

The sorghum series was also fitted as an ARIMA (1,1,(1,13) with 2nd -order harmonic seasonality similar to the model in Yang & Brorsen (1992). The letter "*t*" in the sine and cosine functions refers to the month and the denominator represents the length of the cycle. The diagnostic statistics presented in table 4.4 column three indicates that this is also a statistically adequate representation of the data. The moving average coefficient at lag 13 indicates that values every 13 months away are closely related, which suggests that the harmonic functions are not capturing correlations at near seasonal lags. Both the AIC and the SBC criteria select the harmonic specification over the seasonal dummy model.

In addition to using seasonal dummies and harmonic functions, seasonality can be captured directly with the ARIMA structure by incorporating seasonal correlations into the model. Identification of seasonal ARIMA structures is accomplished through inspection of the seasonal lags of the auto and partial auto-correlation functions but is complicated by the fact that the seasonal pattern often interacts with the nonseasonal pattern in the data. That is, the correlogram for a combined seasonal/nonseasonal process will reflect both elements. The model in the fourth column in table 4.4 is the result of the specification search and includes both autoregressive and moving average coefficients at lag 24, as well as an MA(1) term. The model diagnostics indicate that the model is adequate. The AIC and SBC statistics select that the harmonic specification over the other 3 models. These models are further evaluated for forecasting ability in chapter 6.

In addition to the seasonality in sorghum marketing, other exogenous factors hypothesized to affect the evolution of sorghum prices were examined in the ARIMA framework. Specifically, rainfall levels, the January 1994 devaluation of the currency, the exchange rate between the CFAF and U.S. dollar and world price of rice (Thailand) dollar were examined. Results indicate that none of these factors contribute significantly to explaining the variation in sorghum prices. The insignificance of rainfall, defined as the monthly level of rainfall in Koutiala, a major sorghum producing area, is contrary to expectation since other studies have shown that coarse grain production is largely determined by the variation in weather (Boughton 1994; Dione 1989; D'Agostino 1988). Several alternative specifications for rainfall were also examined, including different lag lengths and using the sum of rainfall from June through September (major rainfall months) as the monthly observation. Rainfall was consistently insignificant. It does suggest that the variation in production levels may not be directly transmitted to market prices.

The ARIMA models were formally investigated for structural change at the point of devaluation using the Chow forecast test. The model was re-estimated for a sub-sample comprising observations from January 1982 to December 1993 and used to predict the percent change in sorghum prices for January 1994 through the end of the sample, September 1996. A large difference between the actual and predicted values is indicative of parameter instability or structural change. For the Chow forecast test, EViews reports two test statistics: an F-statistic and a log likelihood ratio statistic. The statistics for the ARIMA with the seasonal dummies are presented below in table 4.5.

Table 4.5: Chow Forecast Tests - H_0: No structural change		
Break	F-statistic (p-value)	LR statistic (p-value)
January 1994	0.81 (0.76)	33.14 (0.46)

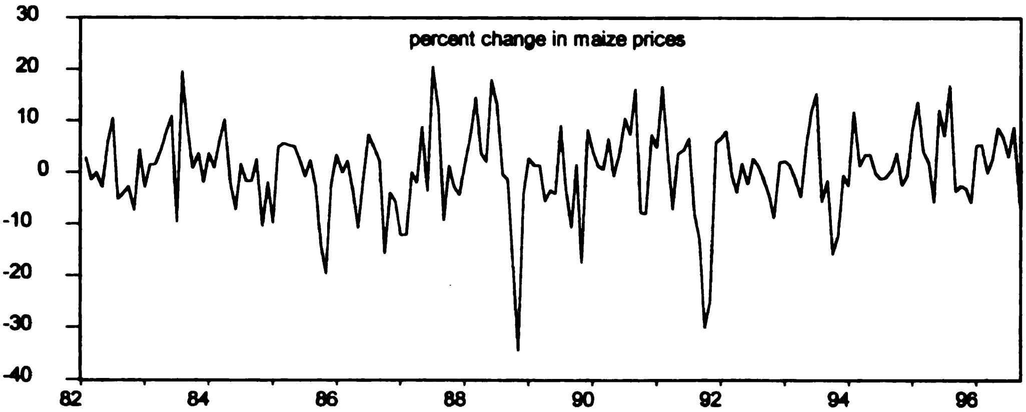
From table 4.5, it is clear that the null hypothesis of no structural change for the devaluation cannot be rejected with either test statistic, and therefore the devaluation dummy variable is not included in the analysis of the sorghum prices.

In summary, the models of sorghum prices presented in this section are all statistically adequate representations of the conditional mean. The correlogram, Q-tests of the squared residuals for each model and Lagrange multiplier test for ARCH effects all suggest that the conditional variance is homoskedastic. The Chow Forecast tests for structural changes indicates that there is none with both the LR and F-statistics failing to reject the null of no structural change at 5% level. Therefore, the ARIMA model with the seasonal dummies, the ARIMA with the harmonic specification, and the seasonal ARIMA are put forward as forecast competitors. These models are further investigated for forecasting performance relative to the random walk model in chapter six. Following the same procedure as the sorghum models, the remainder of this chapter presents the forecast competitors for the maize and rice prices.

4.2.2 ARIMA Models for Maize Prices

Figure 4.5 depicts the evolution of the percentage change in maize prices and correlogram is shown below in figure 4.6.

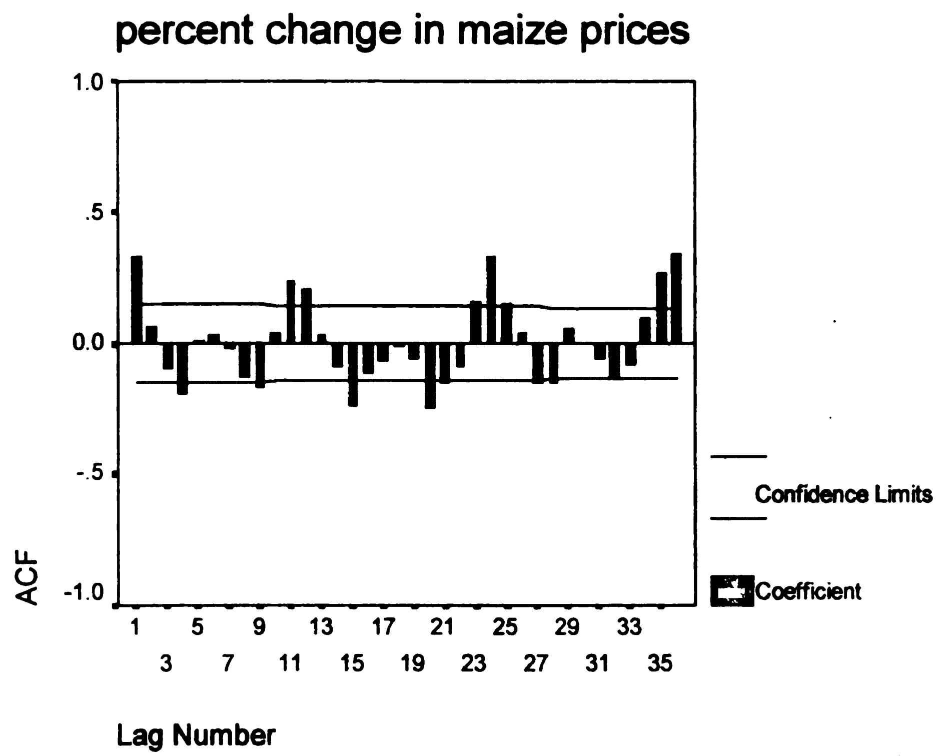
Figure 4.5



The dip in late 1988 corresponds to higher than average rainfall for the critical months of June through September, whereas it is less clear what is driving the dip in late 1991. At 913 mm, rainfall was abundant in 1990, but was slightly less than average in 1991 at 695 mm. One explanation is that producers and traders released large amounts of inventory accumulated in 1990 in 1991.

In figure 4.6, the ACF has the typical seasonal pattern as does the PACF. There are significant spikes (exceeds the 2 standard error band) at lags 1, 12, 20, 24 and 36, clearly indicative of seasonality.

Figure 4.6: Correlogram of the Percent Change in Maize Prices



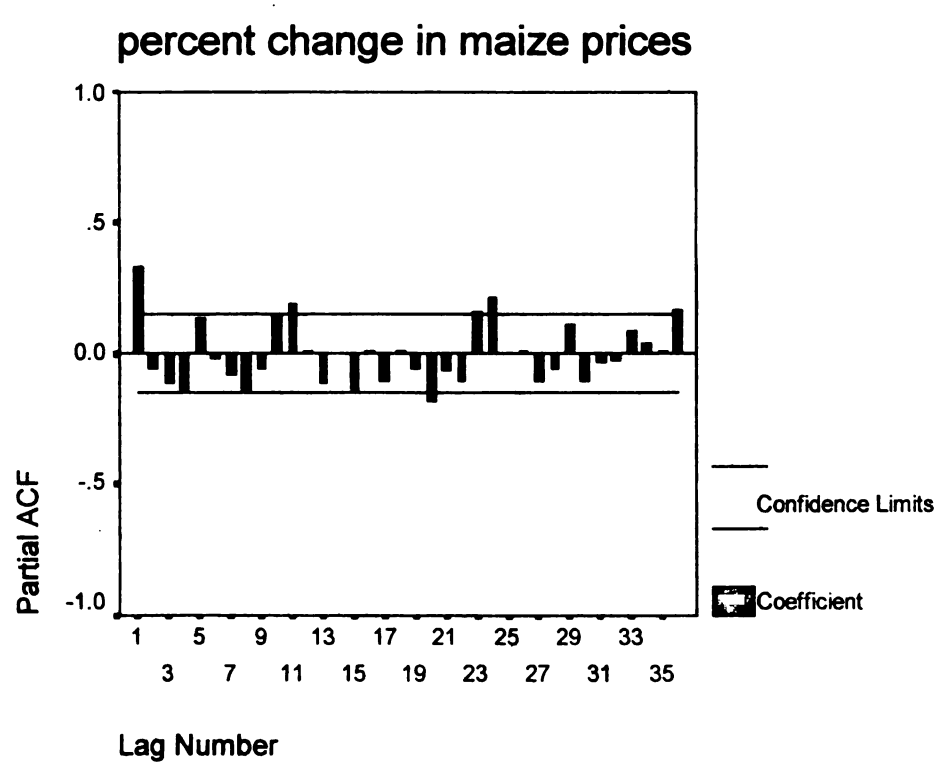


Table 4.6 presents feasible ARIMA representations of the stochastic process that generated the maize data using seasonal dummies, harmonic functions, and seasonal lags to capture the deterministic seasonal component. The maize harvest takes place in October and thus the coefficients on the seasonal dummies are interpreted relative to the harvest month of October. With the exception of November, all the seasonal dummies are positive and significant at the 5% level. Relative to October, the largest percentage increase (13.5%) occurs in July, with the smallest percentage increase (5.3%) occurring in September. Although not significant, the negative sign on the November coefficient is consistent if harvest occurs in November.

The ARIMA model with the harmonic functions is significant and has residuals that approximate white noise, according to the Q-statistic. The seasonal lag model is a higher-order pure moving average model with coefficients at seasonal lags 24 and 36. The MA(1) and MA(20) terms capture the significant spike at lag 1 and lag 20 in the PACF. It is not clear what is consistently occurring every 20 months. It could be anything from rainfall effects to the marketing strategies of producers. All the models were validated statistically. However, the correlogram of the squared residuals suggest potential low-order ARCH effects in the seasonal dummy and harmonic models, and higher-order ARCH effects in the seasonal lag model. This was tested formally with the Lagrange multiplier tests. The results are reported in table 4.7.

Table 4.6: ARIMA Models for the Percent Change in Maize Prices

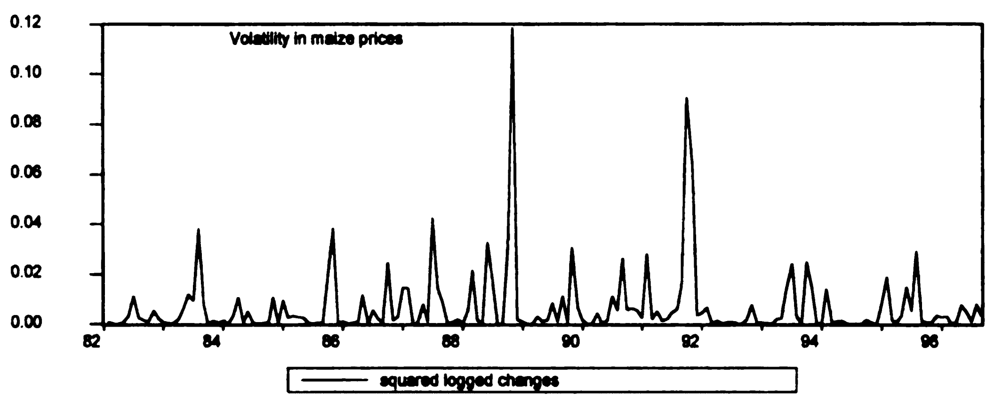
Models	seasonal dummy	harmonic	seasonal lag
Constant	-7.14 (-2.68)	0.39 (0.73)	0.60 (0.82)
January	8.28 (2.35)		
February	11.5 (3.42)		
March	9.78 (3.39)		
April	7.81 (2.63)		
May	8.56 (2.79)		
June	11.1 (3.42)		
July	13.5 (3.89)		
August	10.3 (2.97)		
September	5.29 (1.78)		
November	-3.92 (-1.25)		
December	7.37 (2.39)		
Sin($2\pi t/12$)		2.84 (3.84)	
Cos($2\pi t/12$)		-3.7 (-4.83)	
Sin($2\pi t/6$)		4.62 (5.6)	
Cos($2\pi t/6$)		0.32 0 (0.47)	
AR(1)	0.22 (2.44)	0.18 (1.97)	
AR(12)			
AR(13)		-0.22 (-2.70)	
MA(1)			0.17 (2.83)
MA(12)			
MA(15)	-0.19 (-2.68)		
MA(20)			-0.20 (-2.83)
MA(24)			0.18 (3.05)
MA(36)			0.32 (4.19)
Log likelihood	-578.8	-544.9	-598.4
AIC/SBC	6.77 / 7.02	6.77 / 6.91	6.86 / 6.94
Q(12)/Q(36)	0.39 / 0.27	0.41 / 0.25	0.11 / 0.13
$Q^2(12)/Q^2(36)$	0.48 / 0.26	0.30 / 0.23	0.33 / 0.02

Table 4.7: ARCH(q) Lagrange Multiplier Statistics: $TR^2(q)$			
Order	seasonal dummies	harmonic	seasonal lags
First	4.4 (0.04)	6.14 (0.01)	2.2 (0.14)
Second	4.5 (0.10)	6.75 (0.03)	3.5 (0.17)
Twelve	9.9 (0.62)	11.8 (0.47)	9.2 (0.68)
Thirty-six	34.6 (0.54)	37.0 (0.42)	31.8 (0.67)

The Lagrange multiplier tests indicate that there exists low-order ARCH effects in the harmonic specification and marginally in the seasonal dummy model, while there are no ARCH effects in the seasonal lag model. The p-values are in parentheses.

The volatility in maize prices is hypothesized to be influenced by, *ceteris paribus*, seasonality in marketing and weather. The plot of the squared logged differences of maize prices in figure 4.7 is used to identify patterns in the conditional variance. Two large peaks occur in late 1988 and late 1991, while the rest of the volatility appears to exhibit periodic peaks. The conditional variance of the harmonic specification was fitted as a GARCH(1,1) model, which was investigated for seasonality and rainfall.

Figure 4.7



The results are presented in table 4.8.

Table 4.8: ARIMA with Harmonic Seasonality and GARCH (1,1) Errors	
Constant	0.19 (0.43)
Sin($2\pi t/12$)	3.19 (6.37)
Cos($2\pi t/12$)	-3.76 (-7.06)
Sin($2\pi t/6$)	5.34 (8.17)
Cos($2\pi t/6$)	1.31 (2.24)
AR(1)	0.15 (2.04)
AR(13)	-0.28 (-5.08)
AR(29)	0.16 (2.70)
Conditional Variance	
Constant	0.72 (1.19)
ARCH(1)	-0.05 (-1.14)
GARCH(1)	1.03 (28.7)
Log likelihood	-478.7
AIC/SBC	6.66 / 6.89
Q(12) / Q(36)	0.46 / 0.35
$Q^2(12)$ / $Q^2(36)$	0.32 / 0.02

All the parameters in the conditional mean equation are significant at the 5% level. Rainfall was not significant in the conditional variance equation, while seasonality described by a first-order harmonic specification was significant. However, the correlogram revealed serial correlated residuals at all lags in the conditional variance equation when the harmonic functions were included. The model described in table 4.7 is an adequate fit of the data. The ARCH term is not significant at conventional levels, but the GARCH term is significant at the 0.0% level. ARCH tests on lag 36 indicate that there are no remaining ARCH effects. In summary, 4 models are put forward as forecast contenders, the ARIMA with the seasonal dummies, the ARIMA with the harmonic specification, the seasonal ARIMA model, and finally, the ARIMA with the GARCH(1,1) errors.

4.2.3 ARIMA Models for Rice

The plot of the first differenced rice series is shown below in figure 4.8 and the correlogram is displayed in figure 4.10. Figure 4.8 appears to have a constant mean with periods of high volatility, particularly during the devaluation and post-devaluation periods.

Figure 4.8

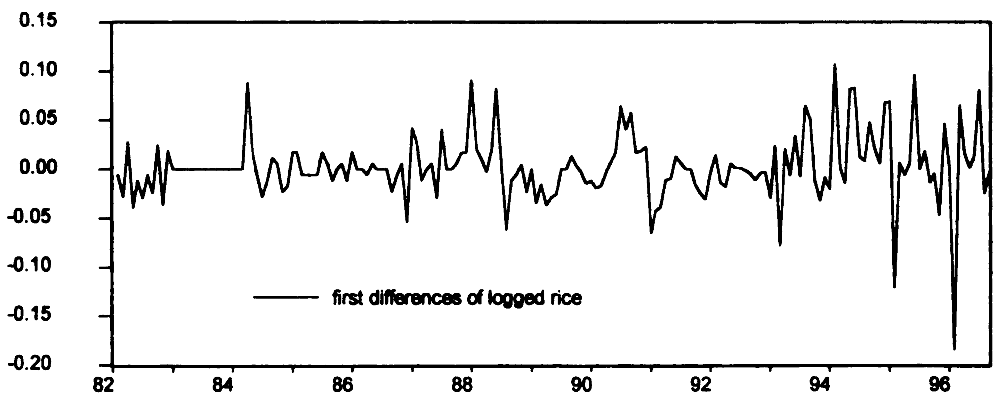
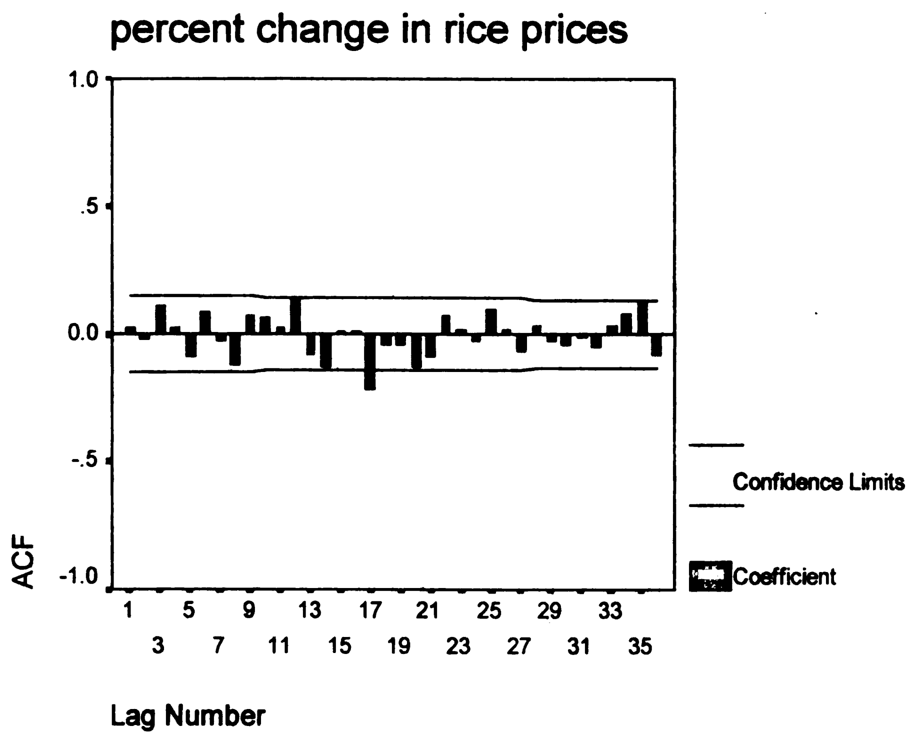
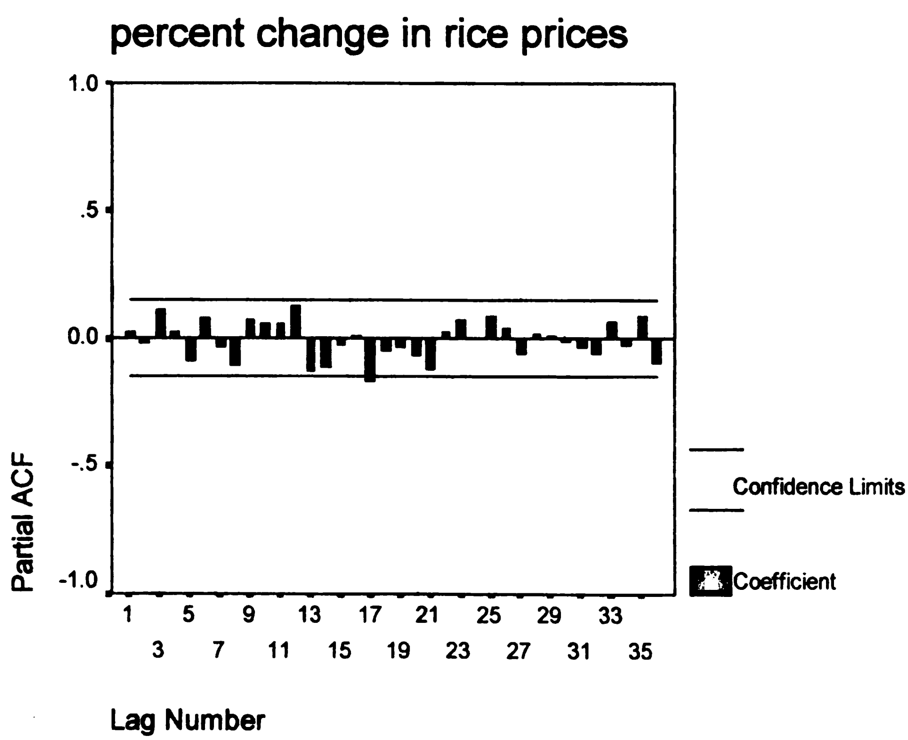


Figure 4.10: Correlogram of the Percent Change in Rice Prices





A binary variable was used to capture the effect of the devaluation. The binary variable equals zero before January 1994, one through December 1994 and zero from January 1995 to the end of the sample, September 1996. A Gauss program for computing the log likelihoods for each month following the devaluation was designed to determine the cutoff point of the impact of the devaluation. December 1994 generated the highest log likelihood. This result is consistent with other studies on the impact of devaluation in Mali. (See Tefft et al.1997). It was concluded that devaluation was a temporary shock to the system that caused retail rice prices to shoot up from January 1994 to December 1994. Formal tests for structural change are examined below.

The autocorrelation and partial autocorrelations functions in figure 4.10 do not exhibit any seasonal pattern or significant spikes, with the exception of lag 17. In fact, the underlying process appears to be a simple random walk. Nonetheless, during the specification search some low-order ARIMA models were examined. The results are reported in table 4.9. The first model is a random walk with a dummy variable for devaluation, and the second model is an ARIMA (1,1,1) with a moving average term at lag 17. The diagnostic tests indicate that both models are adequate representations of the conditional mean, but Q-tests on the squared residuals in both models are suggestive of conditional heteroskedasticity. Indeed, ARCH(q) tests for lags greater than 12 reject the null of no ARCH effects in both models.

Table 4.9: ARIMA Models for Rice		
	p=0; d=1; q=0	p=1; d=1; q=1,17
Constant		-0.00 (-0.02)
Devaluation	3.37 (2.87)	3.23 (2.53)
AR(1)		-0.52 (-3.01)
MA(1)		0.53 (3.22)
MA(17)		-0.28 (-2.46)
Log Likelihood	-459.9	0.11 / -451.7
AIC / SBC	5.23 / 5.26	5.22 / 5.31
Q(12) / Q(36)	0.18 / 0.08	0.22 /0.71
$Q^2(12)$ / $Q^2(36)$	0.01 / 0.29	0.00 / 0.42

To capture the time-varying volatility in the underlying process, the conditional variance of a moving average model (MA(17)) with devaluation was fitted as a GARCH (1,1) model with first-order harmonic specification for seasonality in the variance. The parameter estimates and model diagnostics are presented in table 4.10

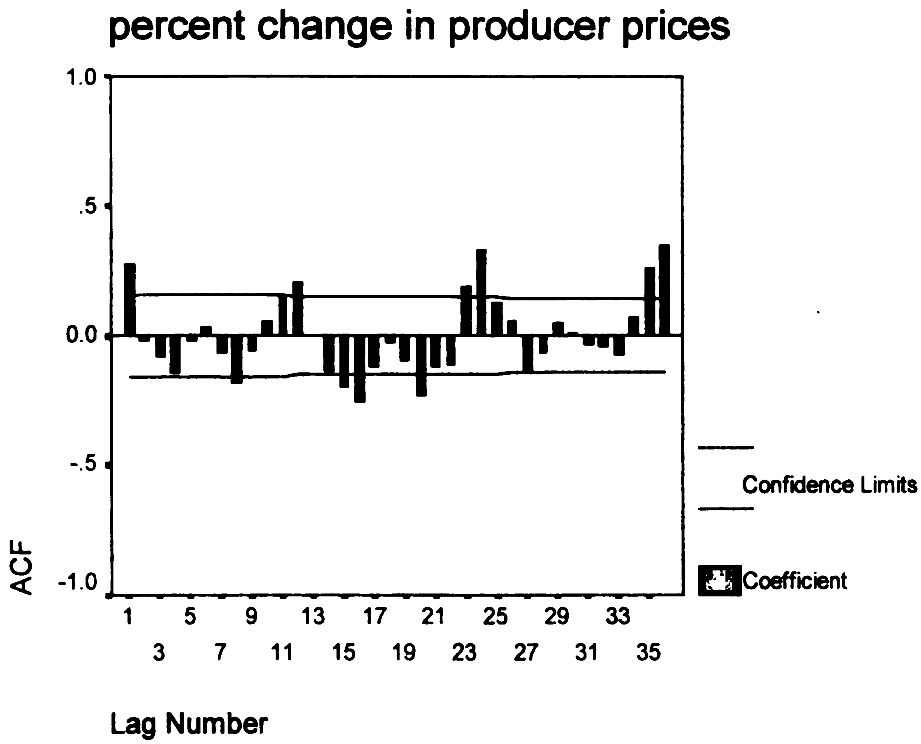
Table 4.10: Moving Average with GARCH (1,1) errors		
MA(17)	-0.20 (-2.66)	Model Diagnostics
Devaluation	2.93 (3.25)	Log Likelihood = -435.0
Conditional Variance		AIC = 5.02 / SBC = 5.15
Constant	1.36 (1.87)	Q(12) / Q(36) = 0.54 / 0.52
ARCH(1)	0.13 (2.02)	$Q^2(12)$ / $Q^2(36)$ = 0.77 / 0.77
GARCH(1)	075 (7.00)	
Sin(2πt/12)	1.66 (2.31)	
Cos(2πt/12)	1.73 (4.51)	

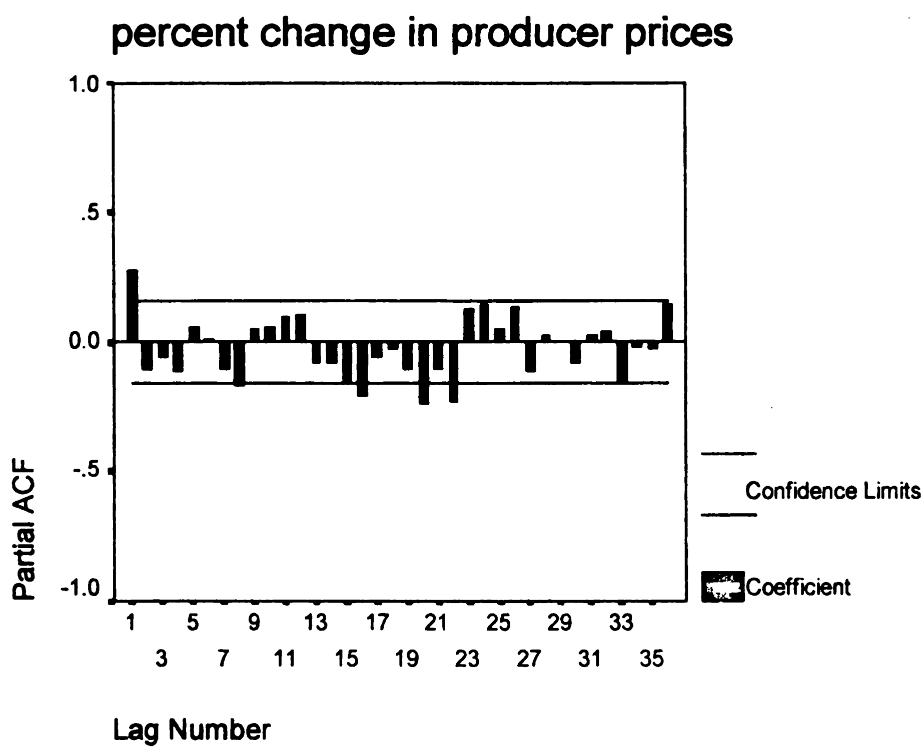
The GARCH parameters are significant at the conventional levels and the Q^2-statistics indicate that the residuals are white noise and that the model does a good job characterizing the conditional heteroskedasticity in the data.

4.2.4 ARIMA Models for Sorghum Producer Prices

The models developed thus far have been used consumer prices from the Bamako-Niarela market. This section uses producer prices, specifically sorghum producer prices from Zangasso, to develop producer price models. The data span from October 1985 to September 1996. Observations for October 1996 to September 1998 were set aside to validate the out-of-sample forecasting performance of the models. Identification efforts followed the same procedures outlined above. Unit root tests indicate that like the retail price series, the producer price series is also nonstationary (τ=-2.22 with a critical value of -3.44). The analysis is therefore performed on the first differences. Figure 4.11 shows the evolution of the percent change in sorghum producer prices in Zangasso and figure 4.12 depicts the correlogram.

Figure 4.12: Correlogram of Sorghum Producer Prices in Zangasso





The graphs show that there is a 75% drop in producer prices in late 1988 which corresponds to a good rainfall year, and that the ACF and the PACF are both indicative of seasonality. August and September are important months for producers because they tend to release stocks during those months if rains are better than average, and store if rains are lower than average. Therefore, a market dummy variable was designed to capture the impact of the flurry of activity in August and September; it equals one in August and September and zero otherwise. An integrated moving average model with second-order harmonic functions and the market dummy variable lagged once, fit the data well, as did a second-order seasonal lag model with the market dummy variable lagged twice. The parameter estimates and diagnostic statistics are reported in table 4.11. All the coefficients are significant at the 5% level and the residuals approximate white noise.

The correlogram of the squared residuals from the harmonic model was suggestive of low-order ARCH effects. Indeed, the Lagrange multiplier tests revealed ARCH effects for lags 1 and 2 (6.2 (p-value of 0.01) and 7.8 (p-value of 0.02) respectively). The final model in table 4.11 is the integrated moving average models with ARCH(2) errors. The Q-tests indicates that there are no remaining ARCH effects. The 3 models are put forward as forecast competitors in chapter 6.

The purpose of this chapter was to identify a set of alternative univariate forecasting models for each commodity. Mulitvariate models are identified in chapter 5. The models developed in chapters 4 and 5 are summarized and further evaluated for forecasting in chapter 6.

Table 4.11: ARIMA Processes for Sorghum Producer Prices

	harmonic	seasonal lag	ARCH(2)
Constant	-1.63 (-1.10)	4.08 (4.78)	-2.16 (-1.73)
$\sin(2\pi t/12)$	11.2 (5.23)		10.5 (5.31)
$\cos(2\pi t/12)$	-6.93 (-5.97)		-8.38 (-7.59)
$\sin(2\pi t/6)$	9.52 (4.58)		8.66 (5.96)
$\cos(2\pi t/6)$	7.28 (4.19)		5.75 (3.51)
Market(-1)	14.92 (2.36)		15.8 (2.29)
Market(-2)		-19.9 (-5.85)	
AR(1)			
AR(24)		0.46 (7.37)	
MA(13)	-0.23 (-2.55)		-0.24 (-3.72)
MA(24)		-0.78 (-3978.3)	
MA(29)	0.21 (2.21)		
MA(36)			0.32 (4.78)
Constant*			113.9 (6.02)
ARCH (1)*			0.26 (1.25)
ARCH (2)*			-0.08 (-2.00)
Log likelihood	-507.5	-410.2	-501.9
AIC/SBC	7.87 / 8.05	7.74 / 7.84	7.83 / 8.07
Q(12)/Q(36)	0.23 / 0.22	0.91 / 0.08	0.27 / 0.05
$Q^2(12)/Q^2(36)$	0.08 / 0.31	0.28 / 0.09	0.67 / 0.62

* conditional variance equation

CHAPTER 5

VECTOR AUTOREGRESSIONS AND COMMODITY PRICE MODELS

5.0 Introduction

In addition to the single equation ARIMA *(p,d,q)* models examined above, several transfer functions were also examined. Transfer functions generalize the univariate methodology by allowing the time path of the dependent variable to be influenced by the time path of an independent or exogenous variable. In the absence of feedback effects, transfer functions can be an effective tool for forecasting (Enders 1995). For example, a transfer function for maize prices is described below in equation (1):

$$lnPz_t = a_0 + A(L)Pz_{t-1} + C(L)lnPs_t + B(L)\epsilon_t \tag{32}$$

where A(L), C(L) and B(L) are polynomials in the lag operator L, and lnPz and lnPs are logarithmic maize and sorghum prices respectively. With a parameter estimate of 0.77, OLS results indicate that sorghum prices are highly significant (t-statistic is 20.27) in explaining the evolution of maize prices.

Transfer function analysis assumes that sorghum prices evolve independently of maize prices and that the maize innovations (i.e., disturbances in VAR language) have no effect on sorghum prices. The critical assumption is that there be no feedback from maize to sorghum. However, reversing the position of maize and sorghum prices in equation (1) and re-estimating, we find that maize is highly significant (t-statistic of 21.22) in explaining the time path of sorghum prices, violating the no-feedback (reverse causality) assumption. Since transfer function analysis cannot capture the true relationship in the presence of feedback, the question of whether the commodity prices are jointly determined is raised, and if modeling the prices as a system of equations would improve forecasting performance. Towards this end, this chapter develops vector autoregression models for forecasting the grain prices. VARs can be useful when there is a paucity of data and knowledge of the underlying system is uncertain. Section 5.1 discusses the conceptual framework for VAR analysis, while methodological issues regarding VARs, including co-integration, are discussed in section 5.2. Granger causality is discussed in section 5.3, while section 5.4 describes the VAR model for the retail prices and section 5.5 discusses the forecast error variance decomposition. The final section, 5.6 presents and discusses the results of a VAR model for sorghum and maize producer prices. The results of the forecast generated from the VAR models are evaluated for forecast accuracy in chapter 6.

5.1 Conceptual Framework

Structural models are often used to determine the relationship between variables in an economic system. Consider a generalized structural model for the endogenous variable y_t:

$$y_t = \beta X_t + \epsilon_t \tag{33}$$

where y_t is a vector of endogenous variables, β is a matrix of structural parameters, X_t is a vector of pre-determined variables hypothesized to effect y_t, and ϵ_t is a vector of structural error terms. In addition to requiring large amounts of data, structural equations suffer from problems of identification in that there is often insufficient information to econometrically recover (identify) the structural parameters. In practice, restrictions derived from economic theory are imposed on the system of equations to achieve identification.

The sometimes subjective imposition of restrictions on system equations was the major criticism of structural models outlined in Sims' (1980) seminal paper on vector autoregressions (VAR) (Charemeza 1997; Enders 1995; Gujariti 1995; Hamilton 1994). VAR models were developed to address some of these concerns. Specifically, a VAR representation of a process makes no *a priori* distinction between endogenous and exogenous variables, and thus identifying restrictions are not necessary. Since there are no exogenous variables in the system, a VAR model is essentially an a-theoretic (non-structural) summary of the dynamics of a group of variables. It is a statistical description of the dynamic interrelations (i.e., correlations) between different variables in a vector, and this summary description of historical data can be extrapolated into useful forecasts.

Formally, the VAR model expresses a variable as a linear function of the past, or lagged values of that variable and all others variables in the system. The standard VAR reduced-from equation is described as:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + Bx_t + \epsilon_t \tag{34}$$

where y_t is a vector of k variables, and p-lagged values of y_t appear in each of the k equations. x_t is a vector of deterministic variables, such as intercept terms, deterministic trends and seasonal dummy variables, etc.,. A_i and B are unrestricted matrices of coefficients to be estimated, and ϵ_t is a vector of individually serially uncorrelated innovations with zero means and constant variances.

Restricted VARs have been used in policy analysis and in the evaluation of commodity price relationships in developing countries (Donovan 1996; Sims 1986), while unrestricted VARs have traditionally been used for forecasting systems of interrelated variables. In many cases the forecasts obtained from VARs are better than the forecasts derived from more complex structural models. Allen's (1994) study of economic forecasting in agriculture found the VAR method to be the single best forecast method. In addition to reducing the identification problem, the VAR approach is relatively simple and less costly than structural systems, and is particularly useful when data are limited and/or knowledge of the underlying economic structure is uncertain. The fourteen years of monthly grain price data used in this study are influenced by uncertain policy and weather effects. This uncertainty coupled with data limitations makes the grain prices good candidates for the VAR approach to forecasting.

5.2 VAR Methodology: Some Practical Issues

In practice, it is not possible to avoid imposing some prior restrictions on a vector autoregression. In fact, the forecasting performance of unrestricted VARs can often be improved by imposing some restrictions (Engle and Yoo 1997; Charemeza 1997). Using mean squared error (MSE) as a performance measure, Engle and Yoo (1987) found that unrestricted VARs only forecast well in the very short run (i.e., four periods or less), and that forecast accuracy indeed improved when restrictions were imposed on the VAR. The literature discusses alternative approaches to imposing restrictions on VARs, including exclusion restrictions in structural VARs already discussed above, Bayesian priors and co-integration[31].

In a VAR, the standard errors for inference can be large because so many parameters are estimated. However, the estimates can be improved if the analyst has any information about the parameters beyond that contained in the sample. For example, it is possible to allow for time-varying elements by formulating the VAR model recursively and imposing *a priori* knowledge by assuming Bayesian priors. The essence behind Bayesian priors in VAR analyses is simply that prior information that improves the estimates of the VAR be included/imposed on the model. In an important paper on Bayesian priors in VARs, Litterman (1986) suggested that the representation of the prior information be based on the belief that the change in an economic time series is impossible to forecast, due to *inter alia,* speculative and arbitrage behavior. The low explanatory power of some of the ARIMA models suggest that the grain prices could be unpredictable in Litterman's framework; particularly since there appears to be considerable uncertainty in the grain markets. However, the literature indicates that this framework is not appropriate for seasonal data or co-integrated systems and thus is not investigated further in this study.

If the series are nonstationary, then another method of imposing restrictions on a VAR to improve forecast accuracy is to impose co-integrating restrictions. In a univariate

---

[31]In a structural VAR, exclusion restrictions are imposed on the matrix of structural coefficients and identification is recursive and the innovations are orthogonalized, where orthogonalized innovations refer to the transformation of the model such that the error terms are no longer contemporaneously correlated. For example, Donovan (1996) used a recursive VAR structure to investigate the effects of monetized food aid on maize prices in Mozambique after exogeneity tests showed that maize prices were significant in predicting food aid deliveries.

model, a stochastic trend can be removed by differencing. In a multi-variate context, stationarity can be achieved if a linear combination of integrated variables is stationary; such variables are said to co-integrated (Engle and Granger 1987). The unit root tests in chapter 4 indicated that all the price series were nonstationary, therefore, the first step in identifying a VAR is to test for co-integration.

5.2.1 Co-integration

Similar to testing for stationarity in univariate analysis, the first step in mulitvariate or VAR modeling is to determine whether the nonstationary price series are co-integrated or share common stochastic trends. Formally, nonstationary variables are said to be co-integrated if there exist a linear combination of the integrated variables that is stationary (Charemeza 1997, Enders 1995 and Hamilton 1994). That is, co-integration will occur whenever the trend in one variable can be expressed as a linear combination of the trends in the other variables. Such a linear combination is called the co-integrating or long-run equilibrium relation[32]. A key feature of co-integrated variables is that their time paths are influenced by the extent of any deviation from long-run equilibrium, such that short-run dynamics are influenced by deviations from the long-run relationship. If the system is to return to long-run equilibrium then the movements of at least some of the variables must respond to the magnitude of the disequilibrium. Such a response is called error correction.

---

[32] The econometric use of the term equilibrium refers to any long-run relationship among nonstationary variables. The equilibrium relationship may be causal, behavioral, or simply a reduced-form relationship among similarly trending variable (Engle and Granger 1987).

Vector error-correction (VEC) models are restricted VARs that have co-integration restrictions built into the specification. In particular, the VEC restricts the long-run behavior of the endogenous variables to converge to their co-integrated relationship, while allowing for a wide range of short-run dynamics (EViews 1997). If co-integration tests reveal that the price variables are indeed co-integrated, then there exist an error correction representation such that the differences respond to the previous period's deviation from long-run equilibrium[33]. If such an error representation exist, then estimating the nonstationary prices as a VAR in first differences is inappropriate and entails a misspecification error. In fact, according to Hamilton (1994), a VAR in differences is a poor approximation of a co-integrated system because the levels contain information useful for forecasting beyond that contained in lagged changes. The important point is if nonstationary series are co-integrated, then the VAR should be specified with error correction terms to eliminate any deviation from long-run equilibrium, and estimated as a vector error correction (VEC) model. If the series are not co-integrated, then the system of nonstationary variables is run in first differences.

5.2.1.1 Co-integration Tests

There are two major ways to test for co-integration: the Engle-Granger methodology which seeks to determine whether the residuals of the equilibrium relationship are stationary; and Johansen's method. Johansen's method is essentially a

---

[33]Granger's representation theorem states that for any set of I(1) variables, error correction and co-integration are equivalent expressions (Charemeza 1997; Enders 1995).

mulitvariate generalization of the Dickey-Fuller tests, which focuses on determining the rank of a matrix, which equals the number of co-integrating relations in a system. Since the statistical properties of Johansen's procedure are generally better and the power of the co-integration tests higher, this study uses Johansen's method to test for co-integration between the sorghum, maize and rice series (Enders 1995).

Note that testing for co-integration when using seasonal data is still under development. The scant literature that is available suggests seasonally adjusting the data before applying standard co-integration tests. However, Hallman (1989) and others argue that the use of seasonally adjusted data to estimate the long run model (i.e., the co-integrating equation) may give rise to inconsistent estimates of the long run parameters. The approach followed in this study is the one suggested by Charemeza (1997) who asserts that the most practical procedure is to assume that stochastic seasonality can be approximated by deterministic seasonal dummy variables or harmonic functions.

Johansen's test for co-integration begins with a determination of lag length using a VAR in levels. The procedure is essentially a mulitvariate generalization of the procedure discussed above for determining lag length in the Dickey-Fuller tests. Lag- length tests using the log likelihood statistic indicated that 2 lags were sufficient for the test VAR which is described below in equation (35).

$$P_t = A_1 P_{t-1} + A_2 P_{t-2} + Bx_t + \epsilon_t \qquad \textbf{(35)}$$

where P_t is a vector containing the logarithm of the three nonstationary time series, x_t is a vector including deterministic seasonality, an intercept and a dummy variable representing devaluation, A_i for $i=1,2$ and B are matrices of coefficients, and ϵ_t is a vector of error terms or innovations in VAR language. The estimated form of the test equation is rewritten as:

$$\Delta P_t = \Pi P_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta P_{t-i} + \mathrm{B}x_t + \epsilon_t \tag{36}$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I, \qquad \Gamma_i = -\sum_{j=i+1}^{p} A_j \tag{37}$$

and I is the identify matrix. Π reflects the impact of lagged Ps on ΔP_t and represents the dynamic adjustment of first differences of variables to levels. The test involves estimating the Π matrix in an unrestricted form and then using the likelihood ratio statistic for testing whether the restrictions implied by the reduced rank of Π can be rejected (Hamilton 1994; Charemeza 1997; EViews 1997).

Before proceeding with the co-integration tests, assumptions about the intercept and the deterministic trend component in the co-integrating equation had to be made, because the asymptotic distribution of the likelihood ratio (LR) statistic depends on the assumption made with respect to the deterministic trend. The test was carried out in EVIEWS which uses the critical values given by Osterwald-Lenum (1992)[34]. Consistent

[34]Note that the critical values do not account for deterministic regressors such as seasonality and devaluation. The test VAR was therefore specified with and without the exogenous regressors. The results were the same.

with Johansen's 1995 paper, EVIEWS allows for five alternative specifications of intercept and trend with different combinations of rank. Without any *a priori* information concerning the long term relationship between the grain prices, the co-integration test was performed using all five specifications. The Akaike information criterion (AIC) and the Schwartz criterion (SBC) were used to choose the most appropriate fit of the data. A summary of the results are reported in table 5.1[35].

Table 5.1: Co-integration Tests and Deterministic Trend Assumptions					
Data trend:	None	None	Linear	Linear	Quadratic
Co-integrating Equation	No intercept No trend	Intercept No trend	Intercept No trend	Intercept trend	Intercept trend
Rank = 1					
AIC	-9.41	**-9.44**	-9.42	-9.41	-9.39
SBC	-8.97	**-8.98**	-8.93	-8.90	-8.85

The bold represents the smallest values. Preliminary results of the co-integration tests resulting from the trend specification tests indicate that the rank is one. The AIC and SBC information criteria select the specification without a deterministic trend in the time series.

The test was re-specified assuming that there was no deterministic trend in the series and includes an intercept in the co-integrating relation. The null hypothesis of zero co-integrating equations is rejected at the 5% level of significance. The test finds one co-integrating equation (rank=1) in the three variable (price) system regardless of the

[35]The statistics in table 5.1 include seasonal terms and devaluation.

assumptions made about the deterministic trend component. The resultant co-integration relation or long-run equilibrium is described below in table 5.2[36]. Eviews reports the asymptotic standard errors; the t-statistics were computed and are in parentheses. The estimated long-run relationship between the sorghum, maize and rice prices suggests that in the long run relative to sorghum prices, maize prices grow at a slower rate (-1.24) and rice prices at a faster rate (0.38).

Table 5.2: Normalized Co-integrating Equation

Log(sorghum)	Log(maize)	Log(rice)	Constant
1.00	-1.24	0.38	-1.02
	(-26.7)	(5.25)	(-2.96)
Log likelihood	846.1		

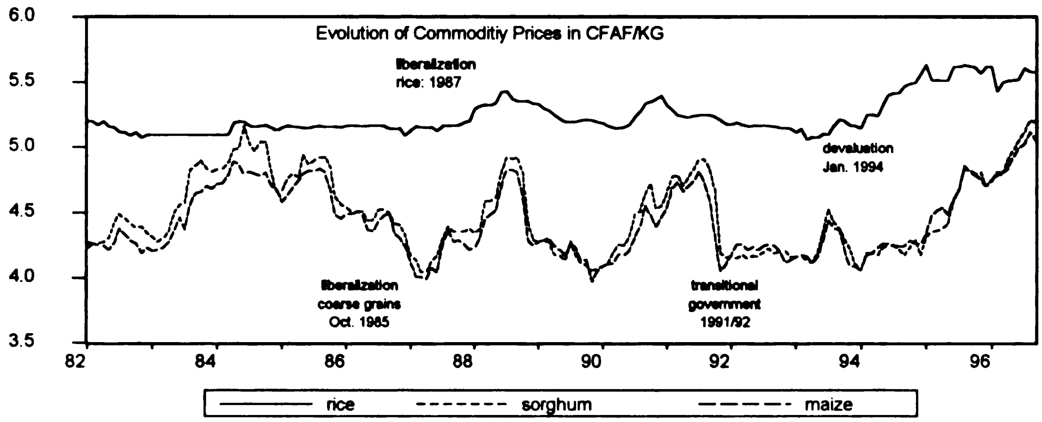
The first step in specifying a VAR for the price series found that the series were co-integrated; therefore the prices are modeled as a VEC. Seasonality and devaluation are modeled as short-run phenomena and are not included in the co-integrating equation, which represents the long-run relationship between the variables. The next steps involve determining the specification of the VEC using Granger causality tests and order selection tests.

[36]The co-integrating equation is not identified unless some type of normalization procedure is undertaken. Eviews adopts a normalization such that the first series in the vector of endogenous variables, in this case sorghum, is normalized to the identity matrix.

5.3 Granger Causality in Grain Prices

Granger causality tests developed by Granger (1969) are used to determine whether one scalar y can help forecast another scalar x. If it cannot, then we say that y does not Granger cause x. Figure 5.1 depicts an overwhelming co-movement between sorghum and maize in the Bamako-Niarela market, such that lagged sorghum prices could be a good predictor of maize prices, and vice versa.

Figure 5.1



Indeed, all the commodity prices appear to be evolving more or less in tandem. Block causality, a mulitvariate generalization of the Granger causality test, is used to formally investigate whether to incorporate a particular variable(s) into a VAR/VEC system. For example, if a forecast of maize prices is more accurate (lower RMSE) when current and lagged values of sorghum prices are included in the model, then sorghum is said to "Granger cause" maize and the two could be modeled as a VAR system (Enders 1995;

Hamilton 1994)[3]7.

Using a trivariate VAR, causality tests were performed in EViews by estimating a VAR using the full information maximum likelihood (FIML) estimator with the Marquandt algorithm and testing for zero restrictions on the VAR coefficients. The block causality test restricts all lags of sorghum prices in the maize and rice equations to be zero, and tests these cross-equation restrictions using a log likelihood ratio test with a chi-squared distribution. The restricted regression excludes lags of one or more of the variables, while the unrestricted regression allows the coefficients on those lags to be nonzero (Hamilton 1994). In summary, Granger causality measures precedence and information content and is a useful tool for testing hypotheses that can be framed as statements about the predictability of a particular series. The issue is to determine whether lags of one variable help to predict any other variables in the system.

Before testing for causality, the order of the VAR was determined by using likelihood ratio tests and the AIC and SBC information criteria to test lag lengths from 1 to 4. The test regressions include 173 observations to accommodate the fourth-order specification as well as harmonic functions describing first and second order deterministic seasonality. The intercept term was excluded since it was statistically insignificant in all

---

[3] If $E_t(PZ_{t+1}|PZ_t) = E_t(PZ_{t+1}|PZ_t, PS_t)$, the only additional information contained in PS_t are the past values of $\{\epsilon_{PSt}\}$. However, such values do not affect PZ_t and thus cannot improve on the forecasting performance of the PZ_t sequence. Thus $\{PS_t\}$ does not Granger cause $\{PZ_t\}$. If the coefficient on the moving average term for PS_t is not equal to zero, $\{PZ_t\}$ is not exogenous to $\{PS_t\}$ and pure shocks to PS_{t+1} (i.e., ϵ_{PSt+1}) affect the value of PZ_{t+1} even though the $\{PS_t\}$ sequence does not Granger cause the $\{PZ_t\}$ sequence (Enders 1995, p.316).

three equations[38]. For a trivariate VAR, the number of zero restrictions required to move from a VAR(2) to a VAR(1) is nine (3x3)[39]. The results are reported in table 5.3

Table 5.3: Test Statistics for Order Selection of VAR/VEC			
Order	Likelihood Ratio χ^2(m=9)/(p-value)	AIC	SBC
1	829.5 (0.00)	-9.34	-8.96
2	19.4 (0.02)	-9.35	-8.81
3	12.0 (0.21)	-9.32	-8.61
4	6.6 (0.68)	-9.25	-8.38

The null hypothesis states that the restriction is valid and at conventional levels of significance, the LR tests cannot be rejected at lags 3 and 4, indicating that restricting the order to two lags is a valid restriction. The AIC also selects two lags, whereas the more parsimonious SBC criterion selects one lag[40]. The goal is to include as many lags as are necessary to capture system dynamics, and since the theory behind Granger causality is couched in terms of the relevance of all past information, the lag length is chosen to correspond to reasonable beliefs about the longest time over which one of the variables

---

[38] A likelihood ratio test for first versus second order deterministic seasonality selected the second order specification with a likelihood ratio statistic of 34.2 and p-value of 0.00. The order selection results were the same with and without the deterministic seasonality components.

[39]From Hamilton (1994. P.297), restrictions determined by $n^2(p_1\text{-}p_0)$ where n is the number of equations and p_1 and p_0 refer to the higher and lower lags respectively.

[40] Recall that with the AIC and SBC criteria, the lowest value is selected. The SBC selects a more parsimonious specification by imposing a larger penalty for additional coefficients.

could help predict the other. Granger causality is thus investigated using two lags and reported in table 5.4.

The large probability values (all greater than 85%) in the rice equations indicate that none of the null hypotheses can be rejected at any conventional level of significance. Therefore, including sorghum and maize prices in the rice equation does not contribute any additional information for predicting the time path of rice prices and thus will not improve the forecast of rice prices. As rainfed crops, sorghum and maize face different production and demand environments than irrigated, tradeable, urban-preferred, politically charged rice. Moreover, past sorghum and maize prices may not contribute significantly to predicting rice prices because the marketed surplus of coarse grains which is a function of, *inter alia,* home consumption needs, storage capacity and liquidity constraints, may be low. Thus, this finding seems consistent with knowledge of the cereals markets in that information about past sorghum and maize prices is not expected to contribute significantly to predicting the future path of rice prices.

Table 5:4: Results of Causality Tests on the Cereals Prices

Null hypothesis	LR~ χ^2	p-value
Maize and Rice prices do not help predict Sorghum prices	46.66	0.00
Rice prices do not help predict Sorghum prices	8.44	0.01
Maize prices do not help predict Sorghum prices	30.44	0.00
Sorghum and Rice prices do not help predict Maize prices	28.66	0.00
Rice prices do not help predict Maize prices	25.26	0.00
Sorghum prices do not help predict Maize prices	12.46	0.00
Sorghum and Maize prices do help predict Rice prices	1.04	0.90
Sorghum prices do not help to predict Rice prices	0.24	0.88
Maize prices do not help to predict Rice prices	0.18	0.91

On other hand, the results do suggest that rice prices will help predict both sorghum and maize prices. The Granger causality between rice and the coarse grains is due primarily to the fact that the grains are substitutes in consumption. Another explanation posits that since rice is more marketed or tradeable than both maize and sorghum, that when maize and sorghum do enter the market rice is a good predictor of market dynamics. For example, in dire need of revenue, the transitional government in 1991/2 reduced the import tariff to encourage rice imports and increase the collection of tariff revenue. In the absence of storage and/or speculative behavior, this rice entered the market and *ceteris paribus* led to falling rice prices and consequently, induced a decline in the price of coarse grains. Therefore, due to the substitutability in consumption, particularly in urban areas like Bamako-Niarela, information contained in past rice prices could indeed help to predict the future path of sorghum prices.

Further examination of the results in table 5.4 indicate that the coarse grains are highly significant in helping to forecast each other, i.e., the null hypotheses of zero coefficients are all rejected at even the 1% level. Although sorghum prices are slightly higher, it is clear in figure 5.1 that maize and sorghum prices have evolved in tandem over the last fourteen years and that information contained in the past prices of one could indeed be a good predictor of the other. Moreover, because the production, demand and marketing environments are similar, when maize prices fall, *ceteris paribus,* sorghum prices are expected to fall. In summary, the results of the causality tests demonstrate that sorghum, maize and rice prices are indeed dynamically related and could be described and forecast with a restricted vector autoregression model.

5.4 VEC and Forecasting

The results of the above tests indicate that a three-variable VEC of order two might yield superior forecasting properties than the univariate models developed in chapter 4. The additional information gleaned from modeling sorghum and maize prices as a system should lead to "better" forecasts. The forecast properties of the rice equation are not expected to dominate those derived from the univariate models because sorghum and maize prices fail to contribute any additional information useful for forecasting rice prices. As a practical question, rice could therefore be excluded from the system, but since rice prices do Granger cause sorghum and maize prices, it is retained in the VEC.

The following VEC(2) was estimated:

$$\Delta P_t = \alpha_i (PS_{t-1} - 1.23PZ_{t-1} + 0.38PR_{t-1} - 2.83) + \gamma_1 \Delta P_{t-1} + \gamma_2 \Delta P_{t-2} + \beta X_t + \epsilon_t \qquad \textbf{(38)}$$

where P is the vector of logged sorghum *(PS)*, maize *(PZ)* and rice *(PR)* prices, γ_1 and γ_2, B are matrices of coefficients to be estimated, x_t is a vector of deterministic variables containing second-order seasonal harmonic functions and a dummy variable representing the devaluation. α_i is the coefficient on the error correction term, referred to as the adjustment parameter. *i* refers to the equation for each endogenous variable and ϵ is a vector of innovations assumed to be contemporaneously correlated but not autocorrelated[41]. The term in parenthesis is the error correction term from table 5.2. The parameter estimates and t-statistics are reported in tables 5.5.

As expected, neither sorghum nor maize are significant in explaining rice prices over time and in fact, devaluation is the only significant variable in the rice equation. Past rice prices 1 and 2 months back are also not significant in explaining the dynamics of the percent change in rice prices. In contrast, past changes of sorghum and maize prices and the first lag of rice are significant in the sorghum equation, as are the most of the seasonal terms. Consistent with the univariate analyses, devaluation is not significant in either the sorghum or maize equations. Finally, maize prices are largely influenced by its own lags and one lag of sorghum prices (at the 10% level) and seasonality.

---

[41]According to Charemeza (1997), the assumption of no serial correlation is not restrictive because any autocorrelation can be absorbed by adding more lagged *lnP's*.

Table 5.5: VEC(2) for Log Cereals Prices with Deterministic Components

	ΔSorghum		ΔMaize		ΔRice	
Co-integration term	-0.01	(-0.12)	0.33	(3.52)	-0.00	(-0.16)
ΔSorghum(-1)	-0.27	(-2.11)	-0.12	(-1.09)	-0.01	(-0.22)
ΔSorghum (-2)	-0.28	(-2.41)	-0.17	(-1.64)	0.03	(0.58)
ΔMaize(-1)	0.49	(3.47)	0.34	(2.67)	-0.01	(-0.18)
ΔMaize(-2)	0.32	(2.41)	0.23	(1.89)	0.05	(0.91)
ΔRice (-1)	0.36	(1.99)	0.07	(0.43)	-0.05	(-0.62)
ΔRice(-2)	0.18	(0.98)	0.03	(0.20)	-0.09	(-1.08)
Sin ($2\pi t/12$)	0.01	(1.50)	0.03	(3.61)	-0.00	(-0.59)
Cos ($2\pi t/12$)	-0.05	(-4.58)	-0.04	(-4.01)	-0.00	(-0.98)
Sin ($2\pi t/6$)	0.02	(2.31)	0.04	(4.49)	0.00	(0.72)
Cos ($2\pi t/6$)	0.02	(1.70)	0.01	(1.29)	0.01	(1.75)
Devaluation	-0.02	(-0.75)	0.00	(0.09)	0.04	(3.71)
Log likelihood	205.8		226.2		352.5	
AIC/SBC	-2.23/ -2.01		-2.46 / -2.24		-3.91 / -3.69	
Q(12) / Q(36)	0.28 / 0.11		0.70 / 0.11		0.29 / 0.35	
Model Statistics Log likelihood = 860.3; AIC/SBC = -9.43 / -8.70						

Q-tests of the residuals from each equation at lags 12 and 36 indicate that the VEC (2) is a statistically adequate representation of the data generating mechanisms. The decomposition of the forecast error variance is discussed in the next section.

5.5 Forecast Error Variance Decomposition

In VAR analysis the decomposition of the variance can be used to ascertain the importance of the interaction between series. Variance decomposition calculates the percentage of the variance in forecast errors attributed to the different shocks over the forecast horizon. Table 5.6 reports the variance decomposition results for the 24th period of model one, while Appendix A presents the variance decompositions for each period of the 24 month forecast sample for each price.

Table 5.6: Variance Decomposition Percentage of 24-month Error Variance			
% of forecast error variance in	Typical shocks in		
	Sorghum	Maize	Rice
Sorghum	92.8	85.19	7.82
Maize	1.16	4.15	0.38
Rice	6.09	10.66	91.79

As expected, most price series explain the preponderance of their own past values; by period 24, sorghum explains over 92% of its own forecast error variance, while rice explains nearly 92% of its own forecast error variance. However, at just over 4%, maize seems to explain very little of its past values, with most (85.2%) of the forecast error variance attributable to sorghum prices. This suggests that shocks to sorghum prices have a larger impact on maize prices than own price shocks. One explanation is that as maize markets are considerably thinner than sorghum markets, when maize does enter the market, it takes its cues from sorghum.

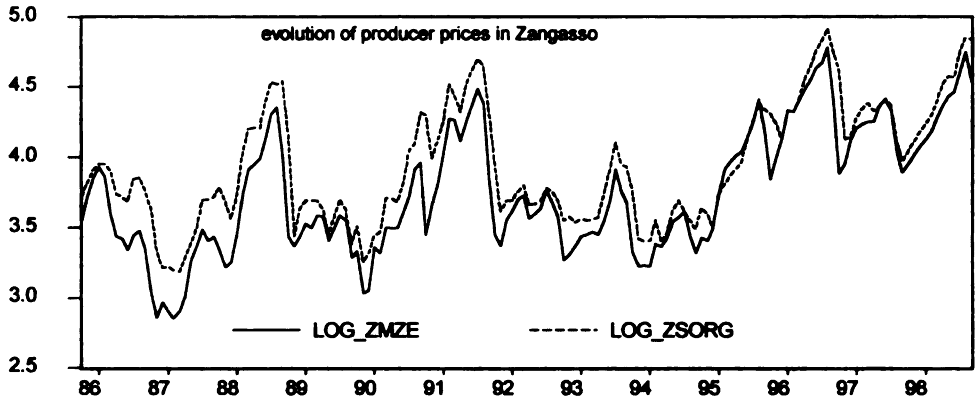
Further analyses of the variance decomposition reveals that as the forecast horizon gets larger, rice prices have a small but growing influence on the forecast error variance of sorghum (from 1% to 6%) prices, whereas maize's influence is the opposite, declining from 6% to 1%. Again perhaps because maize is not a highly marketed commodity in Mali, and rice is, maize explains about ½ a percent on average of the forecast error variance in rice prices. Together, less than 10% of the forecast error variance in the rice series is attributable to sorghum and maize prices. In summary, the variance decomposition analysis underscores the importance of sorghum shocks in predicting maize prices as well emphasized how unimportant sorghum and maize are in predicting rice prices. Along side the univariate models, the VEC(2) is solved and put forward as a forecast competitor. The results are presented and evaluated for forecast accuracy in chapter 6.

The final section of this chapter reports the results of the VEC (4) for rural sorghum and maize prices, covering the period from October 1985 to September 1996. The procedure for developing the model is similar to that described above for the retail price model. Rice is not produced in the Zangasso zone and so producer prices for rice are not included in the VAR analysis for producer prices.

5.6 VEC for Producer Prices in Zangasso

Figure 5.2 illustrates the strong co-movement between sorghum and maize producer prices such that the producer prices could be jointly determined, hence investigation in a VAR framework is justified. Unit root tests revealed that the producer price series for sorghum and maize were nonstationary in levels, but stationary in first differences[42]. Therefore, co-integration tests were performed.

Figure 5.2



The results of the co-integration tests were highly sensitive to the assumptions made regarding the mean and trend in the data and the co-integrating equation. Using lags lengths from 1 to 12, the number of co-integrating relations was anywhere between 0 and 2, with the later being the maximum number. Because of the upward trend in figure 5.2, the specifications that included the linear trend in the data were examined in depth. Tests for lag length found that the residuals approximated white noise in the maize equation at lag 4, but 9 lags were required to approximate white noise in the sorghum equation. The final co-integration test was investigated using 9 lags and a linear trend in the data and the co-integrating (long-run) equation, and exogenous regressors for seasonality and a market

---

[42]The τ-statistic for maize after adjustment for seasonality and a trend is -2.64 with a critical value of -3.44. The sorghum results are discussed in chapter 4.

dummy variable[43]. The LR test (8.57 with critical value of 12.25) indicates that there is one co-integrating equation at the 5% level of significance. Therefore, the nonstationary producer price series are specified as a vector error correction model.

Granger causality tests between sorghum and maize producer prices at 4 and 9 lags indicate that maize prices Granger cause sorghum, but that sorghum prices do not Granger cause maize. (See table 5.7). Since maize producer prices do help to predict sorghum producer prices, modeling the prices as a system can be justified.

Table 5.7: Pairwise Granger Causality Tests with 4 and 9 lags

Null Hypothesis:	F-statistic (p-values):4 lags	F-statistic (p-value): 9 lags
H_0: Maize prices do help predict sorghum prices	13.98 (2.2E-09)	6.53 (2.5E-07)
H_0: Sorghum prices do not help predict maize prices	0.551 (0.699)	0.60 (0.79)

Both a VEC(4) and a VEC(9) were estimated. A likelihood ratio test (23.88 with a p-value of 0.24) selected the VEC(4) over the VEC(9) as did the AIC and SBC statistics. Therefore, the final model was estimated as a VEC(4). The parameter estimates, the co-integrating relation and t-statistics are reported below in table 5.8.

---

[43]The results were the same with and without the exogenous regressors. This is important as the critical values were tabulated without accounting for the exogenous regressors.

Table 5.8: VEC(4) for Producer Prices in Zangasso

	ΔSorghum	ΔMaize
Co-integration term	-0.07 (-0.52)	0.40 (2.89)
ΔSorghum(-1)	-0.33 (-2.15)	-0.12 (-0.77)
ΔSorghum (-2)	-0.13 (-0.88)	0.09 (0.59)
ΔSorghum(-3)	0.08 (0.61)	0.01 (0.05)
ΔSorghum (-4)	0.08 (0.68)	-0.05 (0.40)
ΔMaize(-1)	0.52 (3.47)	0.24 (1.47)
ΔMaize(-2)	0.22 (1.44)	-0.02 (-0.14)
ΔMaize(-3)	0.03 (0.21)	0.04 (0.27)
ΔMaize(-4)	-0.13 (-1.01)	0.01 (0.09)
Constant	0.02 (1.72)	-0.00 (-0.26)
Sin (2πt/12)	-0.01 (-0.26)	0.12 (4.22)
Cos (2πt/12)	-0.05 (-1.98)	-0.05 (-1.83)
Sin (2πt/6)	0.04 (1.86)	0.08 (3.36)
Cos (2πt/6)	0.02 (0.73)	0.09 (3.37)
Market	-0.12 (-2.24)	0.04 (0.63)
Log likelihood	100.2	91.69
AIC/SBC	-1.34/ -1.01	-1.21 / -0.87
Q(12) / Q(36)	0.78 / 0.01	0.17 / 0.49
Model Statistics: Log likelihood = 241.2; AIC/SBC = -3.28 / -2.54		

The co-integrating vector is:

$$\Delta ZP_t = \alpha_i(ZPS_{t-1} - 1.56ZPZ_{t-1} + 0.00Trend + 0.16) + \gamma_p \Delta ZP_{t-p} + \beta X_t + \epsilon_t \qquad \textbf{(39)}$$

where ZP_t is a vector including the sorghum and maize producer prices in Zangasso, i represents each equation, ZPS and ZPZ are the sorghum and maize producer prices respectively, p is the number of lags, which in this case are from 1-4 and β is the matrix of parameters for the exogenous regressors in X. All the parameters are significant at the 5% level in the co-integrating equation.

However, in addition to the exogenous regressors, only the first lags of sorghum and maize are significant at the 5% level. The estimated maize equation indicates that seasonality, and not lagged prices, explains most of the variation in the percent change in maize prices. The market variable, which recall is a dummy variable describing the flurry of market activities that occurs in August and September in producing markets, is significant in the sorghum equation but not the maize equation. This is consistent with knowledge of the producing markets, since maize is not as commercialized as sorghum.

The final table (5.9) describes the variance decomposition of the forecast error in the producer prices. Similar to the results of variance decomposition of the forecast error for the retail prices, sorghum explains 97.8% of its own forecast error variance, while also explaining almost 95% of the error variance in maize prices. From close inspection of the variance decomposition table in appendix B, we note that the ability of maize producer prices to explain own error variance decreases with time, specifically falling from almost 46% in period one to less than 6% in period 24.

Table 5.9: Variance Decomposition Percentage of 24-month Error Variance

% of forecast error variance in:	Typical shocks in	
	Zangasso Sorghum	Zangasso Maize
Zangasso Sorghum	97.8	94.7
Zangasso Maize	2.20	5.28

This chapter discussed the development of, and presented the results of VAR models for the retail grain prices in the Bamako-Niarela market, as well as a VAR for sorghum and maize producer prices in the Zangasso market. The results of the co-integration tests, which is analogous to test for stationarity in the univariate case, found one co-integrating relation in each of the VAR systems; therefore the VARs were specified and estimated as vector error correction models. Inspection of the model residuals indicated that the models were statistically adequate representations of the underlying data generating mechanisms for the grain prices. The VEC models are put forward as forecasting competitors along with the univariate models presented in chapter 4, and evaluated further in chapter 6 for forecasting accuracy.

CHAPTER 6

STATISTICAL EVALUATION OF THE FORECAST COMPETITORS

6.0 Introduction

In an extensive review of forecast competitions in agriculture, Allen (1994) compared several time-series forecasting techniques for their ability to make post-sample forecasts using criteria such as root mean squared error and turning point measures. He found that the VAR and the ARIMA models were "markedly better" than naive forecasting methods, which performed better than other mulitvariate methods. The VEC out-performed the other methods in terms of capturing turning points. This chapter summarizes and compares the results of the univariate models and the VECs and produces and evaluates short-term out-of-sample forecasts. Specifically, 1, 2 and 3 month ahead dynamic forecasts for each commodity are produced, and the forecasting ability of each forecast competitor is statistically evaluated. Conclusions regarding the "best" forecast method are made. The results in this chapter are consistent with Allen's finding, particularly with regards to the VARs ability to predict turning point errors.

Note that the forecasts are made assuming that the pattern identified in the time series and described by the model parameters will continue into the future. During the data sample period the grain markets were liberalized and the currency was devalued, raising the question of potential parameter instability. The results of the unit root tests in the presence of structural change indicated that the series were nonstationary; therefore, the series were modeled as difference-stationary processes. A dummy variable representing devaluation was significant in explaining the evolution of the percentage change in rice prices and is retained in the rice models. Alternatively, the rice series could have been modeled as two distinct series, one pre-devaluation and one post- devaluation. Since the number of post-devaluation observations is limited and recent research (Tefft et al. 1997) on the impact of devaluation on prices in Mali indicated that its impact was temporary, this alternative is not pursued here.

In summary, the forecasts are made assuming that the parameters are stable. The first section discusses the evaluation criteria which are used in this study, while the remainder of the chapter presents and discusses the evaluation statistics for sorghum, followed by maize and then rice.

6.1 Forecast Evaluation Criteria

In *ex ante* forecasting with time-series models, residual uncertainty is the major source of prediction error, hence many of the statistical forecast evaluation criteria focus on evaluating the sum of the squared residuals. Residual uncertainty exists because the disturbances from the equation, which are unknown in the forecast period, are replaced by their expected value of zero, while the actual values are nonzero. The larger the variation in the individual errors, the greater the overall error in the forecasts. Moreover, in dynamic forecasts, residual uncertainty is compounded by the fact that lagged dependent variables and ARMA terms depend on lagged disturbances.

Relatedly, other parts of the forecast evaluation literature assess the utility and reliability of a forecasting technique in terms of a loss function indicating how concerned the user is if the forecast is off by a particular amount. This study assumes that the forecast users are in some sense risk averse and hence require loss functions which impose severe penalties on errors. The quadratic loss function penalizes errors heavily and is a convenient and common measure of forecast accuracy. The forecast is chosen to minimize the mean square prediction error (MSE) and in general is described as:

$$MSE = \sum_{t=1}^{n} (P_t - \hat{P}_t)^2 / n \qquad \textbf{(40)}$$

where P_t and $\hat{P}_t$ are actual and forecasted price, and n is the length of forecast sample. It should be noted that the MSE imposes identical penalties on both positive and negative errors. Regardless of whether the predicted value is 50 points higher or 50 points lower than the actual value, the mean square prediction error is the same. In cases where there is an asymmetric cost to being either too high or too low, then another forecast evaluation criterion might be more appropriate.

There exists a plethora of related forecast error statistics in the literature, including root mean squared error (RMSE), mean absolute error, (MAE), mean absolute percentage error (MAPE), Theil's inequality coefficient (TIC) and others[44]. The RMSE and the MAE depend on the scale of the dependent variable and can be used as relative measures to compare forecasts for the same series across alternative models. The decision rule states that the smaller the RMSE, the MAE, or the MAPE, the better or more accurate the forecasting ability of the model. Theil's U-statistic will be 0 when the forecast are exact,

---

[44]Algebraic expressions for each of the error statistics can be found in most statistics books and are not repeated here.

and equal to 1 if the forecasting technique being evaluated is no better than a naive method of forecasting[45]. Unlike the first two statistics, the MAPE and the TIC are scale invariant, expressing accuracy in relative terms. The RMSE and MAPE are used in this study, with RMSE defined as the square root of equation (40) and MAPE defined below in equation (41).

$$MAPE = [\sum_{i=1}^{24} [(P_t - \hat{P})/P_t] * 100]/24 \tag{41}$$

The above evaluation measures reflect the statistical accuracy of a forecast model. Turning point error (TPE) is an additional evaluation measure which reflects how well a forecast model predicts changes in direction and is also a common evaluation tool. If the forecast user is most concerned with predicting the direction of prices, then TPE is a useful measure. This study evaluates the forecast competitors ability to make 1, 2 and 3-step ahead forecasts using the root mean squared error, mean absolute percentage error and turning point error measures. Before beginning the analysis, it should be noted that an effort was made to evaluate carefully the forecast competitors. Often a forecast method may forecast one observation poorly yet forecast another observation quite accurately. To minimize this sampling error and assure a consistent test of forecast accuracy, the next section describes the procedure used to ensure more consistent results.

---

[45]Theil's U-statistic allows for a relative comparison of formal forecasting methods with naive approaches. A U<1 implies that the forecast competitor is better than the naive method. The smaller the U-statistic, the better the forecasting techniques is relative to the naive method. A U>1 implies that the naive method will produce better results (Makridakis 1978).

6.1.1 Forecasting Consistency: Updating Procedure

Twenty-four observations excluded from the specification search were used for assessing the predictive power of the alternative models. For instance, a seasonal ARIMA model of sorghum prices developed in September 1996 is used to generate a forecast of sorghum prices in October 1996. The squared error is computed $(P-P_f)^2$ and the forecast sample is updated, and a one-period ahead forecast made in October 1996 is generated for November 1996. Again, the squared error is computed and the forecast sample is updated and a one-period ahead forecast made in November 1996 is generated for December 1996, and its squared error computed. This process is repeated for all twenty-four observations in the forecast sample. The mean of the 24 squared errors is computed and the square root is taken of the mean. This procedure is performed for each model and each 1,2 and 3-step ahead forecast horizon for each commodity. The computation of the MAPE $[(P-P_f)/P*100]$ follows a similar procedure. The RMSEs and MAPEs are compared across models. A model with a smaller RMSE, or MAPE is considered to forecast consistently better than an alternative specification with a higher RMSE or MAPE.

Turning point errors are also calculated for each step-ahead forecast over the 24 period sample. Total possible turning points for the 1, 2 and 3-step ahead horizon are 24, 23 and 22 respectively. Updating in this way allows a sample size of 24 for the forecast evaluation. Beginning with sorghum, the remainder of this chapter presents a summary of the forecast competitors for each commodity, as well as the forecast evaluation statistics. The "best", defined as the most accurate , forecast model for each grain price is then identified.

6.2 Predicting Retail Sorghum Prices

The univariate and mulitvariate forecast competitors for the retail sorghum series are summarized below in table 6.1, where the random walk model is included as a point of reference. Forecasts generated from the random walk model are defined by equation (39):

$$P_{t+1} = P_t + E(\epsilon_t) \tag{42}$$

These specifications illustrate alternative representations of the strong seasonal patten present in the sorghum series as well as varying autoregressive and moving average processes. The analyses in chapter 5 indicated that the grain prices were dynamically interrelated, which led to the construction of a VEC. All equations with the exception of the random walk model have white noise residuals, a necessary condition for efficient forecasting. Models (1)-(5) were used for predicting sorghum prices one, two and three months ahead.

Table 6.1: Summary of Fitted Retail Sorghum Models

	Model	$Q_{LB}(12)$	$Q_{LB}(36)$	T
1.	Random Walk	0.00	0.00	176
2.	ARIMA (1,1,1) with seasonal dummies	0.48	0.47	175
3.	ARIMA (1,1,(1,13)) with 2nd -order harmonic functions	0.24	0.59	175
4.	ARIMA ((1,24)1,(1,24)) seasonal lag model	0.65	0.18	152
5	VEC(2) with 2nd-order harmonic & devaluation	0.28	0.11	174

Note: $Q_{LB}(k)$ is the probability value of the Ljung-Box Q-statistic and is a test for white noise at lag (k). T is the number of observations used in estimation.

Table 6.2: Forecast Evaluation Statistics of Sorghum Retail Price Models

	Model 1 random walk	Model 2 seasonal dummies	Model 3 harmonic	Model 4 seasonal lag	VEC
RMSE 1-step	13.89	11.23	11.05	12.75	**10.82**
RMSE 2-step	23.23	17.66	**16.51**	21.35	17.46
RMSE 3-step	28.33	20.29	**18.98**	25.86	21.05
MAPE 1-step	7.32	7.01	**6.66**	7.03	7.12
MAPE 2-step	13.14	11.29	**10.67**	12.29	11.8
MAPE 3-step	16.57	13.97	**12.51**	16.19	14.86
TPE 1-step	10/24 =42%	8/24=33%	8/24=33%	9/24=38%	**7/24=29%**
TPE 2-step	15/23=65%	10/23=43%	11/23=48%	11/23=48%	**9/23=39%**
TPE 3-step	12/22=55%	**8/22**=36%	10/22=45%	10/22=45%	10/22=45%

Table 6.2 presents the results of alternative forecast evaluation statistics for

predicting sorghum price changes 1,2, and 3 months ahead using the 24 period forecast sample. The figures in bold indicate the lowest value in the row, i.e., across models. The VEC has the lowest RMSE for predicting sorghum prices 1 month ahead, followed by the ARIMA with the harmonic specification of seasonality. The random walk has the highest RMSE 1-step ahead. Model 3, the ARIMA with the harmonic specification, has the lowest RMSE and the lowest MAPE for predicting 2 and 3-steps ahead, with the VEC coming in second. The VEC does the best job predicting turning points 1 and 2-steps ahead, while the seasonal dummy model does the best job predicting turning points 3-steps ahead. In terms of accuracy and predicting turning points, the random walk is clearly dominated by the competitors. The seasonal dummy model appears to be more accurate than the seasonal lag model, but not as accurate as the harmonic or VEC models for making short-term predictions about sorghum price changes. Model 3, the ARIMA with the harmonic specification of seasonality, emerges as the consistent winner.

6.3 Predicting Retail Maize Prices

The presentation of the results of the maize forecast competition follow the same format as that of sorghum. The forecast competitors for maize retail prices are summarized in table 6.3, followed by the evaluation statistics in tables 6.4

Table 6.3: Summary of Fitted Retail Maize Models

	Model	$Q_{LB}(12)$	$Q_{LB}(36)$	T
1.	Random Walk	0.00	0.00	176
2.	ARIMA (1,1,15) w/ seasonal dummies	0.39	0.27	175
3.	ARIMA ((1,13),1,0) w/2nd -order harmonic functions	0.41	0.25	163
4.	ARIMA (0,1,(1,20,24,36)) seasonal lag	0.11	0.13	176
5	VEC(2) with 2nd-order harmonic functions & devaluation	0.70	0.11	174

Note: $Q_{LB}(k)$ is the probability value of the Ljung-Box Q-statistic and is a test for white noise at lag (k). T is the number of observations.

Table 6.4: Forecast Evaluation Statistics of Maize Retail Price Models

	Model 1 random walk	Model 2 seasonal dummies	Model 3 harmonic	Model 4 seasonal lag	VEC
RMSE 1-step	11.49	9.47	**9.02**	9.87	9.66
RMSE 2-step	17.31	12.48	**11.83**	14.75	13.57
RMSE 3-step	20.83	12.87	**12.58**	16.61	15.67
MAPE 1-step	6.85	6.10	**5.59**	6.39	6.20
MAPE 2-step	10.34	8.56	**7.93**	9.69	8.86
MAPE 3-step	13.29	8.69	**8.22**	10.52	11.22
TPE 1-step	13/24=54%	**10/24=42%**	**10/24=42%**	12/24=50%	**10/24=42%**
TPE 2-step	12/23=52%	11/23=48%	**10/23=43%**	13/23=57%	11/23=48%
TPE 3-step	12/22=55%	**8/22=36%**	9/22=41%	14/22=64%	9/22=41%

Similar to the sorghum price models, the ARIMA with the harmonic specification also emerges as the most accurate method for forecasting short-term maize prices, followed by the seasonal dummy model. The random walk formulation does not capture the strong seasonal pattern present in the maize series and thus is out-performed by all other specifications. The seasonal dummy model, the harmonic specification and the VEC tie for first place in terms of predicting turning points 1 month ahead, while the harmonic commits the smallest number of turning point errors 2 months ahead. The seasonal dummy specification does the best job predicting turning points 3-steps ahead.

One implication of these results is that a representative farmer who formulates maize price expectations based on a random walk can improve her forecast accuracy by employing any other model in table 6.4. The harmonic specification with the GARCH(1,1) errors was not included in the forecast competition because as the forecast sample was updated, the standard errors of the forecasts exploded. The model was therefore considered unstable.

6.4 Predictions for Retail Rice Prices

The models that were fitted to the monthly rice retail price changes in chapter 4 are summarized below in tables 6.5, and the evaluation statistics are given in table 6.6. Model 4, with the GARCH errors, was an attempt to capture the time varying volatility in the series and has the most lowest RMSE for forecasting 1 and 2-steps ahead. The VEC has the lowest RMSE for predicting rice retail price changes 3-steps ahead.

Table 6.5: Summary of Fitted Rice Models

	Model	$Q_{LB}(12)$	$Q_{LB}(36)$	T
1.	Random Walk	0.35	0.49	176
2.	ARIMA (0,1,0) with devaluation	0.18	0.08	176
3.	ARIMA (1,1,(1,17)) with devaluation	0.22	0.71	175
4.	ARIMA (0,1,17) with GARCH(1,1) errors w/harmonic	0.54	0.52	176
5	VEC(2) with 2nd-order harmonic functions & devaluation	0.29	0.35	174

Note: $Q_{LB}(k)$ is the probability value of the Ljung-Box Q-statistic and is a test for white noise at lag (k). T is the number of observations.

Table 6.6: Forecast Evaluation Statistics of Rice Price Models

	Model 1 random walk	Model 2 random walk w/deval	Model 3 ARIMA (1,1,(1,17)) deval	Model 4 MA(17) w/deval & GARCH	VEC
RMSE 1-step	9.93	9.93	10.09	**9.52**	9.69
RMSE 2-step	15.01	15.01	14.05	**14.03**	14.09
RMSE 3-step	18.73	18.73	17.70	17.59	**17.55**
MAPE 1-step	2.74	2.74	2.81	**2.69**	2.86
MAPE 2-step	4.75	4.75	**4.16**	4.33	4.38
MAPE 3-step	6.10	6.10	**5.29**	5.44	5.84
TPE 1-step	11/24=46%	11/24=46%	12/24=50%	**6/24=25%**	10/24=42%
TPE 2-step	15/23=65%	15/23=65%	**11/23=48%**	12/23=52%	13/23=57%
TPE 3-step	14/22=64%	14/22=64%	**12/22=55%**	**12/22=55%**	**12/22=55%**

The GARCH model commits the smallest number of turning point errors for 1-step ahead, while model 3 commits the smallest number for predicting 2-steps ahead, and ties with the GARCH model and the VEC model for predicting TPEs 3-steps ahead. The random walk models are more accurate at forecasting 1-step ahead than the ARIMA (1,1,(1,17)) model.

6.5 Predicting Sorghum Producer Prices

The univariate and mulitvariate models that were fitted to the monthly sorghum producer price changes in the Zangasso market are summarized below in table 6.7, and the forecast evaluation statistics are given in table 6.8.

Table 6.7: Summary of Fitted Sorghum Producer Price Models

	Model	$Q_{LB}(12)$	$Q_{LB}(36)$	T
1.	Random Walk	0.00	0.00	131
2.	ARIMA (0,1,(13,29)) harmonic w/market	0.23	0.22	131
3.	ARIMA (24,1,24) seasonal lag w/market variable	0.91	0.08	107
4.	ARIMA (0,1,(13,36)) harmonic and ARCH(2)errors	0.67	0.62	131
5	VEC(4) w/harmonic functions and market	0.78	0.00	127

Note: $Q_{LB}(k)$ is the probability value of the Ljung-Box Q-statistic and is a test for white noise at lag (k). T is the number of observations.

Table 6.8: Forecast Evaluation Statistics of Sorghum Producer Price Models					
	Model 1 random walk	Model 2 harmonic	Model 3 seasonal lag	Model 4 ARCH	VEC
RMSE 1-step	11.23	8.71	9.78	**7.56**	9.74
RMSE 2-step	18.92	13.30	14.90	**12.17**	14.38
RMSE 3-step	21.44	15.02	16.54	**14.49**	17.53
MAPE 1-step	10.40	9.33	10.43	**8.35**	8.78
MAPE 2-step	19.26	14.79	16.25	**14.00**	15.62
MAPE 3-step	22.86	17.05	19.32	**16.72**	18.56
TPE 1-step	**6/24**=25%	7/24=29%	11/24=46%	9/24=38%	7/24=29%
TPE 2-step	10/23=43%	10/23=43%	12/23=52%	9/23=39%	**8/23=35%**
TPE 3-step	9/22=41%	9/22=41%	10/22=45%	**8/22=36%**	**8/22=36%**

In the forecast competition for sorghum producer prices, model 4, the ARCH model, emerges as the most accurate across all 3 forecast horizons, followed by the harmonic model. The random walk model commits the smallest number of turning point errors for predicting producer prices 1 month ahead. The seasonal lag model errs the most in terms of predicting turning points for all 3 horizons.

6.6 Summary of the Forecast Competition Results

The most consistently accurate models, as defined by the lowest RMSE and the lowest MAPE, for predicting short-term changes in sorghum and maize retail prices are the ARIMA models with the harmonic specification of seasonality. However, the VEC has a lower RMSE for forecasting sorghum price changes one month ahead. The harmonic specification of seasonality out-performed both the seasonal dummy and seasonal lag models. The integrated moving average model with devaluation and the GARCH(1,1) errors with harmonic functions is the most accurate at predicting changes in rice prices 1 and 2 months ahead; however, the ARIMA without the GARCH errors has a lower MAPE for forecasting 2 and 3 months ahead. The VEC model is more accurate at forecasting rice retail price changes 3 months ahead. For the sorghum producer prices, the ARCH model emerges as the most consistently accurate method for forecasting short-term price changes.

In terms of turning points errors, the VEC is more accurate at capturing turning points in the retail and producer price sorghum models, although the seasonal dummy model is more accurate at capturing turning points 3 months ahead. The GARCH model is considerably more accurate than the VEC (75% versus 58%) at capturing turning points 1 month ahead in the rice retail price changes. For horizon 2 and 3, the results are mixed, with the ARIMA model committing the smallest number of turning point errors 2 months ahead, and the VEC, the ARIMA and the GARCH models all tied for first for predicting turning points 3 months ahead. The results of the turning point predictions for maize are also mixed, with the VEC, seasonal dummy and the harmonic all tying for first place for 1 month ahead; with the harmonic coming in first for 2 months ahead and the seasonal dummy model for 3 months ahead.

In summary, the GARCH and ARCH models emerged as the most consistently accurate forecast methods for the retail rice and sorghum producer price series, while the ARIMA models with the harmonic specification of seasonality were the most accurate at predicting short-term price changes in the seasonal retail sorghum and maize series. After the random walk model, the seasonal lag models turned out to be the least accurate method of making short-term forecast of the changes in grain prices in Mali. Consistent with Allen's (1994) forecast competition, the VEC models, which capture the dynamic interrelatedness of the grain price changes, on average are better at predicting turning points than the univariate models. Because the choice of most accurate forecast model depends on the objective of the forecaster and the end-user, chapter 7 evaluates forecast methods in a decision support framework

CHAPTER 7

ECONOMIC EVALUATION OF PRICE FORECAST MODELS

7.0 Introduction

The uncertainty of future prices makes agricultural market strategy and investment planning difficult. Forecasts of commodity price changes given specified market conditions provide information necessary to carry out the marketing or investment planning process. The grain price forecasting models developed in this study are intended to aid farmers, traders and policymakers forge more efficient production, marketing, investment planning and policy decisions. The premise is that improved forecast models augment the agent's ability to make profit-enhancing decisions. The results in chapter 6 indicated that the developed models were statistically more accurate in making out-of-sample forecasts than the naive model of price expectations. This type of evaluation implicitly assumes that statistical criteria, like root mean squared error, are consistent with, and optimal for, the subsequent use of the forecast in a decision framework.

However, several researchers (Gerlow 1993; Parks et al. 1989; Wright et al. 1986; Brandt and Bessler 1983) argue that although system linearity and normal random disturbances are assumed in most statistical forecasting methods, linear decision rules and quadratic cost functions are rarely met in business applications. Hence, decisions based solely on a statistical evaluation method, such as root mean squared error, will in general, not be optimal. Therefore, the true test of a forecast model's economic performance is to ascertain what impact, if any, the model has on a forecast user's ability to make more efficient or profitable decisions.

This chapter evaluates alternative forecast models in a decision-support framework and tests whether the improved price forecast information leads to more profitable decisions. The results indicate that relative to naive generated forecasts, the improved models do indeed lead to more profitable decisions/actions. This is an important result for Malian policymakers, as the role of government in providing market facilitating services such as price information in a fiscally austere environment is continuously being called into question.

The first part of this chapter discusses the salient concepts for evaluating forecast models in a economic framework, while the remainder of the chapter discusses and analyzes an economic decision. A model is considered to exhibit economic value if it can lead to more efficient and potentially income-enhancing decisions. The decision problem used to test the economic value of the price forecast models centers on a storage decision for a producer in the Zangasso region in Mali. The optimal commodity storage literature and the importance of storage in the Malian context is also discussed.

7.1 Conceptual Considerations and Decision Criteria

The germane question is: which competing forecast method produces the "best" set of forecasts for a given set of decision makers? Most models are generally chosen according to their ability to minimize a statistical loss function. A small body of the commodity price forecast evaluation literature discusses the need to evaluate the performance of alternative models as a function of their end use, rather than the magnitude of their forecast errors (e.g., Gerlow 1993; Leitch and Tanner 1991; Park et. al 1989; and Wright et. al 1986; Brandt and Bessler 1983). The concern is that the statistical criteria may not fully account for the influence of forecasting errors on the resulting decisions and returns. This literature asserts that while improved decisions are the objective of forecast users, the evaluation of forecast accuracy is often not performed in a decision framework. The utility of a forecast model depends on how well it performs in a decision context. For instance, does a forecasting system based on model *A* enable the user to make better decisions than using a forecast based on model *B,* where 'better' is defined by the end-user.

Common measures for economically evaluating forecasts of commodity prices include investigating the effects of decision rules derived from alternative forecasting systems on profit or returns, market timing ability or correctness of decisions. A typical framework involves analyzing buy and sell signals generated from a decision rule that is based on forecasts derived from the alternative forecasting models. The profits and losses resulting from the buy and sell signals are then calculated and compared. To illustrate, Gerlow (1993) developed the following decision rule to guide futures trading strategies of a hog producer:

$$S_{it} = 1 \quad if \quad HPF_{it} > HPC_{t-1} \tag{43}$$

$$S_{it} = -1 \quad if \quad HPF_{it} \leq HPC_{t-1} \tag{44}$$

Equation (43) says to buy if the forecast price (here a forecast of the seven market average cash price for model *i* and time period *t*) in time *t* is higher than the hog price (the seven market average hog price) in time *t-1*, whereas equation (44) generates a sell signal if the forecast price from model *i* is less than or equal to the hog price in time *t-1*.

The returns resulting from the buy and sell signals are calculated as the change in futures prices over the holding period. Thus, the percentage gross, R_{it}, from following a buy or sell signal for model *i* and time *t* is:

$$R_{it} = S_{it}[lnFP_{nt} - lnFP_{mt}] * 100 \tag{45}$$

FP_{nt} and FP_{mt} refer to futures prices of live hogs on the last and first day of time, *t*, respectively. S_{it} is defined by equations (43) and (44). The model that generates the highest mean percentage returns is revealed as the 'best' model, but not necessarily the most statistically accurate. By examining mean returns, the effect of the forecasting errors on economic variables is incorporated into the evaluation process (Gerlow 1993, p.390).

Parks et al. (1989) suggest further that specific information about the user's decision processes and preferences are necessary to identify the "best" forecast model for the end user. In the above example, the trading strategies for the hog producers could have been modified to incorporate risk preferences for the presence of risk in returns (Gerlow 1993; Park et al. 1989). Some studies use the expected utility model as a framework to examine risk-adjusted mean returns, stochastic dominance or mean-variance in regard to various aspects of the distribution of returns. These studies employ risk efficiency criteria to permit an ordering of outcomes for individuals whose preferences conform to certain restrictions.

Following Merton (1981), some studies focus specifically on the accuracy or "correctness" of decisions made based on the forecast model, and not on the accuracy of the forecast model. Merton (cited in Gerlow (1993)) contends that forecasts have positive value only if they cause rational decision makers to alter their expectations about the future. Rather, if knowledge of the forecast does not cause economic agents to alter their expectations, then the information embodied in the forecast has already been assimilated into the market and the forecast has no positive value. To test this, Merton (1981) developed a directional accuracy statistic which is based on the number of times that price is correctly forecast to increase, decrease or remain constant. He called this the test for market timing ability, where market timing implies an ability to accurately forecast direction of price movement.

In a related study by Wright et al. (1986), "correctness of decision" as a forecast evaluation criterion was investigated by examining the actions of a trader engaged in the forward exchange market. To speculate profitably, the trader must correctly predict the direction of the forward rate error. The decision rule stated that if the forecast of the future spot rate is greater than the forward rate, the trader buys foreign exchange forward, and if it is lower, then the trader sells foreign exchange forward. A forecast is considered "correct" if both the actual spot rate and the forecast spot rate are on the same side of the forward rate. In another example, Spreen and Arnade in Parks et. al (1989) evaluated an applied agricultural situation where a producer had to decide whether to overwinter cattle. The decision rule was based on calculating a breakeven price. If the model-generated forecast is greater than or equal to the breakeven price, cattle are fed over the winter and sold in the spring. In this case, an effective forecasting model is one that can consistently predict whether the subsequent price is above or below the breakeven price. The results of their study found that the forecasting methods that exhibited high mean squared errors provided better forecast support when judged by the proportion of correct decisions and profit generated.

These studies suggest that the forecasting method that is the most accurate in terms of statistical criteria is not necessarily the "best" in terms of planning and decision support. Indeed, an accurate forecast may result in a poor decision and an inaccurate forecasts may result in a good decision. Comparing an ARIMA and an econometric model of hog prices, Gerlow (1993) found that the econometric model outperformed the ARIMA model in terms of the economic criteria (mean returns in this study) but scored poorly in terms of statistical criteria. Other studies find a near one-to-one relationship between the results of the statistical and economic forecast criteria. For example, in their study of futures trading of the hog market, Brandt and Bessler in Park (1989) found that two of the most statistically accurate forecast techniques were associated with the highest mean price, while their variances were also high relative to other forecast methods.

Leitch and Tanner (1991) took a slightly different approached and examined the question of why profit-maximizing firms purchase economic forecasts when most statistical criteria rarely reveal major differences between professional forecasting services and a simple naive approach of no change in the variable being forecast. In empirical tests of interest rate forecasts, they found that the conventional forecast evaluation criteria had no systematic relationship to profits. They did find that directional accuracy was related to profits and thus could be used as an evaluation criterion if profits were unobservable. They argue that economists generally assume that firms use forecasts because they add to profits and thus a more accurate test of forecast accuracy is profitability and not the size of the forecast error or its squared value.

In summary, several studies have found that, in some cases, the most statistically accurate forecast models are not the most accurate or "best" models in the context of economic evaluation. Towards this end, this chapter further investigates the forecasting performance of the alternative grain price models in a decision support framework. The model-generated price forecasts are used to guide the post-harvest marketing strategies of a sorghum producer. The forecast models are evaluated using root mean squared error (RMSE), mean price received and percent correctness of decision. Section 7.2 discusses briefly the relevant concepts from the storage literature and outlines the decision framework while section 7.3 discusses the simulations and results.

7.2 Storage Rules

A fundamental decision facing most farmers in Mali who produce storable commodities such as cereal grains is the question of how much and when in the post-harvest marketing season their marketed surplus should be sold. This question constitutes the foundation of the vast literature on (optimal) storage rules, which studies everything from public policies that manage buffer stocks of agricultural commodities, to the inventory strategies of private speculators (Fackler 1995; Williams and Wright 1991; Newbery and Stiglitz 1981; Gislason 1960 and Gustafson 1958). A storage rule is broadly defined as a statistical decision function, which stipulates the level of storage under a given set of relevant economic conditions. Further, a storage rule is considered "optimal" when its derivation is based on a specific objective function, such as consumption smoothing, price stabilization or maximizing the sum of discounted profits for a given period.

The typical approach for determining the level of harvest to stockpile in a given period uses dynamic programming procedures to derive a storage rule conditional on, *inter alia*, supply and demand factors, storage costs and capacity constraints (Myers 1996). The result is an optimal decision rule as a function of the above parameters. It is characterized by the condition that storage today continues until current price per unit plus per unit storage cost is driven up to equality with the present discounted value of the expected future price. If current prices are high, then stocks are sold until the price plus the storage costs are driven down to this level, or until stocks are exhausted (Newbery & Stiglitz 1981; Gilbert 1990). Similarly, Fackler (1995) discusses an optimal stopping problem for producers with on-site storage facilities in which the optimal sales rule is a simple condition on current price. The strategy is to sell everything when current price is high, otherwise store everything into the next period. The next section describes a few stylized facts about the marketing strategies and storage environment in Mali.

7.3 Marketing Strategies and Storage Costs: Some Stylized Facts

In Mali, the level of marketed surplus depends to a large extent on the level of production at the farm household level, while the post-harvest marketing strategies of producers reflect their cash needs. For instance, sorghum farmers who also produce cash crops (e.g., cotton) store most of their marketed surplus at harvest and spread sales over the nine-to-ten month marketing season. Noncash croppers, on the other hand, are forced to sell a greater portion of their surplus at harvest. Indeed, studies reveal that cash croppers in the Zangasso region market on average 15% of their sales at harvest, while noncash croppers market an average 58% at harvest (Dembele 1994)[46]. However, if rainfall is good and the harvest is larger than average, then cash croppers sell only a small proportion (studies say 8%) of their harvest. This is presumably because their cash needs are being met from the cash crops which also benefit from good rains. Analogously, cash croppers increase their harvest sales if rainfall is lower than average to meet cash needs and noncash croppers tend to sell a larger proportion at harvest if rains are goods, and reduce sales when rains are lower than average.

Later in the marketing season, when prices begin to rise, marketed surplus is influenced by producer expectations of rainfall (Dembele 1994). That is, once the rainfall pattern for the current agricultural production campaign is established, the producer decides to release stocks in August/September if the rains are good. The expectation is that yields will be high and prices will be low. However, if the rains are bad, or less than

[46]According to Dembele (1994), this practice has changed in recent years because cotton payments to farmers have been delayed so cash croppers have been forced to sell more at harvest.

average, the producer continues to store in anticipation of supply shortages and higher prices.

The grain stocks will be determined by expected future prices relative to the current price, taking into account the interest and other costs of storage. The sorghum producer stores on-site in mud-clay granaries and the grain is rarely stored for longer than a year. Storage losses are assumed to be low, as is the physical cost of storage. However, the opportunity cost of foregoing sales when the crop is harvested ranges from 12% to 30%[47] (Dembele 1994). Producers face cash flow problems during the marketing season which force them to release the crop at various non-optimal times of the year. The investigation therefore, focuses on evaluating post-harvest marketing strategies on the residual marketable surplus (after cash needs at harvest have been met).

The results of empirical research in Mali (Dione 1989) suggests that the objective of the sorghum producer's marketing strategy is to spread marketed surplus over the post-harvest season to meet cash needs. However, in the later part of the marketing season, due to the uncertainty surrounding the next harvest, the producer is more concerned with meeting household consumption needs. Conditional on good rains, a post-harvest marketing strategy for a cash cropper in Zangasso for January through September might entail marketing:

0% of the marketed surplus in January;
10% in February and March;
40% in April, June and July; and
50% in May, August and September

[47] The interest on a loan in the formal sector is 12% while the interest can be as high as 30% in the informal sector.

Such a marketing rule is designed to meet cash needs during the marketing season and to take advantage of seasonal increases. The low percentage marketed in January-March is to avoid marketing large quantities during times of low-prices. 40% of the residual marketable surplus is allocated to April, June and July to take advantage of rising prices. Most of the surplus is sold in May, August and September. May is planting time for the new crop season, while July and August are historically peak price months. If the rainfall pattern for the upcoming harvest is revealed to be less than average, then to reduce the risk of a poor harvest and protect consumption needs, the proportion marketed in August and September decreases to zero (Dione 1989, Dembele 1994). The optimal storage literature and knowledge of the sorghum market were used to develop a practical storage rule or marketing strategy for the farmer. The decision framework for the evaluation of the alternative forecast models for sorghum producer prices is discussed in the next section.

7.4 Decision Framework

Consider a sorghum producer with marketed surplus in the Zangasso region in southern Mali evaluating post-harvest marketing strategies. Specifically, the producer uses a model-generated forecast of spot prices to guide her decisions to make one-step ahead sell or store decisions over the marketing season, which spans from January to September.

The post-harvest marketing strategy for the producer is patterned after the optimal stopping problem described in Fackler (1995), which consists of a simple condition on current price. The marketing strategy is to sell everything for that month when the current spot price is greater than the forecasted spot price, otherwise store everything into the next period.

$$\textit{Sell when} \quad P_t > P_{t+1}^{forecast}; \quad \textit{store otherwise} \tag{46}$$

For example, in the month of January the producer will store the 5% apportioned for February if the forecast of February prices is greater than the current price in January. If the January price is greater than the forecast of February prices, then the producer sells the 5% in January. The decision is made every month through September for the forecast competitors. Since there are 24 observations in the forecast sample, two 9 month marketing seasons are evaluated. The performance of each forecast model is evaluated by examining the mean price received per kilogram and the percentage of correct decisions generated for each marketing strategy.

7.5 Economic Evaluation of Forecast Models for Sorghum Producer Prices

In chapter 6, the statistical evaluation of the 5 sorghum producer price models revealed that the ARIMA model with the 2nd-order harmonic functions and ARCH(2) errors was the most accurate at forecasting short-term price changes. Accuracy was defined as the lowest RMSE and/or MAPE. The VEC(4) model with seasonality and a market dummy variable was the most accurate (lowest TPEs) at capturing turning points. The forecasts generated from the 5 models were used to make market/store decisions and are further evaluated for forecasting performance using economic criteria. The marketing strategies for the 2 marketing seasons that were generated from the forecast models using the decision rule in equation (46) are presented in tables 7.1. Season 1 covers January 1997 to September 1997, while season 2 covers January 1998 to September 1998. If no sell signals are generated by August, then everything is sold in September.

Table 7.1: Post-harvest Marketing Strategies Generated from Forecast Models

strategy	Forecast Model	Action-sell: season 1	Action-sell: season 2
1	Random walk	all 9 months (9)	all 9 months (9)
2	ARIMA w/harmonic	April, July, Aug (6)	September (9)
3	ARIMA: seasonal lag	January, May (7)	Jan, September (7)
4	ARIMA w/ harmonic and ARCH errors	February, July, August (6)	September (9)
5	VEC w/harmonic and	February, March, July, August (5)	July, August (7)

The numbers in parentheses indicate the months of storage. The strategy that emerged from the naive random walk model is to sell in each period in both post-harvest seasons. The ARIMA model with the harmonic functions generated sell signals for April July and August in season 1, and since no sell signals were generated by August in season 2, the strategy is to sell everything in September. The seasonal lag model generates sell signals in December in both season 1 and season 2, which is sold in January. For season 1, the ARCH model has the producer selling in February, July and August, and only in September in season 2. Finally, after the random walk model, the VEC model generated the most sell signals in season one. In season 2, most of the models indicate that sorghum should be stored until August/September. Marketing strategies based on the random walk and the models that store until September incur the most amount of storage cost, while those based on the VEC model incurs the least amount of storage cost.

Historical analysis (1986-1998) of the percent returns to storage, defined as the post-harvest price in each month less the price prevailing at harvest, divided by the post-harvest price multiplied by 100, revealed July (64.8%) and August (64.2%) to be the months with the highest average gross margins (Goetz 1986)[48]. January is the lowest with an average 9.93%, followed by November at 11.3%. After November, the average gross margins gradually rise slightly in December, fall in January and rise again each month throughout the post-harvest marketing season, peaking in July. The strategies generated from the forecast models appear consistent with the information embodied in the historical gross margins analysis in that sell signals are generated in July/August, the high price months. It is encouraging that the forecast models recognize and are able to capture this market phenomena.

The criteria used to economically evaluate the alternative forecast models are the mean price received and the mean net price received assuming storage costs are constant at 3 CFAF/kg/mo.. Additionally, since information is not available on storage costs, the final column in table 7.2 reports average percent returns to storage, which is compared to

[48]Selected results of the gross margin analysis are included in the discussion.

the opportunity cost of capital[49]. The informal credit rate of 30% in Mali is used as the opportunity cost of capital (Dembele 1994). In season 1, if the producer incorporates the marketing strategy derived from the random walk model and sells in each period, then the mean price received per kilogram for the marketing season is 74.3, which is the same as the VEC model despite the fact that sales occur only in 4 of the months compared to 9 in the random walk model. The VEC is selling in more profitable months. If positive storage costs are assumed, in this case 3 CFAF/kg/mo., then strategy number five based on the VEC model becomes more profitable than strategy number one, because the mean net price is lower in the random walk model due to the 9 months of storage. The VEC followed by the ARIMA with harmonic seasonality, followed by the ARIMA with the ARCH errors yield the greatest mean net prices. The random walk followed by the ARIMA with the seasonal lags yield the lowest mean net prices received.

---

[49]Percent returns are calculated by subtracting the harvest price of 63.25 CFAF/kg from the mean price received and dividing by the harvest price and multiplying by 100.

Table 7.2: Season 1: Economic Results of Post-harvest Marketing Strategies with and w/o positive storage cost

Forecast Model	**Mean Price CFAF/kg**	**Mean Net Price CFAF/kg**	**Average % Returns to storage**
1. Random walk	74.3	47.3	17.5*
2. ARIMA with harmonic	73.2	55.2	15.73
3. ARIMA seasonal lag	70.8	49.8	11.9
4. ARIMA with ARCH	72.4	54.4	14.4
5. VEC with harmonic	74.3	59.3	17.5

* Compared to selling at harvest during December 1997

The percentage rate of return to storage is often used when physical storage costs are minimal and where a large portion of storage costs are due to the opportunity cost of money tied up in the stored commodity (Goetz 1986). If the opportunity cost of money to the sorghum producer is based on the 12% formal credit lending rate, all strategies except number 3 become profitable. However, if the opportunity cost of capital is based on the informal lending rate of 30%, then none of the strategies become profitable.

The results for season 2 are presented below in table 7.3. Recall that three of the models generated marketing strategies where most of the crop was stored for 9 months and sold in September. The first thing to notice is that mean prices in the second season (1998) are higher than the first season (1997) prices. The random walk is dominated by all other strategies in terms of mean price received and average percent returns. The ARIMA with the harmonic specification yields the highest mean price and the same returns to storage as the ARIMA with the ARCH errors. The VEC model generates the highest mean net price.

Table 7.3: Season 2: Economic Results of Post-harvest Marketing Strategies with and w/o positive storage cost

Forecast Model	Mean Price CFAF/kg	Mean Net Price CFAF/kg	Average % Returns to storage
1. Random walk	90.8	63.8	39.0*
2. ARIMA with harmonic	126	99.0	93.3
3. ARIMA seasonal lag	94.6	73.6	45.2
4. ARIMA with ARCH	126	99.0	93.3
5. VEC with harmonic	121.7	100.7	86.8

* Compared to selling at harvest during December 1999

The average mean percentage returns to storage is above 30% in all 5 strategies in season 2, with models 2 and 4 generating the highest rates of return. Because the prices are higher in season 2, unlike season 1, it is profitable for the producer to store using a 30% opportunity cost. If the producer follows strategy number 2 and sells a portion of her harvest in April to meet cash needs at planting time, and spreads the rest of her sales over July and August, she can earn 63.3% above her opportunity cost of capital. And if the producer's objective is to smooth liquidity over the entire marketing season, she can still earn 9% by following strategy number 1 by spreading sales equally over the post-harvest marketing season. However, the results of the historical gross margin analysis indicate that the producer would need to store at least until May to barely break even (31.82%-30%), earning an average 1.82%.

Table 7.4 presents a final criterion for economically evaluating the performance of the forecasts models. Based on the decision rule to sell if the current price is greater than the forecast, correctness of decision describes the number of times the forecaster made the right decision to sell or store for each period. For example, the ARIMA model with the harmonic functions in January 1997 forecasted the price of sorghum in February 1997 to be higher than the current price in January. Therefore, the signal was to store in January. The actual price in February was indeed greater than the January price and thus the correct decision was to store. This analysis was done for each model for each decision period.

Table 7.4: Correctness of Decision

Forecast Model	**Season 1**	**Season 2**	**Average**
1. Random Walk*	55.5%	77.8%	66.7%
2. ARIMA with harmonic	88.9%	44.4%	66.7%
3. ARIMA seasonal lag	77.8%	33.3%	55.6%
4. ARIMA w/ ARCH	55.6%	44.4%	50%
5. VEC w/harmonic	77.8%	33.3%	55.6%

* generated forecast values that are equal to the current value

The random walk and the ARIMA with the harmonic specification of seasonality make the correct sell decision almost 67% of the time, while the ARCH model and the VEC model make correct decisions 56% of the time. The ARCH model, which emerged as the single best model using the root mean squared error criterion, does the poorest job making decisions in this context. Moreover, the VEC model of the changes in sorghum producer prices which was the best at capturing turning points, in terms of correctness of decision, is dominated by the random walk and the ARIMA with the harmonic seasonality. Forecast evaluation is commonly carried out by considering only statistical accuracy using criteria like root mean squared error and in many applications this will be consistent with the needs of the user. However, statistical evaluation may not be consistent with, or optimal for the subsequent use of the forecasts in a decision framework. The concern is that statistical criteria may not fully account for the influence of forecasting errors on resulting decisions and returns. Therefore, evaluation based on economic criteria may provide important additional information on the performance of the forecasting model.

Here mean price received, percent returns to storage and the correctness of decision were applied to the out-of-sample forecasts of five sorghum producer price forecasting models over 2 marketing seasons: January 1997 to September 1997, and January 1998 to September 1998. Averaging the mean price received over the 2 marketing seasons, the ARIMA with the harmonic specification of seasonality at 99.6 CFAF/kg is selected, followed by the ARCH model at 99.2 CFAF/kg. The VEC comes in third at 98 CFAF/kg. In this case, the economic criteria selects a different model than the root mean squared error and the turning point tests, which selected the ARCH and VEC models respectively. Averaging over the 2 seasons, the random walk model is dominated by all other models. The correctness of decision criterion also selects the ARIMA with the harmonic specification and the random walk Finally, these results demonstrate that, *ceteris paribus,* investing in simple improved forecasting models can improve the decision making ability of an average producer in devising profit-enhancing post-harvest marketing decisions in some years.

CHAPTER 8

SUMMARY AND IMPLICATIONS

8.0 Introduction

This research was directed toward two key questions. The first was methodological in nature and focused on developing and evaluating alternative methods of forecasting short-term agricultural prices with limited data. The grain markets in Mali are used as an example. Since the process of grain market liberalization began, the importance of accurate price forecasting for decision makers has increased. One result has been higher demand for improved outlook information on the likely evolution of grain prices. Such information is essential for making, among other things, better marketing and inventory decisions.

However, as is often the case in developing countries, the historical data base is very limited in scope, constricting the capacity to construct structural econometric models of supply and demand. Moreover, much of the forecasting literature argues that such large-scale econometric models may fit the data well, but often fail to forecast well. In fact, many of the time-series models which focus on identifying the properties of a single series or a vector containing interdependent series have been found to forecast short-term prices just as well, and in many cases better, than some structural models.

The second goal of this study was to investigate whether investing in improved forecasting methods is indeed a worthwhile endeavor. In fiscally austere environments, publicly-funded market information systems must continually show evidence of their worth, lest find themselves possibly eliminated. The Malian market information system, the SIM, which regularly disseminates information on weekly grain prices in key trading markets throughout the country, has been so plagued by financial crises that at one point it was inoperable. To create a constituent base to lobby for political support and sustain itself financially, the SIM seeks to add value to its product portfolio by meeting the revealed demand for price outlook information and demonstrating that the information has economic value.

The specific objectives of the study were to:

- develop alternative price models, using limited data, for sorghum, maize and rice prices in Mali that can be used for short-term forecasting;
- evaluate the forecasting ability of alternative price models based on statistical criteria;
- evaluate the economic value of improved price forecast information to a group of users by evaluating the utility of the alternative price models in a decision making framework; and
- draw lessons on which time-series models produce the most accurate and economically useful forecasts with limited data.

Mali is used as a case study, however many developing countries face similar conditions in that the product profile of their market information systems is limited in scope and the value of continuing to publicly collect price information is poorly understood. Moreover, historical data bases are limited, as often is analytical capacity. Therefore, the results of this study have implications broader than the Malian context.

8.1 Research Methods

Using monthly price data from the SIM from January 1982 to September 1998, consumer sorghum, maize and rice prices from the Bamako-Niarela market and sorghum producer prices for the Zangasso market (for the period October 1985-September 1998) were analyzed using time-series techniques. The last 24 observations covering October 1996 to September 1998 were excluded from the specification search process and used to check the out-of-sample forecasting properties of the alternative models. The time-series techniques employed here follow the Box-Jenkins methodology of first identifying any pattern in the data such as seasonality and time trends, by examining the plots and the correlograms. Stationarity was tested for using the augmented Dickey-Fuller (ADF) tests and the Philips-Perron test for testing for unit roots in the presence of structural change. The results of the unit root tests indicated that the data generating process of each series had a unit root, thus the series were modeled in first differences.

Investigation of the autocorrelation and partial autocorrelation functions were used to identify tentative ARIMA models, which were estimated using OLS procedures. The tentative models were validated using various diagnostic tests such as the Ljung-Box Q-statistic, and the AIC and SBC information criteria. Lagrange multiplier or ARCH tests of the squared residuals were used to investigate whether the variance was homoskedastic or heteroskedastic. A necessary condition for efficient forecasting is that the errors approximate the white noise process; thus all the final models included in the forecasting competition met this criterion.

Many agricultural commodities exhibit seasonal patterns, as did the sorghum and maize price changes. Seasonality was modeled using first and second-order harmonic functions, seasonal dummy variables and by directly including seasonal or near seasonal correlations in the ARIMA model. Various other exogenous factors were examined, including alternative specifications of monthly rainfall, world prices as captured in Thailand rice prices, the exchange rate between the U.S. dollar and the CFAF. Two dummy variables were also included in the analysis, one for the 100% devaluation of the CFAF in January 1994, and the other a market variable designed to capture the flurry of market activity that regularly occurs in the producing markets in the months of August and September.

In addition to the single equation ARIMA models, several transfer functions where, for example, sorghum price changes were included as an explanatory variable in the maize equation of price changes, were also examined. Transfer function analysis assumes that sorghum prices evolve independently of maize prices and that the maize disturbances have no effect on sorghum prices. The critical assumption is that there be no feedback from maize to sorghum. Further analysis indicated that the no feedback assumption was indeed violated and that the interdependent relationships between the prices were best captured in a VAR framework. Therefore, the 3 price series are modeled as a VAR with seasonal components and a dummy variable representing devaluation. Further investigation of the VAR for co-integration indicated that the series were best described as a VEC. The VEC models were validated in much the same way as the univariate models and the best models were put forward as forecast competitors.

The valid univariate and multivariate models for each commodity were entered into a forecasting competition, which takes place in chapter 6. Three evaluation criteria, the root mean squared error, the mean absolute percentage error and percentage of turning point errors were used to score the competitors for their ability to make predictions 1, 2 and 3 months ahead. The competitor with the lowest score emerged as the winner.

To demonstrate the value of investing in improved price forecasting techniques, model-generated marketing strategies of a sorghum producer in the Zangasso region of Mali were compared to marketing strategies generated from a naive, random-walk model. The optimal storage literature and knowledge of the sorghum market were used to develop a practical storage rule or marketing strategy for the producer based on the price forecasts generated from the alternative models. After being statistically evaluated in the forecasting competition in chapter 6, the same producer price models were used to generate store/sell signals for 2 marketing seasons. The economic criteria used to evaluate the models included mean price received, mean net price received and the percentage of correct decisions. The model with the highest mean price and highest percentage of correct decisions was declared the winner. The exercise is designed for illustrative purposes and abstracts away from risk preferences, marketing responsiveness, etc., Some of these issues are discussed below. The results of the statistical evaluation of the producer price models in chapter 6, and the economic evaluation in chapter 7, were then compared.

8.2 General Results

The sorghum and maize price series exhibited strong seasonal patterns which were investigated using harmonic functions, seasonal dummies and seasonal ARIMAs. None of the exogenous regressors were significant at the 5% level in explaining the evolution of sorghum price changes for the period of study. In particular, the rainfall variable, which was based on various specifications and lag lengths of monthly rainfall from Koutiala, was not significant. This is in stark contrast to empirical studies of coarse grain production in Mali (Dione 1989) which found rainfall to be the single most important variable in explaining variations in production.. Even though the coarse grains are substitutes in consumption for rice, the devaluation, which made rice imports more costly and hence increased domestic rice prices, was not significant in explaining the evolution of sorghum price changes. Therefore, the univariate forecast models for sorghum were largely ARIMA models with seasonal components. The VEC models also include seasonal components.

The results of the forecasting competition indicated that the ARIMA with the second-order harmonic specification of seasonality was the most accurate model for forecasting sorghum price changes 2, and 3 months ahead, while the VEC had the lowest root mean squared error for predicting 1 month ahead. Much of the forecasting literature indicates that VARs are considerably better at capturing turning points. This is evident in the sorghum series, where the VAR emerges at the most accurate model at predicting turning points 1 and 2 steps ahead, while the seasonal dummy specification actually is better at predicting turning points in the sorghum series 3 months ahead.

Relative to the sorghum series, modeling procedures suggested that the maize series might be more volatile. Indeed, some of the identified models suggested that the maize price series had time-varying volatility or a heteroskedastic conditional variance, thus implying that periods of low (high) volatility in the maize series are followed by other periods of low (high) volatility. The maize markets have traditionally been thinner than either the sorghum or rice markets, which could lead to uncertain market volume and hence more volatile prices. Nonetheless, the ARIMA with the harmonic specification of seasonality emerged as the consistent winner for most accurately predicting maize price changes 1,2 and 3 months ahead. The results of the turning point tests are less consistent, and depend on the forecast horizon. The VAR, the harmonic and the seasonal dummy model all tie for first in predicting turning points 1 month ahead.

The results of the forecast competition for rice are not as consistent as were the competition results for the coarse grain models. Rice was not modeled as a seasonal series since the autocorrelation and partial autocorrelation functions did not indicate that the conditional mean exhibited a seasonal pattern. The tests for conditional heteroskedasticity indicated that the conditional variance exhibited time-varying volatility. Indeed, the most accurate model for predicting changes in rice prices 1 and 2 months ahead in the Bamako-Niarela market, is the GARCH model. Even though the conditional mean did not exhibit seasonality, the conditional variance of the rice series did, and therefore, the conditional variance equation included seasonal terms which were significant at the 5% level. At 75%, the GARCH model was by far the most accurate at capturing turning points in the rice series, followed by 58% in the VEC.

Of the 5 models in the sorghum producer price competition, the ARCH model was unambiguously the winner for most accurately predicting short-term price changes in the Zangasso market. The VEC was the winner for capturing turning points 1, 2 and 3 months ahead. The results from the statistical forecasting competition for sorghum producer prices were compared to the results from the economic evaluation. The ARIMA with the harmonic specification of seasonality emerged as the clear winner in terms of highest mean price received and percentage of correct decisions, followed by the ARCH and then the VEC models. These results suggest that the intended use of the forecast influences the type of model selected to generate the forecast and the criteria used to evaluate the forecasting technique. The objective of avoiding extremely large forecast errors might suggest a forecast approach different from that associated with the goal of predicting price turning points in the market. Similarly, short-term marketing strategies would require a different set of predictions than long-term investment planning.

Using the Zangasso sorghum producer as an example, if the concern was to avoid extremely large forecast errors, then the ARIMA with the harmonic specification of seasonality and the ARCH(2) errors would be the best model for that objective. However, if the producer is more concerned with capturing the direction of price changes in the market, then modeling the prices as a VEC model would yield the best results. And finally, if the producer is basing her post-harvest marketing decisions on strategies generated from the alternative forecast models, then using the ARIMA model with the harmonic specification without the ARCH errors would yield the highest return.

8.3 Complements and Extensions to Information

This study assumes that the producer or forecast user can improve her ability to make economic decisions with a better forecast of future prices. However, information is but one constraint to improved decision making in the Malian context. Several empirical studies (e.g., Dimithes 1997; Boughton 1994; Dembele 1994; Dione 1989; d'Agostino 1989) on Mali have cited access to credit as one of the major constraints to increasing marketing responsiveness. Research has shown that non-cash croppers are often forced to sell their harvest at non-optimal times in order to meet immediate cash needs (e.g., taxes and school fees), selling when prices are low and re-entering the markets to buy when prices are high. Evidence shows that cash croppers in the southern producing zone in Mali are able to better spread their sales over the post-harvest marketing season, taking advantage of seasonality in prices. Easier access to credit by the non-cash croppers would improve their ability to profit economically from seasonality in prices.

Marketing extension is another necessary condition for facilitating market responsiveness amongst producers. The dissemination of extension services in Mali is accomplished through the rural development organizations and more recently through farmer/trader associations, where the more successful rural development institutions focus on the production and marketing of cash crops like cotton and irrigated rice and much less on the coarse grains. One goal of the agricultural extension programs in the U.S. is to help farmers understand and interpret, among other things, market information. Such an extension program would prove invaluable in the Malian setting where adult literacy rates are less than 10%.

8.4 Implications

What does it mean for the various categories of economic agents in a country like Mali to have broad access to improved price forecasting techniques? A food grain producer with access to credit, storage facilities and an understanding of basic marketing concepts can improve his household food security by pursuing better marketing strategies and reduce some of the risk and uncertainty associated with holding grain stocks by incorporating price forecasts into his information set.

Analogously, a policymaker charged with managing the national security stock can use the forecasts of grain prices to determine better when and in which markets to release grains. For example, a consistent forecast of high prices in a particular market might lead the national stock manager to release grain in that market, causing prices to fall, hence easing the pressure on net buyers. Private traders and speculators with the appropriate infrastructure (trucks, assemblers, etc.,) can perform spatial arbitrage by buying in low price markets and selling in high price markets, increasing competition in those markets.

8.5 Further Research

This study is but a first attempt to develop price forecasting models using the data from the Malian market information system, and much more can be done. This research focused on developing and evaluating alternative forecasting models in the context of the limited available data. The models can be easily updated as more observations become available and/or as other factors hypothesized to influence price become available. Such information can be incorporated into the models and further evaluated using statistical and economic criteria.

The evaluation of the post-harvest marketing strategies assumed that producers formulated their expectations about price using a simple random walk model. Future research could include identification and an empirical analysis of the way in which Malian producers actually formulate their expectations about price. The method is likely to be more sophisticated than the simple random walk. Future research could also include information about risk preferences.

References

Allen, P. Geoffrey (1994). *Economic Forecasting in Agricultural* in Interntional Journal of Forecasting Volume 10. Elsevier Science. Pp.81-135.

Antonovitz, Frances and Terry Roe (1984). *The Value of a Rational Expectations Forecast in a Risky Market: A Theoretical and Empirical Approach*. American Journal of Agricultural Economics, Volume 66, Number 5.

Bapna, S.L. and K.R. Rao. (1987). Supply and Price Outlook for Crops: A Study Based on Preharvest Market Information in Gujarat. Oxford & IBH Publishing Co. PVT. LTD. New Delhi.

Brandt Jon and David Bessler (1983). *Price Forecasting and Evaluation: An Application in Agriculture*. Journal of Forecasting. Vol. 2, 237-248.

Brorsen, B. Wade (1998). *Can Preharvest Marketing Strategies Be Used to Increase Income?* Review of Agricultural Economics. Volume 20, Number 2, Fall/Winter 1998.

Bowerman, Bruce and Richard O'Connell (1993). Forecasting and Time Series: An Applied Approach. Third Edition. The Duxbery Advanced Series in Statistics and Decision Sciences, Duxbury Press, Belmont, California.

Carlson, John (1977). *A Study of Price Forecasts* in Annals of Economic and Social Measurement. Volume 6.

Charemeza, Wojciech and Derek Deadman (1997). New Directions in Econometric Practice: General to Specific Modelling, Cointegration and Vector Autoregression. Second Edition. Edward Elgar, Cheltenham, UK.

CILSS (1998). Food Security and Agricultural Subsectors in West Africa: Future Prospects and Key Issues Four Years After the Devaluation of the CFA Franc. Policy conference organized by CILSS November 30-December 2 1998. Dakar Senegal. Permanent Interstate Committee for Drought Control in the Sahel. Institut du Sahel.

Danthine, J.P (1992). *Information, Futures Prices, and Stabilizing Speculation* in The Theory of Futures Markets Edited by Paul Weller. Blackwell Publishers, Oxford, UK.

Davidson Russel and R James G. Mackinnon, Estimation and Inference in Econometrics. Oxford University Press. New York. 1993.

Dembele, Niama Nango. (1994) Economic Analysis of Traders' Response to Cereals Market Reforms in Mali. Ph.D. Dissertation, Department of Agricultural Economics, Michigan State University.

Donovan, Cynthia (1996). Effects of Monetized Food Aid on Local Maize Prices in Mozambique. Ph.D. Dissertation in Agricultural Economics, Michigan State University.

Enders Walters (1995). Applied Econometric Time Series. John Wiley & Sons, INC. New York.

EViews User's Guide 1997. Quantitative Micro Software. Irvine, CA, USA.

Fackler Paul and Michael Livingston (1995). *Optimal On-Farm Storage*. Paper presented at Michigan State University, Department of Agricultural Economics. Authors are from the Department of Agricultural and Resource Economics, North Carolina State University, Raleigh, North Carolina.

Ferris, John (1998). Agricultural Prices and Commodity Market Analysis. WCB/ McGraw-Hill, Boston, Massachusetts.

Gerlow, Mary, Scott Irwin and R-Re Liu (1993). *Economic Evaluation of Commodity Price Forecasting Models* in International Journal of Forecasting. Volume 9, Elsevier Science Publishers B.V. Amsterdam. Pp. 387-397.

Ghosh, S.; C.L. Gilbert and A.J. Hughes Hallett (1987). Stabilizing Speculative Commodity Markets. Chapters 1 and 2. Clarendon Press, Oxford.

Gilbert, Christopher and Theodosios Palaskas (1990). *Modelling Expectations Formation in Primary Commodity Markets* in Primary Commodity Prices: Economic Models and Policy. Eds. Winters and Sapsford. Center for Economic Policy Research, Cambridge University Press, Cambridge.

Gislason, Conrad (1960). *Grain Storage Rules*, Journal of Farm Economics. Volume 42, pp.576-595.

Goetz Stephan and Michael Weber (1986). *Fundamentals of Price Analysis in Developing Countries Food Systems: A Training Manual to Accompany the Microcomputer Software Program "MSTAT"*. MSU International Development Papers. Working Paper N. 29. Department of Agricultural Economics, Michigan State University. East Lansing, Mi.

Goetz, Stephan. (1992). *Household Marketing Strategies in Africa* in American Journal of Agricultural Economics, Volume 74, Number 2.

Gujarati, Damodar (1995). Basic Econometrics. Third Edition. McGraw-Hill, Inc. New York.

Gustafson, Robert (1958). "Implications of Recent Research on Optimal Storage Rules", Journal of Farm Economics, Volume 40, pp.290-300.

Hayenga, Marvin, Aaron Johnson and Bruce Marion, Eds. (1978). Market Information and Price Reporting in the Food and Agricultural Sector. Proceedings of a Conference Sponsored by North Central Regional Committee 117. Madison, Wis., May 24-25.

Helmberger, Peter and Jean-Paul Chavas (1996). The Economics of Agricultural Prices. Prentice Hall, Upper Saddle River, New Jersey.

Holden, D., D.A. Peel and J.L. Thompson (1985). Expectations: Theory and Evidence. St. Martin's Press, New York.

Judge, George, W.E. Griffiths, R. Carter Hill, Helmut Lutkepohl and Tsoung-Chao Lee (1985). The Theory and Practice of Econometrics. Second Edition. Wiley Series in Probability and Mathematical Statistics. New York.

Leitch, Gordon and J. Ernest Tanner (1991). "Economic Forecast Evaluation: Profits versus the Conventional Error Measures, *American Economic Review*, Volume 81, Pp. 580-590.

Just, Richard and Gordon Rausser (1981). *Commodity Price Forecasting with Large-Scale Econometric Models and the Futures Market*. American Journal of Agricultural Economics, Volume 63, Number 2

Maddala, G.S. (1990)."Estimation of Dynamic Disequilibrium Models with Rational Expectations: The Case of Commodity Markets"in Primary Commodity Prices: Economic Models and Policy. Eds. Winters and Sapsford. Center for Economic Policy Research, Cambridge University Press, Cambridge.

Makridakis Spyros and Steven Wheelwright (1978). Forecasting: Methods and Applications. John Wiley & Sons, Santa Barbara, CA.

Mehta, Mona (1989). An Analysis of the Structure of the Wholesale Cereals Market in Mali. Unpublished Plan B Paper, Department of Agricultural Economics, Michigan State University.

University of Minnesota, Department of Applied Economics (1997). Midwest Outlook Conference. Papers.

Ministere du Developpement Rural et de L'Eau, Cellule de Planification et de Statistique (March 1998). Recueil des Statistiques du Secteur Rural Malien. Republique du Mali.

Myers, Robert (1996). *Notes on Dynamic Models in Agricultural and Resource Economics: Chapter 6 Optimal Storage Rules.* Dynamic Programming Class Notes

Myers, Robert J. (1994). *Time-Series Econometrics and Commodity Price Analysis: A Review.* Review of Marketing and Agricultural Ecnomics. Vol. 62, no.2.

NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management (1990). Editor Marvin Hayenga. Chicago, Illinois, April 23-24.

NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management (1992). Editor Marvin Hayenga. Chicago, Illinois, April 20-21

Nelson C.R. and C.I. Plosser (1982). *Trends and random walks in macroeconomic time series: some evidence and implications.* Journal of Monetary Economics, Volume 10.

Nerlove, Marc; David M. Grether; and Jose L. Carvalho (1995). Analysis of Economic Time Series: A Synthesis. Revised Edition. Academic Press, San Diego. A volume in Economic Theory, Econometrics, and Mathematical Economics.

Newbery, D.M.G. and J.E. Stiglitz (1992). "Futures Markets and Risk Reduction" in The Theory of Futures Markets Edited by Paul Weller. Blackwell Publishers, Oxford, UK.

Newbery David and Joseph Stiglitz. The Theory of Commodity Price Stabilization: A Study in the Economics of Risk. Clarendon University Press, Oxford. 1981

Ooms, Marius (1994). Empirical Vector Autoregressive Modeling. Springer-Verlag, Berlin.

Park Wayne; Philip Garcia and Raymond M. Leuthold (1989). " Using a Decision Support Framework to Evaluate Forecasts" in *North Central Journal of Agricultural Economics.* Volume 11, Pp. 233-242.

Price D.H.R. and J.A. Sharp. (1986). "A Comparison of the Performance of Different Univariate Forecasting Methods in a Model of Capacity Acquisition in UK Electricity Supply. *International Journal of Forecasting.* Volume 2, Elsevier Science Publishers B.V. Amsterdam. Pp. 333-348.

Rausser, Gordon (1982) Editor. New Directions in Econometric Modeling and Forecasting in U.S. Agriculture. North Holland. New York.

Sims, Christopher (1986). *Are Forecasting Models Useable for Policy Analysis.* Federal Reserve Bank of Minneapolis. Quarterly Review. Winter.

Steffen, Philip Nathan (1995). The Roles and Limits of the Grain Market in Assuring Household Food Security in Northeastern Mali: Implications for Public Policy Vol.II, Ph.D. Dissertation, Department of Agricultural Economics, Michigan State University.

Tefft James, John Staatz and Josue Dione (1997). *Impact of the CFA Devaluation on Sustainable Growth for Poverty Alleviation: Preliminary Results.* Comite Permanent Interetats de Lutte Contre la Secheresse dans le Sahel. Institut du Sahel and PRISAS, Bamako, Mali.

Theil, H. (1958). Economic Forecasts and Policy. North-Holland Publishing Company, Amsterdam.

United States Department of Agriculture, ERS (1997). Rice: Situation and Outlook Yearbook. Market and Trade Economics Division, Economic Research Services, U.S. Department of Agriculture, December 1997, RCS-1997.

Williams, Jeffrey and Brian Wright (1991). Storage and Commodity Markets. Cambridge University Press, Cambridge.

Winters L. Alan and David Sapsford (1990). Primary Commodity Prices: Economic Models and Policy. Eds. Winters and Sapsford. Center for Economic Policy Research, Cambridge University Press, Cambridge.

Winters L. Alan and David Sapsford (1990). *Primary Commodity Prices: An Introduction to the Major Policy and Modelling Challenges* in Primary Commodity Prices: Economic Models and Policy. Eds. Winters and Sapsford. Center for Economic Policy Research, Cambridge University Press, Cambridge.

Wisner Robert, E. Neal Blue and E. Dean (1998). *Preharvest Marketing Strategies Increase Net Returns for Corn and Soybean Growers* in Review of Agricultural Economics Volume 20, Number 2, Fall/Winter.

Wohlgenant, Michael K. (1985). "Competitive Storage, Rational Expectations, and Short-run Food Price Determination". American Journal of Agricultural Economics.

Wright, D.J.; G. Capon; R. Page; J.Quiroga; A.A.Taseen and F. Tomasini (1986). "Evaluation of Forecasting Methods for Decision Support" in International Journal of Forecasting. Volume 2, Elsevier Science Publisher B.V., North Holland. Pp. 139-152.

Xiao, Jingyue (1991). A Food Security Study in Mali: Toward Harmonized Food Policy for Rural Farm Households. Unpublished Master's Thesis, Department of Agricultural Economics, Michigan State University.

Yang, Seung-Ryong and B. Wade Brorsen (1992). *Nonlinear Dynamics of Daily Cash Prices*. American Agricultural Economics Association. Volume 74, Number 3.

Zulauf, Carl and Scott Irwin (1998). *Market Efficiency and Marketing to Enhance Income of Crop Producers* in Review of Agricultural Economics. Volume 20, Number 2, Fall/Winter.

MICHIGAN STATE UNIV. LIBRARIES
31293018342075