ANALYSIS OF EFFICIENCY GAINS IN COMMODITY PRICE FORECASTING USING ARMA MODELS WITH VARYING LEVELS OF DATA AGGREGATION

by

LUIS MOISÉS PEÑA LÉVANO

(Under the direction of Octavio Ramirez)

ABSTRACT

This study evaluates the efficiency gains in forecasting three commodity prices (live cattle, coffee and cotton) using different ARMA models with varying levels of temporal aggregations (weekly, monthly, quarterly and annually). More specifically, it evaluates whether the disaggregated models can produce more accurate aggregated price predictions than the corresponding aggregated models. The commodity prices were adjusted using the Consumer Price Index (CPI). Likewise, they had a non-stationary behavior and heteroskedasticity issues; therefore they were subject to detrending and transformations using GLS. Under the three different scenarios, disaggregation levels effectively provided an efficiency gain in forecasting, and the best models were the weekly models. The same behavior was consistent across all possible levels of aggregations, i.e. monthly models had a better performance than quarterly and annual models in forecasting quarterly and annual prices.

INDEX WORDS: Disaggregation, Unit Root Test, Commodity Behavior, Trend in Commodity Pricing, MSE in Empirical Analysis.

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LUIS MOISÉS PEÑA LÉVANO

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ANALYSIS OF EFFICIENCY GAINS IN COMMODITY PRICE FORECASTING USING ARMA MODELS ON VARYING AGGREGATION LEVELS OF DAILY CASH PRICES

by

LUIS MOISÉS PEÑA LÉVANO

Major Professor: Octavio Ramirez

Committee: Jack Houston
T.N. Sriram

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
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DEDICATION

Dedicated to God, my inspiring family, best friends and to all those who believe in the richness of learning.

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CHAPTER 1

INTRODUCTION

1.1 Problem Statement

An efficient forecast is defined as the prediction from an optimal model that is as close as possible to the true experimental value in a particular period of time. The efficiency of a forecast depends on several factors, such as data reliability and an optimal modelspecification (Nordhaus, 1987). A way to improve the forecast efficiency that has been overlooked in practice is to select an optimal level of data aggregation for building the model and then making the desired forecast.

For approximately 40 years, the forecasting efficiency gains that can be obtained by building time series models in which the data are optimally aggregated has been studied sporadically. Amemiya and Wu (1972)formulated a measurement for forecasting efficiency losses due to data-aggregation using short-order autoregressive models [AR(1) and AR(2)]. In contrast, Tiao (1972) conducted similar analyses for moving average [MA(1) and MA(2)]processes and showedthat for short-term predictions in non-stationary series, the gain in forecasting accuracy could be significant when disaggregated data is used. Koreisha and Fang (2004) discovered the theoretical improvement in the performance of quarterly forecasts when using short-order ARMA monthly models [I.e., ARMA(1,2) and ARMA(2,1)].

Nevertheless, comprehensive empirical studies of the efficiency gains that can be achieved through temporal disaggregation have only been conducted in recent years. Ramirez (2012) analyzed four time series (US oil spot price, US Federal fund rate, US/Japan exchange rate, 10-year US bond yield) and concluded that efficiency gains are feasible when long-order disaggregated ARMA models are used for prediction instead of more aggregated models (i.e., weekly models are better than quarterly models to predict quarterly prices, monthly models are better than quarterly models to predict quarterly prices, etc.).

Interestingly, an empirical study focused on the potential beneficial effects of temporal disaggregation in commodity price forecasting has not been conducted, even though commodities markets are extremely important for the economic performance of the U.S. agricultural sector. For instance, in the U.S., three major agricultural commodity markets are live cattle, cotton and coffee. The statistics show the relevance of each of those markets:

- U.S. live cattle and calf production was valued at $ 37.0 billion in 2010 and US cattle inventory stood at a total of 92.6 million head in January 1, 2011 (USDA, 2012).
- The United States is ranked as the third leading exporter of raw cotton in the world market, and cotton-related products and services generated approximately$25.0 billion in annual revenue and were responsible for 200,000 jobs in 2008 (USDA, 2012).
- In fiscal year 2011, The United States' population consumed over half a million pounds of coffee (USDA, 2011).

Since timingand volatility play important roles in these markets,an unexpected change in prices can have significant impact on investors' revenues due to the large volume of these commodities being traded in both the cash and futures markets (Gjolberg and Bengtosson, 1997). Therefore, better forecasts of the cash prices would lead to better decision making by:

- Agribusiness investors, who can compare production costs with future prices and decide on their levels of production of alternative commodities or whether or not to hedge in options and futures markets.
- Banking lenders, because this information could help them assess whether the borrowers would be able to re-pay their production loans and interest.

1.2 Objectives

Through the use of large datasets consisting of approximately 60 years of daily prices of each of the three cash commodity (coffee, cotton and live cattle) markets and suitable ARMA models for different levels of data aggregation (weekly, month, quarterly and annual), the primary objective of this study is to evaluate the efficiency gains in forecasting using different levels of temporal aggregations. Specifically, the study assesses: whether the weekly models can produce more accurate monthly, quarterly and annual price predictions than the corresponding monthly, quarterly and annual models; whether the monthly models can yield more precise quarterly and annual predictions than quarterly and annual models; and whether the quarterly models can produce more accurate annual predictions than the corresponding annual models.

1.3 Organization

The present study is divided into five chapters:

- Chapter 2 describes the cash commodity markets for cotton, corn and live cattle in United States and statistics related to each of these commodities.
- Chapter 3 reviews and summarizes the existing literature related to price forecasting for these three commodities and on forecasting efficiency using different econometric and time series approaches.
- Chapter 4 discusses the data and the inter-temporal behavior of each time series, introduces the theoretical framework, and relates the specific methods and procedures to be used in the study.
- Chapter 5 discusses the empirical results,
- The final chapter provides the conclusion a summary of the study.

CHAPTER 2

OVERVIEW OF THE COMMODITY MARKETS

2.1 Current State of the U.S. Live Cattle Market

U.S. live cattle markets represent an important sector of U.S. economy, valued at $ 37.0 billion in 2010, and U.S. cattle inventory reported a total of 92.6 million head in January 1, 2011 (USDA, 2012). With respect to the raw materials needed to raise live cattle, in recent years, pastures have improved in the Southern areas of United States due primarily to high precipitation in 2011 and 2012. However, during the last two years, the La Niña effect has being present, causing a severe drought in Texas. In addition, corn prices have been high. As a result, feeder cattle prices have recently increased to over $ 200 per cwt. (USDA, 2012).

In regard to processing, cow slaughter in December 2011 was up 5 % compared to December 2010, and the inventory (which had decreased annually on a steady basis) on January 2011 was around 3 % less than forty years ago. Currently, there is a problem of negative margins per animal, because there has been an increment in net placements but a reduction in placement weights, which is causing lighter cattle weight and thus lighter finished weight (USDA, 2012).

In regard to cattle and beef trade market, Mexico has been a major partner to the U.S. for many years. Figure 2.1 presents the recent historical trends of U.S. cattle imports from

Mexico. US cattle imports are forecast to be 2.025 million head in 2012,or 2 % lower than in 2011 (USDA, 2012).

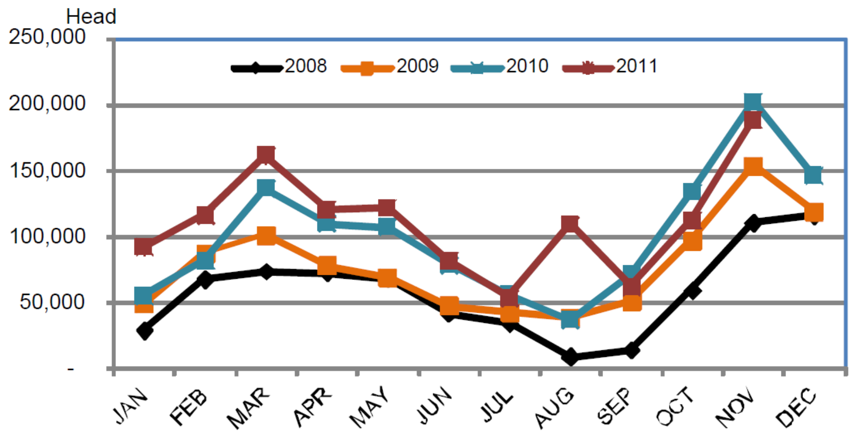

Figure 2.1 U.S. Monthly cattle imports from Mexico, 2008 – 2011
Source: USDA – ERS, 2012. http://www.ers.usda.gov/Data/MeatTrade/CattleMonthly.htm

Figure 2.2 shows the trend of US beef imports from Mexico. In most of the cut categories, the trend is positive with rapid increments in the last four years.

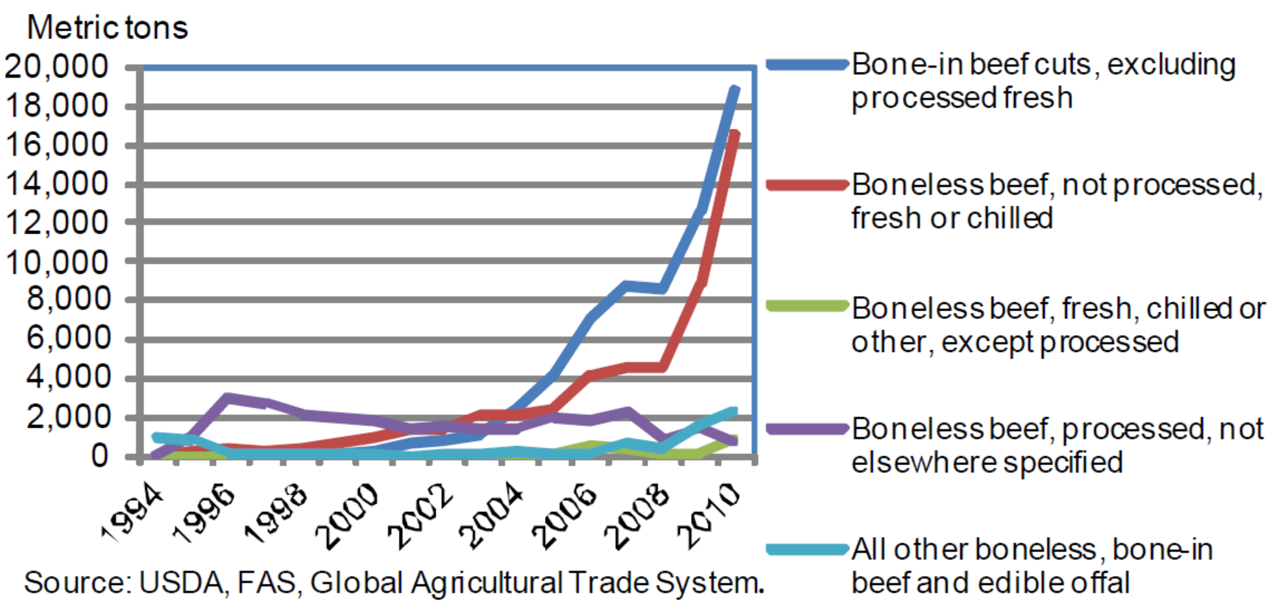

Figure 2.2 U.S. Beef imports from Mexico, 1994 – 2011
Source: USDA – FAS, Global Agricultural Trade System, 2012.

2.2 Current State of the U.S. Cotton Market

U.S. cotton markets are recognized as one of the most important in the world. The United States is ranked as the third leading exporter of raw cotton in the world market and cotton-related products and services generated approximately $25.0 billion in annual revenue and were responsible for 200,000 jobs in 2008 (USDA, 2012).

According to USDA, despite the fact that only 13.2 million acres will be planted, which is 11 % less than in 2011; the U.S. cotton crops in 2012 are projected to reach 17.0 million bales, which is 9 % above 2011. Figure 2.3 shows that while upland acreage decreased in each of the Cotton Belt regions, the levels of contribution of every region to total production is almost constant during the last five years (USDA, 2012).

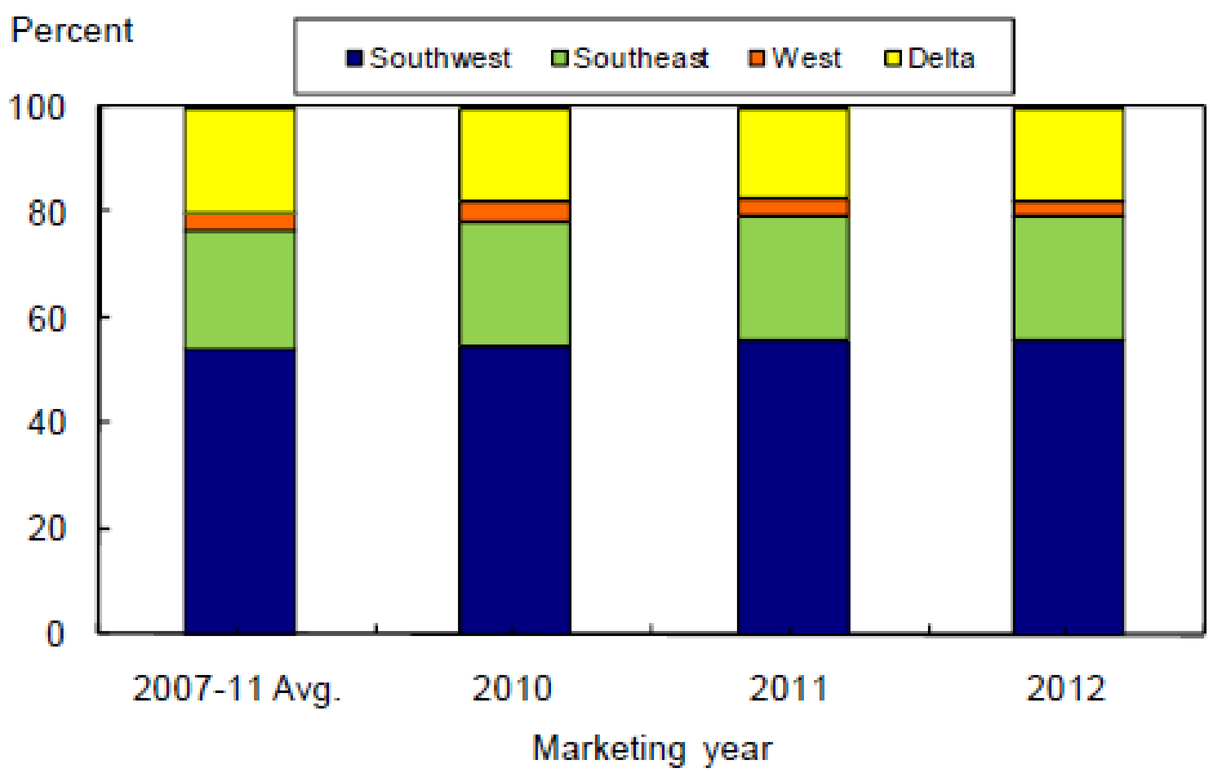

Figure 2.3 Upland cotton area shares, by region
Source: USDA, Crop Production reports, 2012.

2.3 Current State of the U.S. Coffee Market

U.S. coffee markets are relatively more constant compared to U.S. cotton and live cattle markets. Likewise, a very small percentage of the coffee consumed in United States is produced Hawaii. Imports primarily consist of coffee from Brazil, Colombia, Guatemala and Mexico. The New York Board of Trade (NYBOT) allows trading in two types of coffee: Arabica and Robusta. The United States was forecast to increase coffee consumption nearly to 9,600 tons (USDA, 2010).

Figure 2.4 illustrates the behavior of coffee prices over the last two years, where it can be observed that they had a non- constant pattern (2010-2012). Retail coffee price is highly seasonal, and the volume traded in November and December is 10times higher than the annual average while during May to September it is about 10 % lower(USDA, 2012).

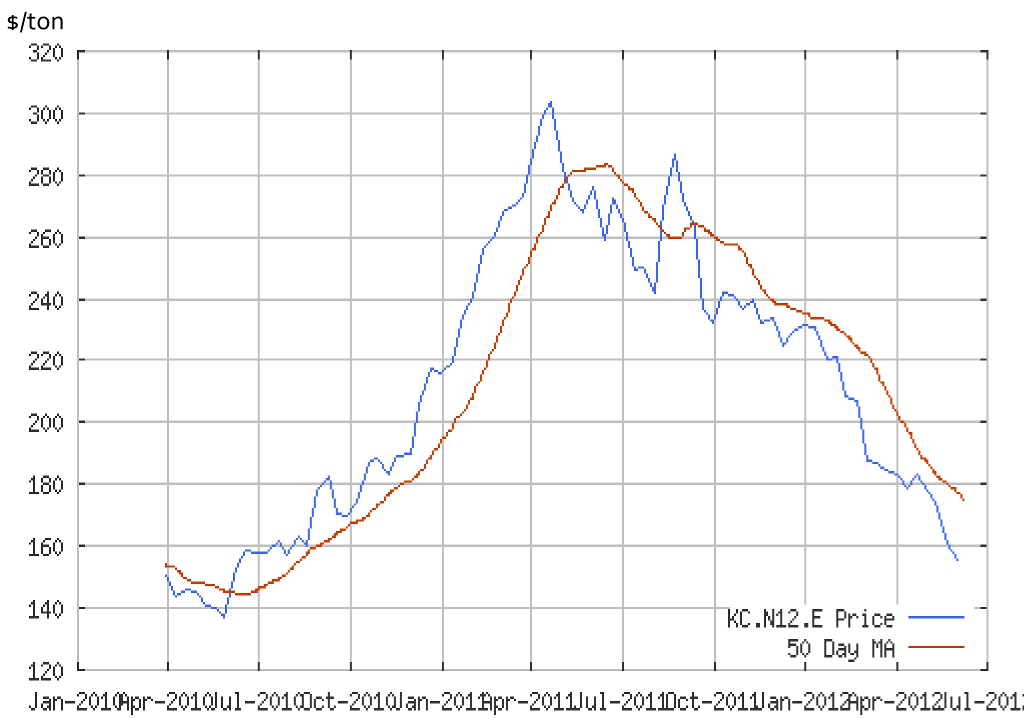

Figure 2.4 Coffee prices ($/ton) from January 2010 to May 2012 in New York Board of Trade
Source: New York Board of Trade data. 2012.

CHAPTER 3

LITERATURE REVIEW

Forecasting theory posits that the dataset has to be reliable and the optimal model is assumed to be the true model that characterizes the true model process that characterizes the commodity price behavior. An additional factor that this study explores is the effect of the aggregation level of the data of the model's forecast. The concept is to build models that incorporate the highest amount of information about prices and their cyclical behavior into the forecasts. This chapter is divided in two sub sections: the first section(3.1) draws on the accumulated findings and methods used in previous studies to improve forecasting in commodity markets; the second section (3.2) focuses on previous literature about the effect of temporal aggregation in forecasting efficiency, mainly theoretical econometric models and derivations.

3.1 Previous studies in commodity price forecasting

3.1.1 Producer Expectations

The first theoretical models encountered in the literature that analyzes futures and cash prices were based on producer expectations. Heady and Kaldor (1954) analyzed the price expectations of 200 farmers in Iowa, using semiannual prices from December 1947 to June 1949. They found that only 52% of individual producer expectations fell within 10% of the actual prices, and that the producer expectations were skewed to the right (i.e., toward higher prices). Fisher and Tanner (1978) conducted an economic analysis of 55 Australian wheat farmers to determine the best method to predict their price expectation. Nevertheless, even the expectation model that fit the data best only had an R-square of 20%. They attributed the poor performance of their models to a possible relation of supply and demand information and the stable wheat price that was observed in the period analyzed. Eales et al. (1990) also studied the producers' expectations in the Australian wheat market from 1987 to 1988, and concluded that expectations were on average very similar to the future price, but there was a notable difference with respect to the variability of the market price. Schroeder et al. (1990) used surveys to collect information about how the producers say they form their price expectations. Kenyon (2001) analyzed the ability of producers to predict the harvest prices of soybeans and corn using expectation models and monthly data from 1991 to 1998. The producer expectations were elicited though a survey at the annual Virginia Corn-Soybean Conference. The results showed that the price expectations were highly correlated with actual cash and futures prices. The difference between the actual and expected producer price was \$0.20 to \$0.30 per bushel. Interestingly, Kenyon also concluded that producer expectations followed a right-skewed distribution for both of those commodities and that producers are significantly underestimating the probability of large soybeans price changes.

3.1.2 Simultaneous equations and Autoregressive Conditional Heteroskedastic (ARCH) models

Simultaneous equations models have been also used for the determination of spot (cash) and futures prices. Initially, the models were developed for storable commodities (Peston and Yamey, 1960; Stein ,1961; Dewbre, 1981), and then models for non-storable commodities began to appear (Kawai, 1983). The main difference between non-storable and storable commodities is that in the first one, the basis (i.e., future price minus spot price) depends on the marginal cost of storage. Empirical simultaneous models, with no rational expectations and for non-storable commodities, were developed by Leuthold and Hartmann (1979), who refined the model forecast approach to semi-strong market efficiency for hogs. Leuthold and Garcia (1992) applied this method to live cattle with a null hypothesis of an efficient market and no presence of a random walk, which they couldn't reject. Giles et al. (1985) and Goss et al. (1992) built more elaborate simultaneous equation models, with rational expectations, but for storable commodities.

Barry and Gulay (1999) expanded the literature by studying price determination in the Australian live cattle market (a non-storable commodity) using simultaneous rational expectations (RE) models of spot and futures markets. They found that prices in those markets depended on expected increases in consumption. Augmented Dickey-Fuller and Phillips Perron tests for unit roots produced ambiguous results, which suggested that spot and future price, the expected real income, and consumption of beef have followed a linear polynomial trend. The optimal model for forecasting the futures prices was an ARIMA (1, 1, 5) model, chosen because it had the lowest Mean Squared Error (MSE), however it was emphasized that there was evidence of Autoregressive Conditional Heteroskedastic (ARCH) effects in the conditional variance and these effects were represented as an Exponential Generalized ARCH [E-GARCH (1, 3)] process to capture the variance behavior. Additionally, they concluded that in the Australian live cattle market there was presence of semi-strong efficient market.

Dhuyvetter et al. (2005) sought improvements in the forecasting of feeder cattle prices, through hedonic regression models and a composite average forecasting model. Their main variables were corn price and weight. The accuracy of these models was inversely related to the weight of the feeder cattle.

3.2 Temporal aggregation studies

The potential efficiency gains in forecasting as a result of the temporal disaggregation of the data have been sporadically explored during the previous four decades. Amemiya and Wu (1972)were the first ones in investigating disaggregated series; they formulated a measurement for forecasting efficiency losses due to data aggregation using short-order autoregressive [AR(1) and AR(2)]processes. Tiao (1972) conducted similar analyses using shot-order moving average [MA(1) and MA(2)]processes. He showed that for short-term predictions in non-stationary series, the gain in forecasting accuracy could be significant when disaggregated data is used. Lutkepohl (1987) analyzed different aggregation levels using ARMA models assuming that the true parameters were unknown. He compared the Mean Squared Error (MSE) of the predictions from disaggregated versus the aggregated ARMA models. He showed that aggregated forecast from a disaggregated ARMA model was more accurate than the aggregated forecast from an aggregated ARMA model.

More recently, Koreisha and Fang (2004) evaluated the forecasting efficiency contrasting also aggregated models and different disaggregation levels. In their theoretical evaluation the data series, they used short-order ARMA[(2,1) and (1,2)] processes. They showed that the disaggregated (monthly)model had a better performance than the aggregate (quarterly) model in forecasting quarterly values. Hence, a monthly model could be used to improve the performance of the quarterly predictions.

The first comprehensive empirical study of the forecasting of disaggregation was conducted by Ramirez (2012), who investigated the effects of aggregating weekly observations of four data series (US oil spot price, US Federal fund rate, US/Japan exchange rate and 10-year US bond yield) to forecast monthly, quarterly and annual values using long-order ARMA models. Using the Mean Square Errors of the out-of-sample forecasts (MSE) as a criterion for comparison between models based on different levels of data aggregation, he found consistent and substantial efficiency gains when disaggregated models were used for prediction instead of aggregated models. Specifically, he showed that the weekly models produce more accurate monthly, quarterly and annual price predictions than the corresponding monthly, quarterly and annual models; the monthly models yield more precise quarterly and annual predictions than the corresponding quarterly and annual models; and the quarterly models render more accurate annual predictions than the corresponding annual models.

The aim of this research then is to examine whether similar forecasting efficiency gains can be garnered through the use of longer-order ARMA models based on disaggregated data for the forecasting of agricultural commodity prices.

CHAPTER 4

THEORETICAL UNDERPINNING AND THE EMPIRICAL MODEL SPECIFICATION

4.1 The Data Series

The data for this study include nominal daily prices from the USDA Chicago (1948-1971; 1988-2011) and USDA Omaha (1971-1987) databases for three commodities:

Live Cattle: A total of 15,965 observations, from 01/02/1948 to 08/02/2011 with prices given in dollars per hundred pounds.

Live cattle nominal prices have followed a positive trend, without major sudden fluctuations, very stable during the first 25 years and then increasing steadily afterwards.

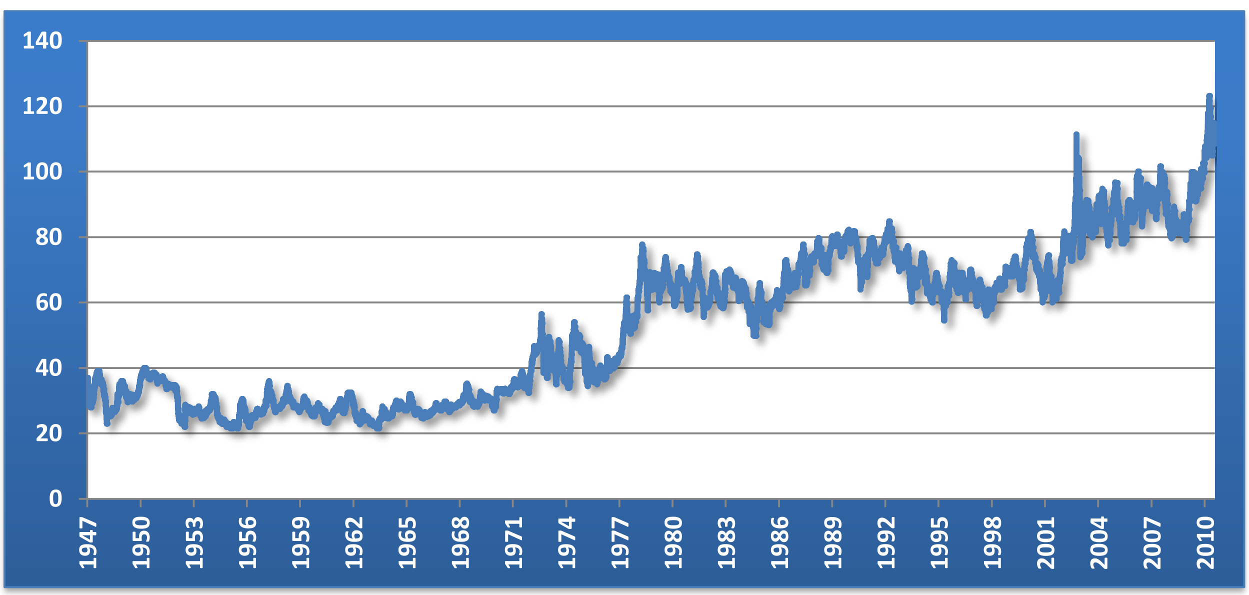

Figure 4.5 Live Cattle Daily Prices ($/100 lbs.) from 1948 to 2011
Source: USDA, Datastream 2012.

Coffee: The total number of observations includes 15,364 nominal daily prices in dollars per 100 pounds, from 01/02/1948 to 04/24/2009.Figure 4.2 shows that the behavior of coffee price is not as stable as live cattle. Specifically, note the price variability seems to be increasing over time, raising suspicion that this series may not have a constant variance. Coffee market was dominated by a cartel agreement from 1962 and 1989 called The International Coffee Agreement (ICA). Two very notorious peaks are observed during that period: In 1977, 1985. However, due to very high profits in the market attracted to African countries, thus, Brazil shares declines from 40% in 1962 to 24% in 1988 (BBC News, 2001). As a result, during the period of 1975 – 1993, the price began to gradually decrease with periodic spikes, and then exhibited an abrupt increase during the following six years, achieving an historical peak in 1999. According to ICO composite index, prices fell 22 % at the end of 1999, 25 % in 2000 and 29 % in 2001 reaching a very low nominal price of 52 dollars per 100 pounds. This dramatic fall issue has been attributed to an international cartel failure in the coffee global market (FAO, 2004).

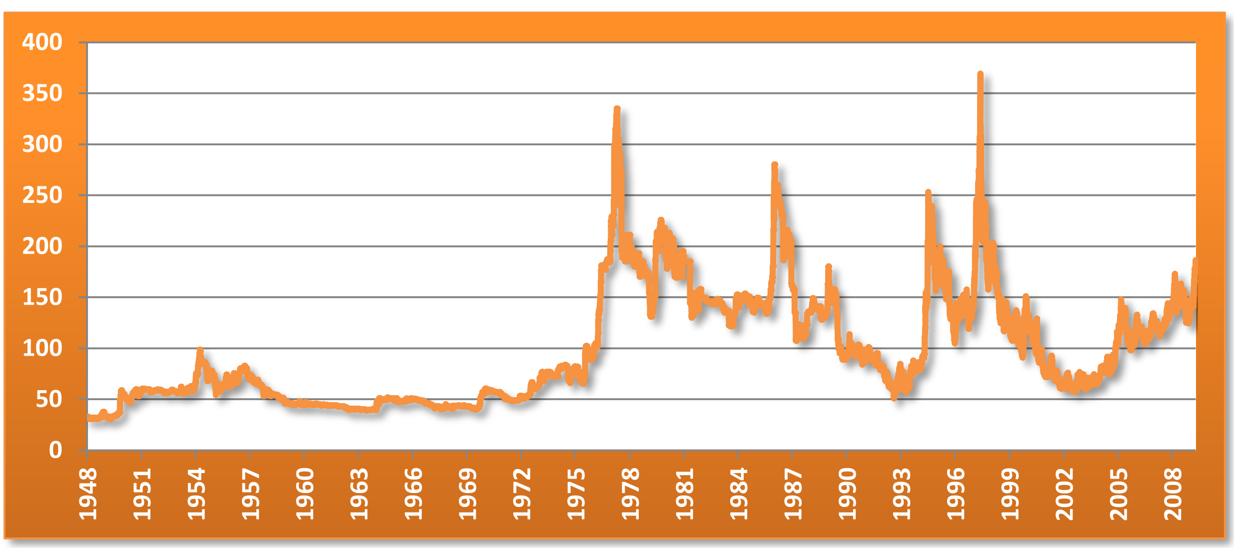

Figure 4.6 Daily Coffee Prices (US dollars per 100 pounds) from 1948 to 2009
Source: USDA, Datastream 2012.

Cotton: A total of 8,211 nominal daily prices observations in U.S. dollars per pound from 01/02/1979 to 08/02/2011.

Figure 4.3 presents the behavior of nominal cotton prices during the last 40 years. Nominal prices were relatively stable until 2010,followed by a significant upward spike. Thereafter, in 2011, the prices declined quickly but still settled at a higher level than their historical average (Textile Exchange, 2011). This temporal price increase in this period was possibly due to the severe weather that affected globally cotton crops in 2010. This spike was worse than expected in the news (PPIA, 2011; CNN, 2010). Therefore it could be consider as a black swam event.

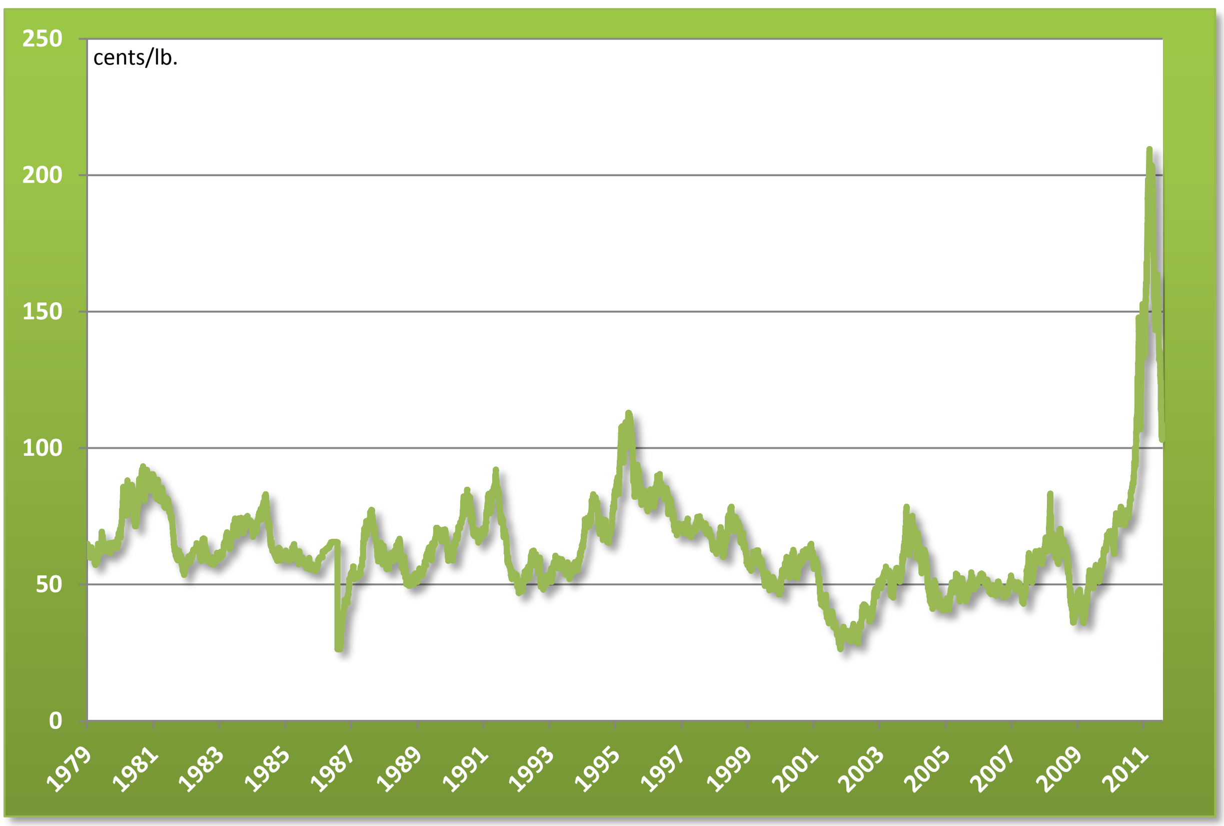

Figure 4.7 Cotton Daily Prices (cents per pound) from 1948 to 2011

Source: USDA, Datastream 2012.

4.2 Real Price Series

The raw data were adjusted using the Consumer Price Index (CPI) with the base year being 1982. The reasons for choosing the CPI instead of Producer Price Index (PPI) is that the PPI is mainly used to adjust revenues for the measurement of real output growth of finished goods, but it does not take into consideration transportation cost. Whereas, the CPI is commonly used to adjust income and expenditures of purchased goods in a particular market. In addition, the CPI does not take into consideration the origin of the goods (Bureau of Labor Statistics, 2012). This latter characteristic of the CPI gives it an advantage for evaluating the real value of commodities, such as coffee, which are imported from other nations.

Live Cattle: The behavior of the real cattle prices is the opposite of the nominal prices. They exhibit trend and a decreasing level of volatility over time.

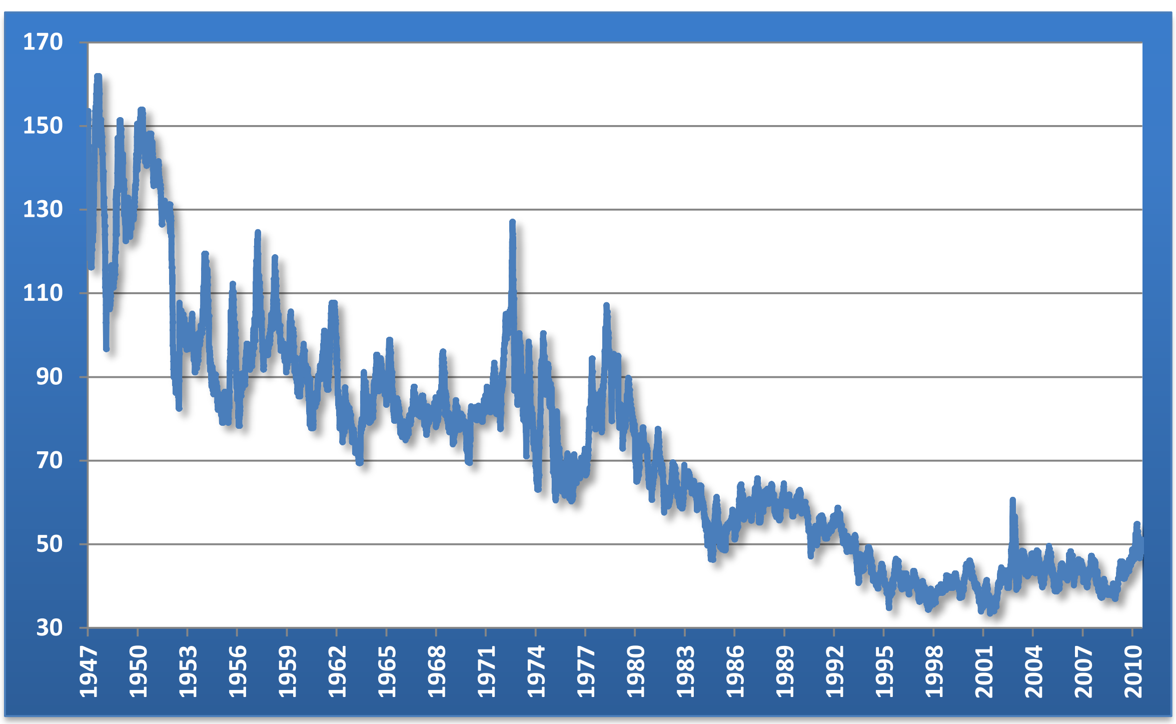

Figure 4.8 Live Cattle Daily Real Prices (USD per hundred pounds) from 1948 to 2011
Source: USDA, Datastream 2012.

Coffee: Figure 4.5 shows the movement of real prices. They also seem to exhibit a negative trend and varying levels of volatility over time. Their highest surge occurred in 1977, but there have been several other less prominent spikes during the last 60 years, as well as long periods of low prices.

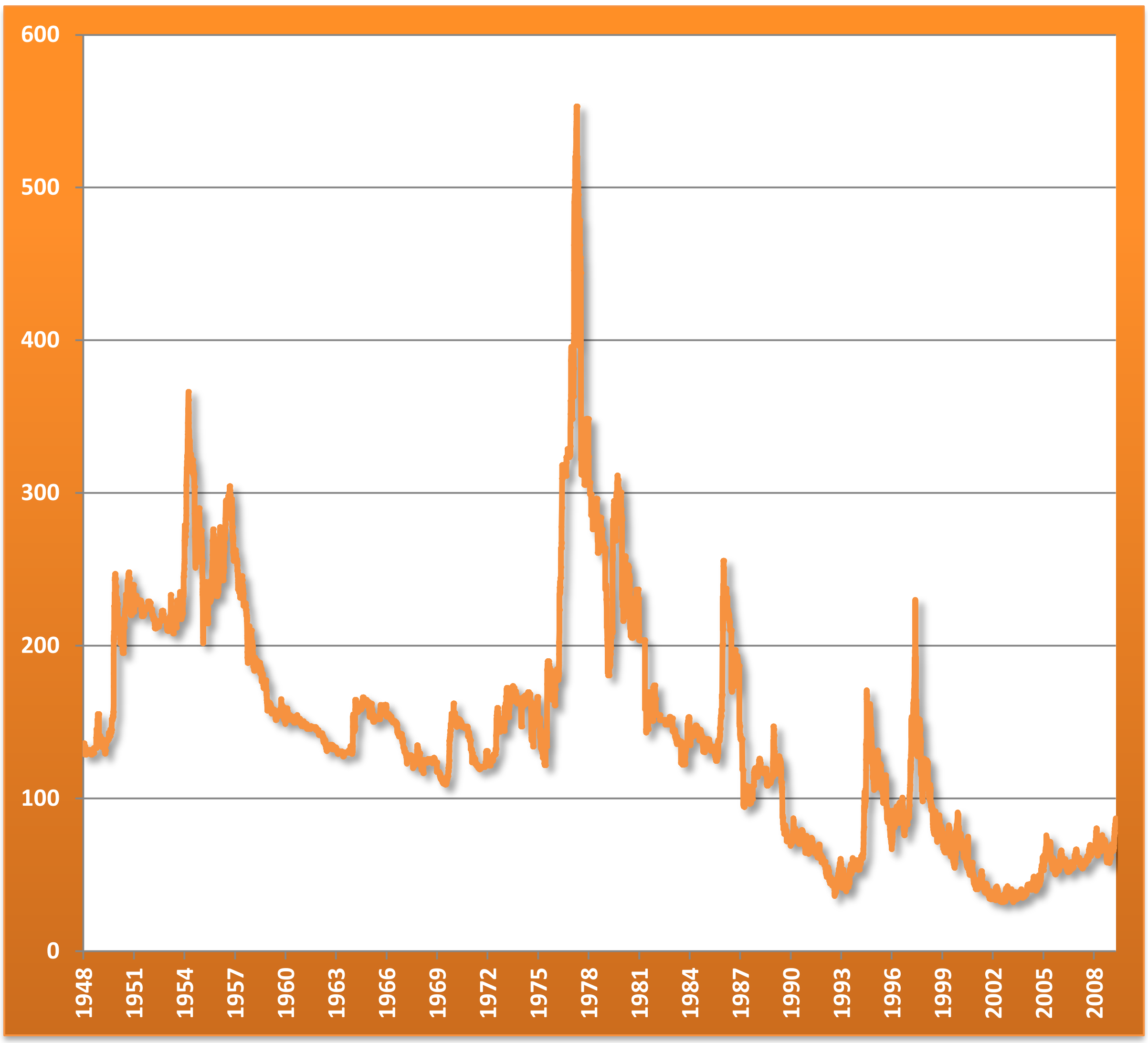

Figure 4.9 Daily Real Coffee Prices (US dollars per 100 pounds) from 1948 to 2009

Source: USDA, Datastream 2012.

Cotton: Real cotton prices follow a negative trend until 2009. However, Figure 4.6 shows that, even after the inflation adjustment, their highest peak and variation occurred in the period of 2010-2011.

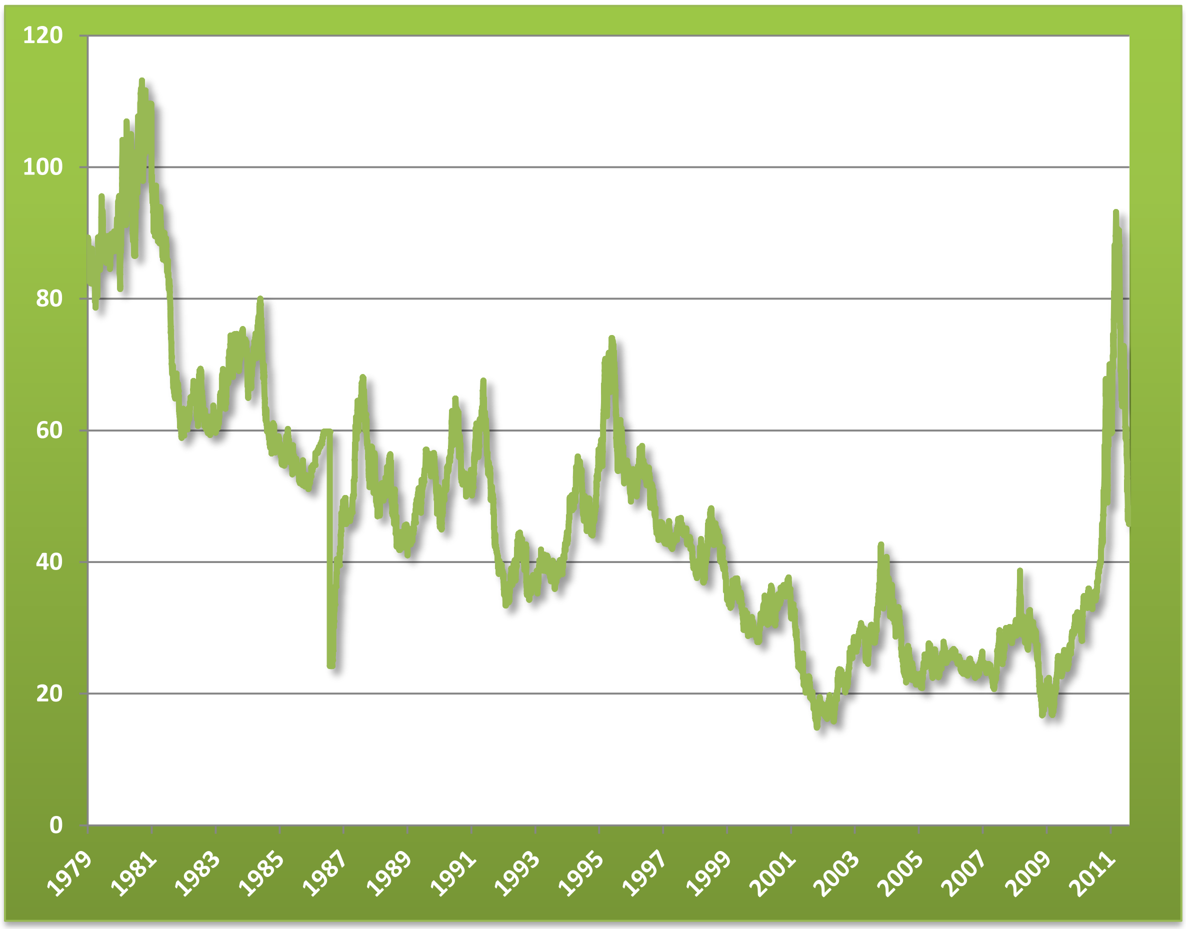

Figure 4.10 Daily Real Cotton Prices (US dollars per pound) from 1948 to 2009

Source: USDA, Datastream 2012.

4.3 Aggregation into weekly data

The daily data for each commodity ywere aggregated into weekly data series. Monday was used as the first day of the week for aggregation purposes. The decision about the reference day was based on the fact that cash prices generally changes more substantially after the weekend.

4.4 Stationary behavior of the time series

Let $\{X_t\}$ be a stochastic process (collection of random variables) whose cumulative distribution function is $F_X(x_{t_1+\tau}, \ldots, x_{t_k+\tau})$. Then, $\{X_t\}$ is stationary if, for all k and for all τ, over the times $t_1, \ldots, t_k$:

$$F_X(x_{t_1+\tau}, \ldots, x_{t_k+\tau}) = F_X(x_{t_1}, \ldots, x_{t_k}) \quad \textbf{(1)}$$

Since τ doesn't affect F_X, the cumulative distribution is not a function of time. This property is the main reason why a constant mean and a constant variance are assumed in a stationary process (Priestley, 1988).

4.4.1 The Unit Root Test

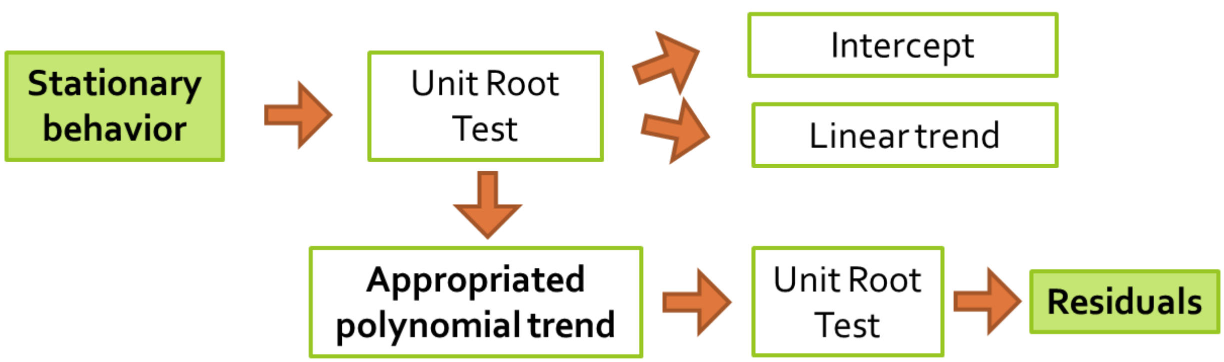

Figure 4.11 Analysis of the stationary behavior of the three data series

It was observed in the previous figures (4.4 to 4.6) that the commodities prices could exhibit non-stationary behavior. Therefore, it was necessary to verify these properties. For the analysis of stationary behavior, we tested the series using the Unit Root Test (Ramirez, 2011).

Unit root is a time stochastic process that evolves through time, which can cause problems in statistical inference if it is not addressed correctly. Stationarity of the commodity prices $\{Y_T\}$ was evaluated using the Dickey-Fuller test (1979) and Phillips-Perron test (1988) without an intercept or a time trend:

$$Y_t - Y_{t-1} = e_T = \rho e_{t-1} + V_t \quad \textbf{(2)}$$

in which the difference in prices at times ***T*** and ***T-1*** is the error term at time **T** and lag 1. If the coefficient ρ is 1, the process is said to be non-stationary. If ρ is less than 1 (in other words, their values lie within the unit circle), the process is stationary. Thus, the process can be evaluated using the following statement: the Unit Root Null Hypothesis (Ho) assumes that $\{X_T\}$ is a stationary process (Sargan and Bhargava, 1983). The null hypothesis of the unit root was tested using a level of significance (α) of 0.10 in all the cases.

When the null hypothesis was not rejected, we proceeded to compute different polynomial degrees to find an adequate systematic trend of the series with respect to time. Specifically, first, second and third degree polynomials were evaluated:

Linear: $$Y(t) = \alpha_0 + \alpha_1 t + \hat{\omega}_t \quad \textbf{(3a)}$$

Quadratic: $$Y(t) = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \hat{\omega}_t \quad \textbf{(3b)}$$

Cubic: $$Y(t) = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \hat{\omega}_t \quad \textbf{(3c)}$$

where Y is weekly prices; t represents time, {t=1,…,n} (where n is the number of observations), and $\hat{\omega}_t$ is the model's residual. In this case, the models were estimated using OLS once an appropriate polynomial is identified, the series was de-trended and the residuals $\{\hat{\omega}_t\}$ were tested using Dickey-Fuller and Phillips-Perron tests to make sure that the de-trended data are stationary.

4.5 Heteroskedasticity in Time Series Analysis

Hetoroskedasticity in the data can occur when the variance is not constant across observations (in other words, it's related to time):

$$E[u_t^2] = \sigma_t^2 \quad \textbf{(4)}$$

Where *E[.]* is the expected value; $\boldsymbol{u_t^2}$represents the residual squared and $\boldsymbol{\sigma_t^2}$thevarianceat a time $\boldsymbol{t}$ (Gujatari and Porter, 2009). Figure 4.8 illustrate the steps for the heteroskedasticity analysis of the three commodities.

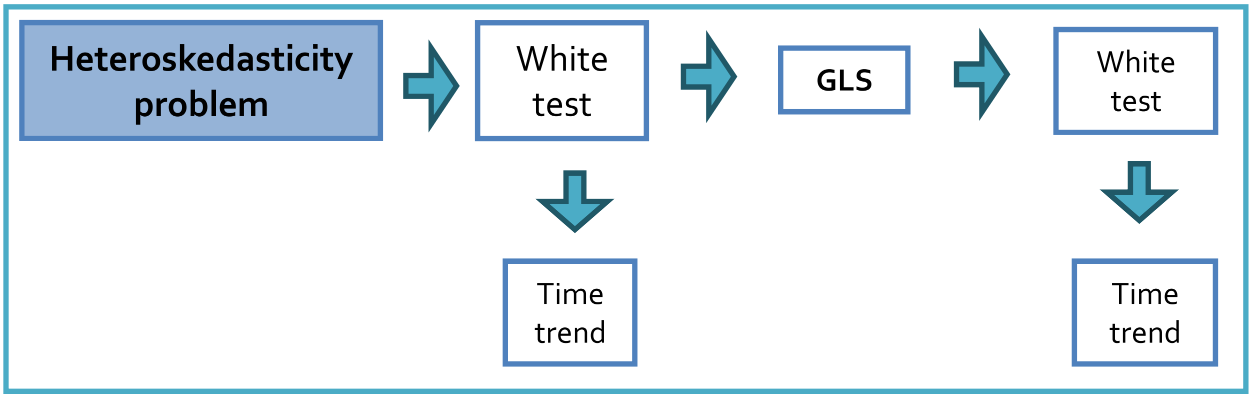

Figure 4.12 Heteroskedasticity analyses of the three data series

4.5.1 Detection of Heteroskedasticity

White tests(White, 1980) were conducted to evaluate whether the de-trended residuals $(\boldsymbol{\widehat{\omega}_1}, \dots, \boldsymbol{\widehat{\omega}_t})$ fulfill the constant variance assumption for each commodity. An auxiliary regression was computed:

$$\boldsymbol{\widehat{\omega}_i^2 = \beta_0 + f(t) + \widehat{v}_i} \qquad \textbf{(5)}$$

in which the dependent variable was the square of the de-trended residuals $\boldsymbol{\widehat{\omega}_i^2}$***(i=1,…,n),*** $\boldsymbol{\beta_0}$ was the intercept**,** the systematic component was the time trend $\{\boldsymbol{f(t)}$**;** i.e., linear, quadratic or cubic}, and $\boldsymbol{\widehat{v}_i}$was the residual of the auxiliary regression. The time trend depended on the behavior of the weekly prices. The R^2 from this auxiliary regression was used to compute the Lagrange Multiplier **(LM):**

$$\boldsymbol{LM = n * R^2 \sim \chi_{p-1}^2} \qquad \textbf{(6)}$$

The null hypothesis (***H₀***) in this test is homoscedasticity.$H_0$is rejected when ***LM*** is greater than the Chi-Square table value at a particular level of significance (in this case, 0.10) and ***(p-1)*** degrees of freedom (White, 1980).

4.5.2 Addressing Heteroskedascity

If $H_0$is rejected, a transformation using GLS was required to address the problem:

$$\boldsymbol{p_t = \psi * y_t = \psi * g(t) + \psi * \widehat{\omega}_t} \qquad \textbf{(7a)}$$

$$\boldsymbol{w_t = \psi * \widehat{\omega}_t} \qquad \textbf{(7b)}$$

where $\boldsymbol{\psi}$ is the appropriate transformation***,*** $\boldsymbol{y_t}$is the original data price, $\boldsymbol{g(t)}$is the appropriate polynomial time trend found in section 4,4,$\boldsymbol{p_t}$is the transformed price and $\boldsymbol{w_t}$is the transformed residual. The White Test was computed again on $\boldsymbol{w_t}$to verify that the behavior of the transformed series fulfill the assumption of constant variance over time. The appropriate transformation for each commodity can be found as discussed in section 5.2.

4.6 The aggregation levels of the commodity data

Figure 4.13 Aggregation levels for the data series

As Figure 4.9 describes, the weekly series of each of the three commodities were aggregated into four different levels: Weekly, monthly, quarterly and annual average prices. For the purpose of comparison, it was assumed that a month was equivalent to four weeks, a quarter equal to three months and a year equal to four quarters. Thus, a total of 12 series of observations were analyzed in the study.

4.7 ARMA models framework

A stationary time series $\boldsymbol{w_t}$ can be expressed as an ARMA process:

$$\boldsymbol{\phi(B)w_t = \theta(B)e_t} \qquad \textbf{(8)}$$

where $\boldsymbol{\phi(B)}$ and $\boldsymbol{\theta(B)}$ are functions of finite polynomials using the back-shift operator *B* and $\boldsymbol{e_T}$ is a white noise process with a constant variance $\boldsymbol{\sigma_w^2}$ (Box and Jenkins, 1976; Pindyck and Rubinfield, 1998). In this case, since $\boldsymbol{w_t}$ is stationary and homoscedastic, an **ARMA (p, q)** model is used instead of an **ARIMA (p, d, q)** model.

4.8 Criteria of selection for the best ARMA models

As shown in the figure 4.9, a total of 600 ARMA (p, q) models were tested over the various levels of aggregation (weekly, monthly, quarterly and annual). This number results from a combination of p x q orders (p=0,1,…,24; q=0,1,…,24). According to Box and Jenkins (1976), as the values of p and q increase, the time series process becomes more complex. Because of this reason, it is anticipated that the weekly models will follow complex ARMA models that could approach p=24 and q=24.

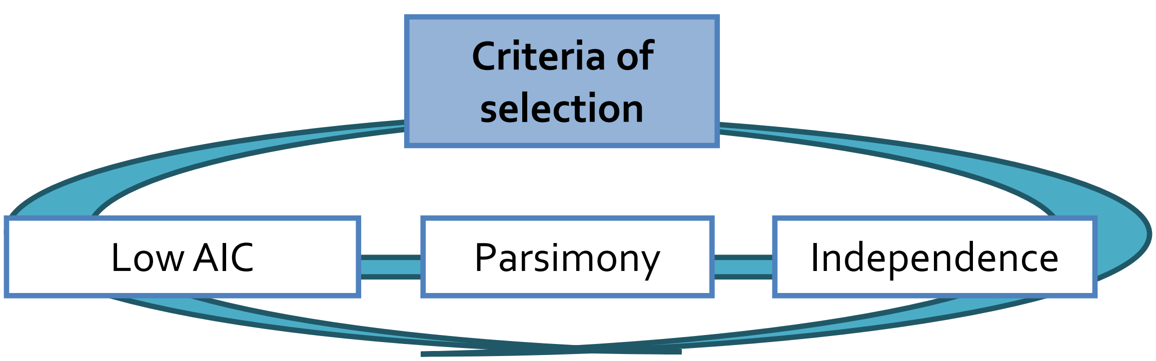

Figure 4.14 Criteria of selection of the true models

When the data are aggregated into monthly, quarterly or annual series, it is likely that ARMA models with lower orders in p and q can be used. In regard to the selection of the appropriate ARMA orders (Figure 4.10), two criteria were combined, while also checking for independence of the error terms:

a) Low AIC (Akaike Information Criterion) defined as:

$$\boldsymbol{AIC = 2k - 2\ln(L)} \qquad \textbf{(10)}$$

where $\boldsymbol{k}$ is the number of parameters ***(k=p+q)*** and $\boldsymbol{L}$ is the maximum value of the likelihood function of the model being evaluated (Akaike, 1973).

b) Parsimony criterion: Models with the least number ***(k)*** of parameters ***(k = p+q)*** (Boehner, 1957; Lewontin, 1970).

Generally the model with the lowest AIC was selected unless there was another much more parsimonious model with only slightly higher AIC and independent residuals (Ramirez, 2011).

Independence: Independence was evaluated by testing for autocorrelation using Ljung-Box Pagan test (Ljung and Box, 1978):

$$\boldsymbol{Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k}} \qquad \textbf{(11)}$$

where **h** is the number of lags and $\boldsymbol{\hat{\rho}_k^2}$is the square autocorrelation between the residuals.

$$\boldsymbol{RR = \{Q > \chi^2_{1-\alpha,\, h}\}} \qquad \textbf{(12)}$$

The rejection region (RR) for this test is when Q has a value greater than a Chi-square with h degrees of freedom, at a desired $\boldsymbol{\alpha}$ level of significance. The null hypothesis (H_0) assumes independence. If its residuals were not independent according to this test, the model couldn't be selected as the best specification (Box and Pierce, 1970; Ljung and Box; 1978).

Thus, the best model was selected according to having one of the lowest AIC values while also being parsimonious and exhibiting independent errors.

4.9 Out-of-Sample Test and MSE as measurement of forecasting efficiency

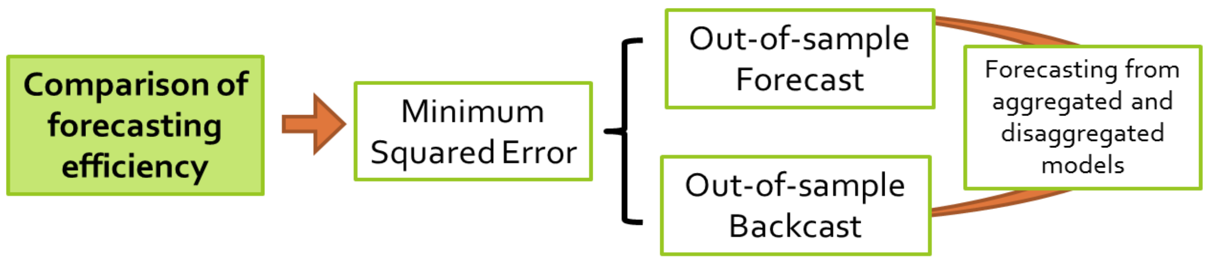

Figure 4.15 Tests for the comparison of forecasting efficiency

The comparison of forecasting efficiencies between two ARMA models was based on the minimum squared errors (MSE) of the models. The MSE of a model is computed as follows:

$$MSE = \frac{\sum_{i=1}^{m}(w_i - \hat{w}_i)^2}{m} \qquad \textbf{(15)}$$

where m is the number of predictions, w_i is the empirical value and $\hat{w}_i$ is the predicted value from the ARMA model. MSE is equal to the mean of the sum squared of the residuals (Amemiya and Wu, 1972; Nijman and Palm, 1990).

Figure 4.16 Forecasting and backcasting comparisons

Two tests were used for the comparison in forecasting efficiency between two ARMA models (Figure 4.11): out-of-sample forecasting and out-of-sample backcasting. For both tests, 960 weekly observations were taken out of the data series.From these 960 observations, a total of 240 monthly, 80 quarterly and 20 annual comparisons were made (Figure 4.12).

In the comparison in forecasting efficiency of the two models, one of them was an aggregated model used to forecast an aggregated value, and the other one was a less aggregated ARMA model used to forecast the same aggregated value. Figure 4.13 illustrates the procedure of how to get the aggregated forecast values from a disaggregated model. In this case, four forecast weeks were averaged to obtain the monthly forecast; the average of three and twelve monthly and weekly predictions, respectively, resulted in a quarterly forecast; and an average of 4, 12 and 48 quarterly, monthly and weekly predictions, respectively, were equal to an annual forecast.

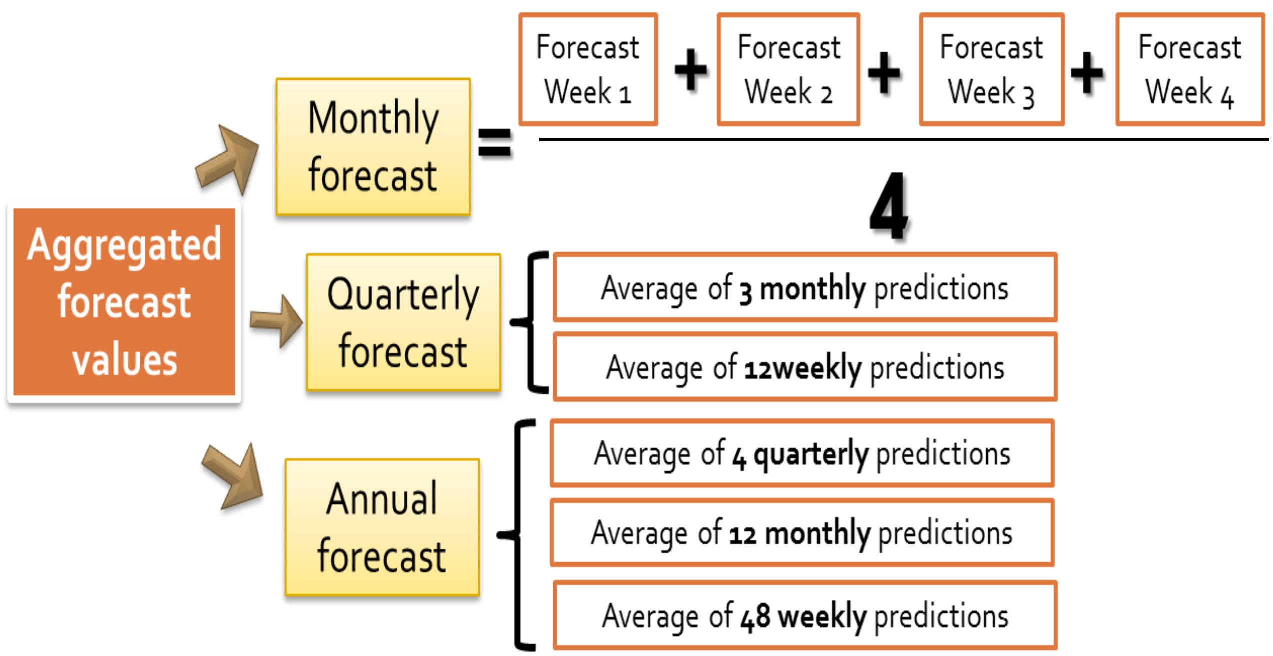

Figure 4.17 Procedure to obtain the aggregated forecast values

Figure 4.14displays the six comparisons made in the out-of-sample forecasting and backcasting tests. The first group of comparisons was made based on the monthly forecasts, where the MSE of the weekly model was compared to the MSE of the monthly model in order to predict the monthly values. The second group of comparisons was based on the efficiency in forecasting quarterly values; the MSE of the quarterly model was compared to the MSE of the weekly and monthly models. The third and last group of comparisons was based on the efficiency in predicting the annual prices; the MSE of the annual model was compared to the MSE of the weekly, monthly and quarterly models.

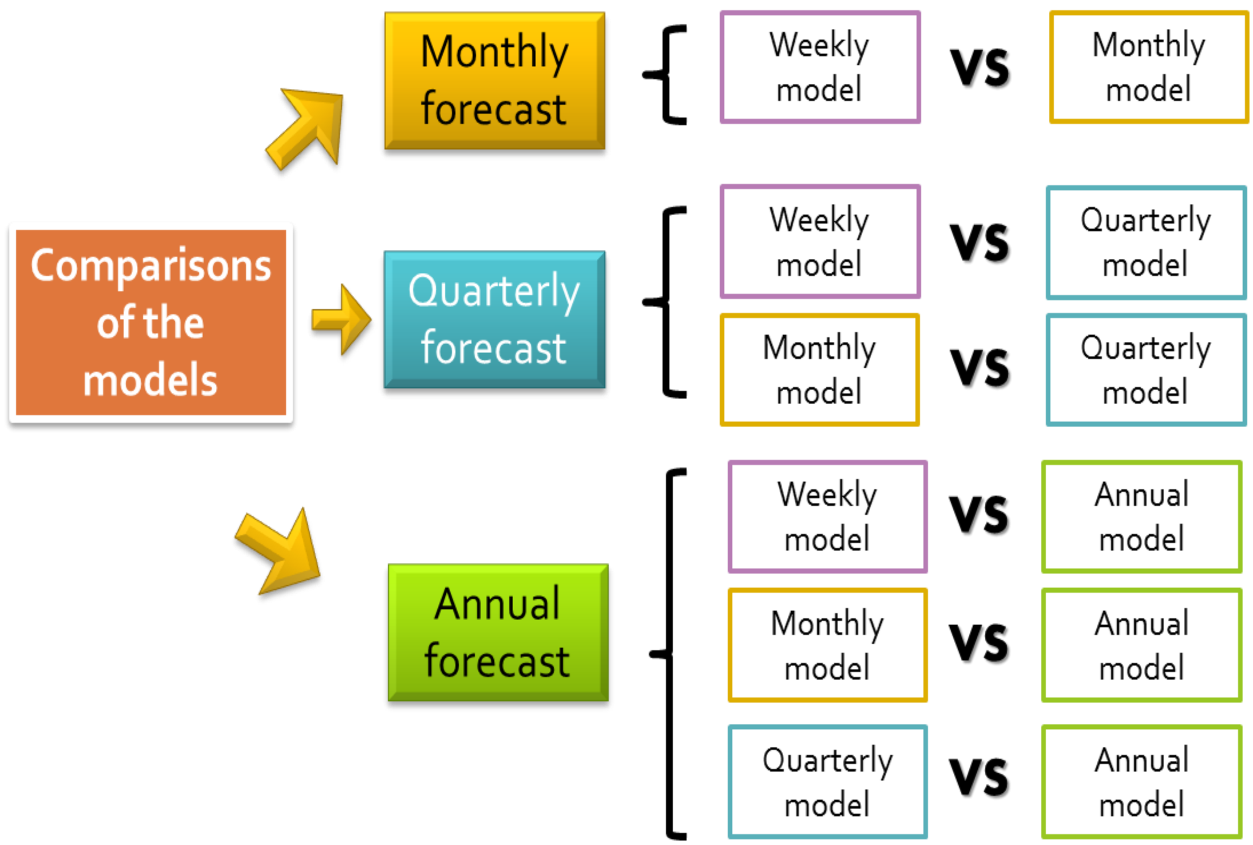

Figure 4.18 Comparisons between two ARMA models based on the MSE

The procedure of the MSE comparison was based on the method developed by Koreisha and Fang (2004) and Ramirez (2012):

$$\%\Delta \boldsymbol{MSE} = \frac{(\boldsymbol{MSE_{dm}} - \boldsymbol{MSE_{am}})}{\boldsymbol{MSE_{am}}} \qquad \textbf{(16)}$$

where $\boldsymbol{MSE_{dm}}$ is the MSE of the disaggregated model, $\boldsymbol{MSE_{am}}$ is the MSE of the aggregated model and $\%\Delta\boldsymbol{MSE}$ is the percent difference between $\boldsymbol{MSE_{dm}}$ and $\boldsymbol{MSE_{am}}$. Therefore, $\%\Delta\boldsymbol{MSE}$ represents the percentage gain or loss in efficiency when an aggregated value is forecasted using a disaggregated model, as opposed to using the corresponding aggregated model.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Unit Root Test Results

Table 1 summarizes the results of the Dickey-Fuller unit root tests. Without any allowance for a time-trend, all commodities appear to have a non-stationary behavior (Phillips-Perron gave similar results). However, when an appropriate polynomial trend is incorporated for each of the three commodities (Ouliaris, Park and Phillips, 1989),all of them show a stationary behavior according to both the unit root tests.

Table 5.1.Dickey-Fuller Unit Root Test Results

Commodity	Dickey-Fuller test before the transformation	Adequate polynomial trend	Dickey-Fuller test after detrending
LIVE CATTLE	-1.98	QUADRATIC	-5.73*
COFFEE	-1.28	CUBIC	-3.40*
COTTON	-1.52	LINEAR	-3.02*

* Reject Ho of a unit root at at a significance level of less than 1%

5.2 White Test Results

Table 5.2 suggests that the three commodities suffer from inter-temporal heteroskedastic problems, with the Lagrange Multiplier test values being very high in all cases. The most likely patterns of heteroskedasticty for live cattle, coffee and cotton prices were determined to be quadratic, linear and linear, respectively.

Interestingly, for all the commodities, the GLS transformation necessary to achieve homoscedasticity was the same. That is, to divide the detrended price values by the reciprocals of the squared residuals from the artificial regression used in the White Test. After this transformation is incorporated, the residuals exhibit a constant variance over time for all of commodities if constant variance is no longer rejected.

Table 5.2 White Test Results and GLS Transformations

Commodity	Lagrange Multiplier: Before GLS Transformation	Behavior	Lagrange Multiplier: After GLS transformation
LIVE CATTLE	480.11	QUADRATIC	0.26*
COFFEE	13.78	LINEAR	4.31**
COTTON	6.59	LINEAR	1.59*

* Ho of homoscedasticity cannot be rejected at the 20% significance level or less.

** Ho of homoskedasticity cannot be rejected at the 1% significance or less.

5.3 Best ARMA models

Tables 5.3, 5.4, 5.5 and 5.6present the best model orders selected for each of the three commodities according to the AIC and parsimony criteria for the weekly, monthly, quarterly and annual aggregation levels. Specifically, they show the order which achieved very low AICs while being reasonably parsimonious and exhibiting independently distributed residuals.

Table 5.3 Best ARMA weekly model order selected for each commodity

Commodity	AIC[1]	P[2]	Q[3]	24[4]	48[4]	96[4]	240[4]	600[4]	P+Q[5]
Live Cattle	-3.0133	12	18	0.9995	0.9987	0.8582	0.2519	0.9604	**30**
Coffee	-6.6678	18	16	0.9999	0.9919	0.9600	0.0553	0.9997	**34**
Cotton	-2.0367	6	4	0.9871	0.9051	0.9414	0.9990	1.0000	**10**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 24, 48, 96, 240, and 600: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table 5.4 Best ARMA monthly model order selected for each commodity

Commodity	AIC[1]	P[2]	Q[3]	12[4]	24[4]	72[4]	120[4]	144[4]	P+Q[5]
Live Cattle	0.2356	12	6	0.9998	1.0000	0.8510	0.9821	0.9919	**18**
Coffee	-0.5235	11	7	0.9999	0.9917	0.8772	0.9918	0.9863	**18**
Cotton	0.0046	2	4	0.9071	0.9772	0.9839	0.9845	0.9996	**6**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 12, 24, 72, 120, and 144: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table 5.5 Best ARMA quarterly model order selected for each commodity

Commodity	AIC[1]	P[2]	Q[3]	4[4]	8[4]	12[4]	24[4]	60[4]	P+Q[5]
Live Cattle	0.4181	5	0	0.9979	0.9979	0.9975	0.7145	0.9071	5
Coffee	0.1401	1	11	0.9975	1.0000	0.9998	0.9973	0.9999	12
Cotton	0.1510	3	0	0.8875	0.5708	0.3967	0.7675	0.9319	3

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 4, 8, 12, 24, and 60: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table 5.6 Best ARMA annual model order selected for each commodity

Commodity	AIC[1]	P[2]	Q[3]	2[4]	4[4]	8[4]	10[4]	12[4]	P+Q[5]
Live Cattle	0.1362	2	0	0.9687	0.9268	0.9731	0.9292	0.9503	2
Coffee	0.1110	1	1	0.9421	0.5766	0.6554	0.6133	0.5968	2
Cotton	0.0743	1	1	0.9977	0.9847	0.9965	0.9884	0.9851	2

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 2, 4, 8, 10, and 12: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

The best-model results for each commodity can be summarized as follows:

- ***Live Cattle:*** ARMA (12, 18) weekly model, ARMA (12, 6) monthly model, AR (5) quarterly model and AR(2) annual model.
- ***Coffee:*** ARMA(18, 16) weekly model, ARMA (11,7) monthly model, ARMA(1,11) quarterly model and ARMA(2,1) annual model.
- ***Cotton:*** ARMA(6, 4) weekly model, ARMA (6,1) monthly model, AR(3) quarterly model and ARMA(1,1) annual model.

From the above results, it is evident that as the data are more aggregated, the orders of the ARMA models become shorter, which is similar to what was observed in Ramirez (2012).Coffee is the commodity with the largest ARMA orders in all the cases closely followed by live cattle. In contrast, cotton prices exhibited much shorted ARMA orders in the weekly, monthly and quarterly models. Likely reasons for these differences can be attributed to: the period of storage that every commodity requires and proportion produced in competitive versus concentrated industries and black swam events that can affect the commodities in a particular period of time.

All the selected ARMA models fulfilled the three previously outlined criteria: having one of the lowest possible AICs as well as low number of parameters (parsimony criteria) and independent error terms (see appendix E through G for details).

5.4 Out-of-sample test results and MSE

Table5.7, 5.8, 5.9, 5.10, 5.11 and 5.12display the results of the one-period-ahead forecasting and backcasting contests for live cattle, cotton and coffee prices, respectively. The comparisons show that:

Live Cattle: There are substantial efficiency gain when using the ARMA (12,18) weekly model to forecast and backcast the quarterly (25% and 46%, respectively) and monthly (15.3% and 28.2%, respectively) prices relative to the quarterly AR (5) and monthly ARMA (12, 6) models.

Likewise, there’s a significant gain in using the ARMA (12,6) monthly model over AR (5) quarterly model for forecasting quarterly prices (18.6% and 38.5%, respectively), which corroborates the results of Ramirez (2012). In short, when forecasting monthly or quarterly prices, the model based on the lowest level of aggregation performs best by a wide margin.

Table 5.7 Out-Of-Sample Forecasting Results for Live Cattle Prices

Model 1 vs. Model 2	MSE Model 1	MSE Model 2	Efficiency difference
W-M vs. M-M[1]	0.03997	0. 04716	**15.25%**
W-Q vs. Q-Q[2]	0.11704	0.15606	**25.01%**
W-A vs. A-A[3]	0. 21819	0. 26076	**16.32%**
M-Q vs. Q-Q[4]	0. 12698	0.15606	**18.63%**
M-A vs. A-A[5]	0. 18616	0. 26076	**28.61%**
Q-A vs. A-A[6]	0. 23039	0. 26076	**11.65%**

Table 5.8 Out-Of-Sample Backcasting Results for Live Cattle Prices

Model 1 vs. Model 2	MSE Model 1	MSE Model 2	Efficiency difference
W-M vs. M-M[1]	0.04568	0.06363	**28.21%**
W-Q vs. Q-Q[2]	0.17333	0.32070	**45.95%**
W-A vs. A-A[3]	0.41193	0.37810	**-8.95%**
M-Q vs. Q-Q[4]	0.19723	0.32070	**38.50%**
M-A vs. A-A[5]	0.39948	0.37810	**-5.66%**
Q-A vs. A-A[6]	0.41039	0.37810	**-8.54%**

W-M vs. M-M refers to a comparison between the MSE of the monthly forecast from the weekly model (MSE Model1) and the MSE of the monthly forecasts from the monthly model (MSE Model 2).
W-Q vs. Q-Q refers to a comparison between the MSE of the quarterly forecast from the weekly model (MSE Model1) and the MSE of the quarterly forecasts from the quarterly model (MSE Model 2).
W-A vs. A-A: refers to a comparison between the MSE of the annual forecast from the weekly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).
M-Q vs. Q-Q refers to a comparison between the MSE of the monthly forecast from the monthly model (MSE Model1) and the MSE of the quarterly forecasts from the quarterly model (MSE Model 2).
M-A vs. A-A refers to a comparison between the MSE of the annual forecast from the monthly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).
Q-A vs. A-A refers to a comparison between the MSE of the annual forecast from the quarterly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).

Table 5.9 Out-of-sample forecasting results for coffee prices

Model 1 vs. Model 2	MSE Model 1	MSE Model 2	Efficiency difference
W-M vs. M-M[1]	0.01312	0.01973	**33.50%**
W-Q vs. Q-Q[2]	0.04205	0.05739	**26.72%**
W-A vs. A-A[3]	0.08650	0.12284	**29.58%**
M-Q vs. Q-Q[4]	0.04329	0.05739	**24.57%**
M-A vs. A-A[5]	0.13592	0.12284	**-10.64%**
Q-A vs. A-A[6]	0.09233	0.12284	**24.84%**

Table 5.10 Out-of-sample backcasting results for coffee prices

Model 1 vs. Model 2	MSE Model 1	MSE Model 2	Efficiency difference
W-M vs. M-M[1]	0.01032	0.01789	**42.30%**
W-Q vs. Q-Q[2]	0.02076	0.04677	**55.61%**
W-A vs. A-A[3]	0.10355	0.16411	**36.90%**
M-Q vs. Q-Q[4]	0.03353	0.04677	**28.32%**
M-A vs. A-A[5]	0.11071	0.16411	**32.54%**
Q-A vs. A-A[6]	0.11340	0.16411	**30.90%**

W-M vs. M-M refers to a comparison between the MSE of the monthly forecast from the weekly model (MSE Model1) and the MSE of the monthly forecasts from the monthly model (MSE Model 2).
W-Q vs. Q-Q refers to a comparison between the MSE of the quarterly forecast from the weekly model (MSE Model1) and the MSE of the quarterly forecasts from the quarterly model (MSE Model 2).
W-A vs. A-A: refers to a comparison between the MSE of the annual forecast from the weekly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).
M-Q vs. Q-Q refers to a comparison between the MSE of the monthly forecast from the monthly model (MSE Model1) and the MSE of the quarterly forecasts from the quarterly model (MSE Model 2).
M-A vs. A-A refers to a comparison between the MSE of the annual forecast from the monthly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).
Q-A vs. A-A refers to a comparison between the MSE of the annual forecast from the quarterly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).

Table 5.11 Out-of-sample forecasting results for cotton prices.

Model 1 vs. Model 2	MSE Model 1	MSE Model 2	Efficiency difference
W-M vs. M-M[1]	0.02709	0.03379	**19.83%**
W-Q vs. Q-Q[2]	0.06082	0.09472	**35.79%**
W-A vs. A-A[3]	0.06686	0.19521	**65.75%**
M-Q vs. Q-Q[4]	0.05379	0.09472	**43.21**
M-A vs. A-A[5]	0.07848	0.19521	**59.80%**
Q-A vs. A-A[6]	0.08885	0.19521	**54.49%**

Table 5.12 Out-of-sample backcasting results for cotton prices.

Model 1 vs. Model 2	MSE Model 1	MSE Model 2	Efficiency difference
W-M vs. M-M[1]	0.05456	0.08295	**34.22%**
W-Q vs. Q-Q[2]	0.10961	0.21502	**49.03%**
W-A vs. A-A[3]	0.29820	0.46946	**36.48%**
M-Q vs. Q-Q[4]	0.12630	0.21502	**41.26%**
M-A vs. A-A[5]	0.33523	0.46946	**28.59%**
Q-A vs. A-A[6]	0.40853	0.46946	**12.98%**

W-M vs. M-M refers to a comparison between the MSE of the monthly forecast from the weekly model (MSE Model1) and the MSE of the monthly forecasts from the monthly model (MSE Model 2).
W-Q vs. Q-Q refers to a comparison between the MSE of the quarterly forecast from the weekly model (MSE Model1) and the MSE of the quarterly forecasts from the quarterly model (MSE Model 2).
W-A vs. A-A: refers to a comparison between the MSE of the annual forecast from the weekly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).
M-Q vs. Q-Q refers to a comparison between the MSE of the monthly forecast from the monthly model (MSE Model1) and the MSE of the quarterly forecasts from the quarterly model (MSE Model 2).
M-A vs. A-A refers to a comparison between the MSE of the annual forecast from the monthly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).
Q-A vs. A-A refers to a comparison between the MSE of the annual forecast from the quarterly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).

In the case of annual forecasts, the evidence from live cattle prices is not that conclusive. When looking at the average between the forecasting and backcasting efficiency comparisons (Table 5.7 and 5.8), the disaggregated model perform better (4% higher efficiency on weekly versus annual, 12% higher on monthly versus annual, and 2% higher on quarterly versus annual), the annual forecast from the annual model exhibit a lower MSE than those from the weekly, monthly and quarterly in the backcasting comparisons (Table 5.8)

The explanation of this lack of conclusiveness is likely due to an insufficient number of observations of annual comparisons. That is, there are only 20 observations available for the annual forecasting and 20 for the back casting comparisons, versus 80 for the quarterly, 240 for the monthly and 960 for the weekly comparisons.

Coffee: Significant gains in efficiency are observed in both the forecasting (table 5.10) and backcasting (table 5.11) comparisons between the ARMA (18,16) weekly model and to the ARMA (11, 7) monthly model (33.5% and 44.2%, respectively), the ARMA (1, 11) quarterly model (26.7% and 55.6%, respectively), and the ARMA (1, 1) annual model (29.5% and 36.9% respectively). That is, the weekly models are much more precise in predicting monthly, quarterly and annual coffee prices than the monthly, quarterly and annual models, respectively.

Similarly high gains are found when comparing the MSE of the forecasts/backcasts from the ARMA (11, 7) monthly model with those from the ARMA (1, 11) quarterly model to predict quarterly prices (24.6% and 28.3%, respectively) and the ARMA (1, 11) quarterly model versus the ARMA (1, 1) annual model when forecasting annual prices (24.8% and 30.9%, respectively). Still, there is one inconsistent result when comparing the efficiency of the annual model forecast, where the MSE of the forecast from the annual model is 10% smaller than that of the monthly model. However, this is reversed on the case of backcasting, where the monthly model is 32% more efficient than the annual model. On average, forecasting and backcasting, the monthly model showed a gain in efficiency by 11% compared to the annual model.

Cotton:In the case of cotton prices ,the efficiency gains using models based on disaggregated versus aggregated data were consistent and substantial in both out-of-sample forecasting (table 5.11) and out-sample backcasting (5.12) contests. For monthly forecasting, the ARMA (6, 4) weekly model showed an efficiency gain of 19.8% (forecasting) and 34.2%, (backcasting) in comparison to the ARMA (2, 4) monthly model. For quarterly forecasting, the said weekly model was 35.8% and 49.0% more efficient than the AR (3) quarterly model and it was 65.7% and 36.5% more accurate than the ARMA (1, 1) annual model to annual forecasting. The results are similarly striking when comparing the quarterly forecasting and backcasting accuracy of the ARMA (2, 4) monthly model with that of the AR (3) quarterly model (43.3% and 41.2% higher) and its annual forecasting precision with that of the ARMA (1, 1) annual model (59.8% and 28.6% higher). Finally the efficiency of the annual forecasts/backcasts from the AR (3) quarterly model is 55% and 13% higher than the ARMA (1, 1) annual cotton price model.

Table 5.13 displays the average gain of forecasting and backcasting results for all three commodities. For the three cases, the efficiency gains are substantial when using weekly models to forecast the monthly and quarterly prices relative to quarterly and monthly models. Similarly high gains are found when comparing on average the MSE of the forecasts from the monthly models with those from the quarterly to predict quarterly prices. Interestingly, on average, there is evidence of efficiency gains in annual forecasts from the monthly and quarterly models with those from the annual model prices. The only case of annual forecast in which the evidence is not that conclusive is the gain in annual forecast when comparing on average the MSE of the weekly models and the annual models; as previously outlined, this is likely due to the insufficient number of observations for the annual comparisons.

In summary, the results for the three commodities are consistent with each other in the fact that a disaggregated model, on average, it is on average preferred because it gives a more efficient forecast, which is consistent with Tiao (1972), Amemiya and Wu (1972), Koreisha and Fang (2004) and Ramirez (2012) studies.

Table 5.13 Average of forecasting and backcasting results for all the three commodities

Model 1 vs. Model 2	Average Efficiency gain in Live Cattle	Average Efficiency gain in Coffee	Average Efficiency gain in Cotton
W-M vs. M-M[1]	21.73%	37.90%	27.02%
W-Q vs. Q-Q[2]	35.48%	41.16%	42.41%
W-A vs. A-A[3]	-8.95%	33.24%	51.11%
M-Q vs. Q-Q[4]	38.50%	26.44%	42.24%
M-A vs. A-A[5]	11.48%	10.95%	44.19%
Q-A vs. A-A[6]	1.55%	27.87%	33.73%

W-M vs. M-M refers to a comparison between the MSE of the monthly forecast from the weekly model (MSE Model1) and the MSE of the monthly forecasts from the monthly model (MSE Model 2).
W-Q vs. Q-Q refers to a comparison between the MSE of the quarterly forecast from the weekly model (MSE Model1) and the MSE of the quarterly forecasts from the quarterly model (MSE Model 2).
W-A vs. A-A: refers to a comparison between the MSE of the annual forecast from the weekly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).
M-Q vs. Q-Q refers to a comparison between the MSE of the monthly forecast from the monthly model (MSE Model1) and the MSE of the quarterly forecasts from the quarterly model (MSE Model 2).
M-A vs. A-A refers to a comparison between the MSE of the annual forecast from the monthly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).
Q-A vs. A-A refers to a comparison between the MSE of the annual forecast from the quarterly model (MSE Model1) and the MSE of the annual forecasts from the annual model (MSE Model 2).

CHAPTER 6

CONCLUSIONS

6.1 Summary and conclusions

Empirical data of three different commodity prices were evaluated in this study: Live cattle, coffee and cotton at closing daily prices. Under the three scenarios, the commodities were subjected to a transformation due to their non-stationary behavior (dependence to the time period) incorporating quadratic, cubic and linear polynomials respectively. Likewise, all the commodities required transformations for ameliorating heteroskedasticity, illustrating the presence of volatility.

The three commodity prices were aggregated into four different levels of aggregation: weekly, monthly, quarterly and annual, with very large samples based on 60 years of historical data in which it was assumed that the true model parameters are known. The models were selected according to AIC and parsimonious criteria in which it was verified that the residuals were independent and identically distributed.

Under the three different scenarios, disaggregation levels effectively provided an efficiency gain in forecasting, and the best models for this, in the three commodities (live cattle, cotton and coffee) were always the weekly models [ARMA (12, 18),ARMA (18, 16) and ARMA (6, 4), respectively]. The same behavior was consistent across all possible levels of aggregations[i.e., monthly models ARMA(12,6),ARMA (11, 7) and ARMA (2, 4), respectively] over the quarterly models [AR (5),ARMA (1, 11) and AR (3), respectively].

Interestingly, in the case of annual forecast the evidence from the commodities prices [from AR (2, 0); ARMA (1, 1) and ARMA (1, 1) respectively] is not that conclusive. One explanation of this lack of conclusiveness is an insufficient number of observations of annual comparisons. That is, there are only 20 observations available for the annual forecasting and 20 for the back casting comparisons, versus 80 for the quarterly, 240 for the monthly and 960 for the weekly comparisons.

The results were consistent with the previous theoretical studies of Tiao (1972), Amemiya and Wu (1972), Koreisha and Fang (2004) using short-order ARMA models. The results were also consistent with the empirical study of Ramirez (2012) in oil prices, bond yields, exchange and federal fund rates. Finally, it can be concluded the efficiency gain for each commodity is markedly different, perhaps due to the specific cyclical behavior and volatility of their prices. That is, each commodity must be tested for its best polynomial trend and aggregation traits, depending on the requirements of the decision(s) to be made from the forecast.

7.2 Implications of the study

This study has important implications in the literature not only in the agribusiness area but in the economic topics. It suggests that it is very valuable to work with the most disaggregated level available to keep a higher level of information and accuracy in the researches.

A practical view of this implication is related to the unemployment forecast given by US. Department of Labor, in which monthly data are used, however, the data are averaged in quarterly observations to be used in a quarterly model (FRED, 2012). This study recommends the use of the monthly data to be used in a monthly model to forecast monthly observations; this modification would lead to better predictions of unemployment rates.

Likewise, this study shows the importance of the averaging orders. This means that if we have disaggregated data we will obtain better predictions when we use a disaggregated model first and then averaging the forecast to get aggregated predictions rather than averaging first the disaggregated data to use it in an aggregated model to obtain aggregated forecast.

7.3 Further research

In this study, the heteroskedasticity issue was addressed using a GLS transformation. However, a better approach will be explored for the commodity prices: The use of Autoregressive Conditional Heteroskedastic (ARCH) models to evaluate and correct the non-constant variance problem.

On the other hand, this study will be expanded to analyze the commodity prices using the most disaggregated level of the dataset: Daily prices. This new aggregation level will let to confirm or reject the conclusions of the study. The methodology to determine the daily models will follow the new methodology in which the ARCH models will be incorporated.

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APPENDIX A:

RESULTS OF THE UNIT ROOT TESTS FOR THE THREE COMMODITIES' ADJUSTED PRICES WITHOUT ANY TRANSFORMATION

Table A.1. Augmented Dickey-Fuller UNIT ROOT Test for Live Cattle Prices

		Critical Values					
	ADF Stat[1]	1%	5%	10%	90%	95%	99%
No Intercept	**-1.9849**	-2.5836	-1.9573	-1.6311	0.9031	1.2861	2.0061
Intercept	**-3.2224**	-3.4583	-2.8710	-2.5937	-0.4516	-0.1060	0.5367
Intercept and Time Trend	**-5.7647**	-3.9978	-3.4318	-3.1617	-1.2603	-0.9563	-0.3057

[1]ADF stat: Augmented Dickey-Fuller Statistics

Table A.2. Phillips-Perron UNIT ROOT Test for Live Cattle Prices

	PPt[1]	1%	5%
No Intercept	**-2.1390**	-2.5836	-1.9573
Intercept	**-3.3713**	-3.4583	-2.8710
Intercept and Time Trend	**-6.0225**	-3.9978	-3.4318

[1]PPt: Phillips-Perron statistic value

Table A.3 Augmented Dickey-Fuller UNIT ROOT Test for coffee prices

	Critical Values						
	ADF Stat [1]	1%	5%	10%	90%	95%	99%
No Intercept	**-1.2795**	-2.5836	-1.9573	-1.6311	0.9031	1.2861	2.0061
Intercept	**-2.5280**	-3.4583	-2.8710	-2.5937	-0.4516	-0.1060	0.5367
Intercept and Time Trend	**-3.5265**	-3.9978	-3.4318	-3.1617	-1.2603	-0.9563	-0.3057

[1]ADF stat: Augmented Dickey-Fuller Statistics

Table A.4 Phillips-Perron UNIT ROOT Test for coffee prices

	PPt[1]	1%	5%
No Intercept	**-1.8795**	-2.5836	-1.9573
Intercept	**-2.4695**	-3.4583	-2.8710
Intercept and Time Trend	**-3.4568**	-3.9978	-3.4318

[1]PPt: Phillips-Perron statistic value

Table A.5 Augmented Dickey-Fuller UNIT ROOT Test for cotton prices

	Critical Values						
	ADF Stat[1]	**1%**	**5%**	**10%**	**90%**	**95%**	**99%**
No Intercept	**-1.5210**	-2.5836	-1.9573	-1.6311	0.9031	1.2861	2.0061
Intercept	**-2.6900**	-3.4583	-2.8710	-2.5937	-0.4516	-0.1060	0.5367
Intercept and Time Trend	**-3.0127**	-3.9978	-3.4318	-3.1617	-1.2603	-0.9563	-0.3057

[1]ADF stat: Augmented Dickey-Fuller Statistics

Phillips-Perron UNIT ROOT Test for

	PPt	**1%**	**5%**
No Intercept	**-1.5447**	-2.5836	-1.9573
Intercept	**-2.6051**	-3.4583	-2.8710
Intercept and Time Trend	**-2.9242**	-3.9978	-3.4318

[1]PPt: Phillips-Perron statistic value

APPENDIX B:

RESULTS OF THE ANALYSIS FOR THE POLYNOMIAL TREND FOR THE THREE COMMODITIES

Table B.1. Live cattle polynomial trend results

Description	Coefficient	St.Dev.[1]	t value
Intercept	174.034040,	2.153333,	***80.820765,***
Linear	-0.012091,	0.000515,	***-23.474129,***
Second degree	-19420.624473,	692.344674,	***-28.050515,***

[1]St. Dev: Standard deviation

Table B.2. Coffee polynomial trend results

Description	Coefficient	St.Dev.[1]	t value
Intercept	131.718857,	16.448697,	***8.007860,***
Linear	-0.044526,	0.007587,	***-5.868954,***
Second degree	25749.843952,	5983.422001,	***4.303531,***
Third degree	-0.000279,	0.000041,	***-6.864441,***

[1]St. Dev: Standard deviation

Table B.3 Cotton polynomial trend results

Description	Coefficient	St.Dev.[1]	t value
Intercept	71.833752,	0.631557,	***113.740710,***
Linear	-0.030517,	0.000651,	***-46.888506,***

[1]St. Dev: Standard deviation

APPENDIX C:

RESULTS OF THE UNIT ROOT TESTS FOR THE THREE COMMODITIES ADJUSTED PRICES INCORPORATING THE POLYNOMIAL TREND EFFECTS

Table C.1. Augmented Dickey-Fuller UNIT ROOT Test for live cattle prices

		Critical Values					
	ADF Stat[1]	1%	5%	10%	90%	95%	99%
No Intercept	**-5.7313**	-2.5836	-1.9573	-1.6311	0.9031	1.2861	2.0061
Intercept	**-5.7304**	-3.4583	-2.8710	-2.5937	-0.4516	-0.1060	0.5367
Intercept and Time Trend	**-5.7294**	-3.9978	-3.4318	-3.1617	-1.2603	-0.9563	-0.3057

[1]ADF stat: Augmented Dickey-Fuller Statistics

Table C.2. Phillips-Perron UNIT ROOT Test for live cattle prices

	PPt[1]	1%	5%
No Intercept	-6.5466	-2.5836	-1.9573
Intercept	-5.8845	-3.4583	-2.8710
Intercept and Time Trend	-5.8833	-3.9978	-3.4318

[1]PPt: Phillips-Perron statistic value

Table C.3. Augmented Dickey-Fuller UNIT ROOT Test for coffee prices

		Critical Values					
	ADF Stat[1]	1%	5%	10%	90%	95%	99%
No Intercept	**-3.4024**	-2.5836	-1.9573	-1.6311	0.9031	1.2861	2.0061
Intercept	**-3.4018**	-3.4583	-2.8710	-2.5937	-0.4516	-0.1060	0.5367
Intercept and Time Trend	**-3.4011**	-3.9978	-3.4318	-3.1617	-1.2603	-0.9563	-0.3057

[1] ADF stat: Augmented Dickey-Fuller Statistics

Table C.4. Phillips-Perron UNIT ROOT Test for coffee prices

	PPt[1]	1%	5%
No Intercept	-5.1212	-2.5836	-1.9573
Intercept	-3.3184	-3.4583	-2.8710
Intercept and Time Trend	-3.3180	-3.9978	-3.4318

[1] PPt: Phillips-Perron statistic value

Table C.5 Augmented Dickey-Fuller UNIT ROOT Test for cotton prices

		Critical Values					
	ADF Stat[1]	1%	5%	10%	90%	95%	99%
No Intercept	**-3.0172**	-2.5836	-1.9573	-1.6311	0.9031	1.2861	2.0061
Intercept	**-3.0160**	-3.4583	-2.8710	-2.5937	-0.4516	-0.1060	0.5367
Intercept and Time Trend	**-3.0127**	-3.9978	-3.4318	-3.1617	-1.2603	-0.9563	-0.3057

[1]ADF stat: Augmented Dickey-Fuller Statistics

Table C.6 Phillips-Perron UNIT ROOT Test for cotton prices

	PPt[1]	1%	5%
No Intercept	**-3.2060**	-2.5836	-1.9573
Intercept	**-2.9325**	-3.4583	-2.8710
Intercept and Time Trend	**-2.9242**	-3.9978	-3.4318

[1]PPt: Phillips-Perron statistic value

APPENDIX D:

RESULTS OF THE WHITE TEST FOR THE THREE COMMODITIES

Table D.1. White test results for live cattle prices

Description	Chi-Square Value	P-value
Before the transformation	480.107140	0.000000
After the transformation	0.263827	0.876417

Table D.2. White test results for coffee prices

Description	Chi-Square Value	P-value
Before the transformation	13.789464	0.000204
After the transformation	4.305398	0.037992

Table D.3. White test results for cotton prices

Description	Chi-Square Value	P-value
Before the transformation	6.590673	0.010251
After the transformation	1.591034	0.207178

APPENDIX E:

RESULTS FROM THE ARMA MODELSELECTION FOR LIVE CATTLE PRICES

Table E.1 Best 15 ARMA weekly models sort by AIC criterion

AIC[1]	P[2]	Q[3]	24[4]	48[4]	96[4]	240[4]	600[4]	P+Q[5]
-3.0142	22	16	1.0000	0.9999	0.8996	0.2932	0.9788	**38**
-3.0133	**12**	**18**	**0.9995**	**0.9987**	**0.8582**	**0.2519**	**0.9604**	**30**
-3.0122	15	21	1.0000	1.0000	0.9707	0.3914	0.9844	**36**
-3.0115	21	21	1.0000	1.0000	0.9978	0.6884	0.9983	**42**
-3.0113	20	21	1.0000	0.9999	0.9029	0.3276	0.9937	**41**
-3.0100	17	21	1.0000	1.0000	0.9652	0.3773	0.9837	**38**
-3.0091	22	23	1.0000	1.0000	0.9979	0.8004	0.9995	**45**
-3.0080	19	11	1.0000	0.9997	0.7969	0.1608	0.9361	**30**
-3.0076	14	18	0.9999	0.9999	0.7440	0.1284	0.9274	**32**
-3.0065	14	21	0.9999	0.9983	0.8933	0.339	0.9781	**35**
-3.0063	21	15	1.0000	0.9996	0.8727	0.1892	0.9598	**36**
-3.0060	19	12	1.0000	0.9999	0.8483	0.1652	0.9394	**31**
-3.0059	20	11	1.0000	0.9999	0.8472	0.1682	0.9398	**31**
-3.0056	21	13	1.0000	0.9996	0.8711	0.1763	0.9492	**34**
-3.0047	20	12	1.0000	0.9999	0.8699	0.1897	0.9502	**32**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 24, 48, 96, 240, 600: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table E.2 Best 15 ARMA monthly models sort by AIC criterion

AIC[1]	P[2]	Q[3]	12[4]	24[4]	72[4]	120[4]	144[4]	P+Q[5]
0.2356	**12**	**6**	**0.9998**	**1.0000**	**0.8510**	**0.9821**	**0.9919**	**18**
0.2360	11	8	1.0000	0.9997	0.6777	0.9374	0.9551	**19**
0.2377	13	8	0.9998	1.0000	0.8034	0.9722	0.9892	**21**
0.2378	9	10	1.0000	0.9989	0.5334	0.8851	0.9420	**19**
0.2388	13	6	0.9999	1.0000	0.8474	0.9790	0.9895	**19**
0.2388	16	19	1.0000	1.0000	0.9858	0.9995	0.9998	**35**
0.2395	9	12	0.9999	1.0000	0.8664	0.9874	0.9937	**21**
0.2401	12	13	0.9998	1.0000	0.9098	0.9930	0.9973	**25**
0.2402	20	16	1.0000	1.0000	0.9969	0.9997	0.9999	**36**
0.2405	10	12	1.0000	1.0000	0.8542	0.9891	0.9949	**22**
0.2406	11	7	0.9998	1.0000	0.7561	0.9515	0.9810	**18**
0.2406	13	7	0.9999	1.0000	0.8275	0.9759	0.9889	**20**
0.2407	15	9	0.9948	1.0000	0.8835	0.9884	0.9957	**24**
0.2409	14	7	1.0000	1.0000	0.8432	0.9787	0.9893	**21**
0.2410	13	9	1.0000	1.0000	0.8440	0.9847	0.9929	**22**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 12, 24, 72, 120, 144: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table E.3 Best 15 ARMA quarterly models sort by AIC criterion

AIC[1]	P[2]	Q[3]	4[4]	8[4]	12[4]	24[4]	60[4]	P+Q[5]
0.4166	7	2	0.9992	1.0000	1.0000	0.9816	0.9672	**9**
0.4180	1	4	0.9987	0.9993	0.9991	0.8291	0.9366	**5**
0.4181	**5**	**0**	**0.9979**	**0.9979**	**0.9975**	**0.7145**	**0.9071**	**5**
0.4195	5	1	0.9998	0.9998	0.9996	0.7882	0.9428	**6**
0.4196	6	0	0.9998	0.9997	0.9995	0.7695	0.9383	**6**
0.4197	1	5	0.9998	0.9992	0.9997	0.8482	0.9397	**6**
0.4198	2	4	0.9996	0.9992	0.9996	0.8446	0.9394	**6**
0.4202	9	3	0.9994	1.0000	0.9998	0.9988	0.9942	**12**
0.4206	6	6	0.9999	1.0000	0.9999	0.9967	0.9930	**12**
0.4207	4	2	0.9561	0.9944	0.9971	0.8264	0.9235	**6**
0.4212	1	6	1.0000	1.0000	0.9999	0.8462	0.9349	**7**
0.4212	3	4	1.0000	1.0000	0.9999	0.8448	0.9367	**7**
0.4214	7	0	0.9998	1.0000	0.9998	0.8160	0.9459	**7**
0.4215	2	5	0.9999	0.9995	0.9998	0.8494	0.9377	**7**
0.4215	5	2	0.9998	0.9998	0.9996	0.7881	0.9428	**7**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 4, 8, 12, 24, 60: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table E.4 Best 15 ARMA annual models sort by AIC criterion

AIC[1]	P[2]	Q[3]	2[4]	4[4]	8[4]	10[4]	12[4]	P+Q[5]
0.1361	1	1	0.9984	0.9641	0.9841	0.9607	0.9742	**2**
0.1362	**2**	**0**	**0.9687**	**0.9268**	**0.9731**	**0.9292**	**0.9503**	**2**
0.1374	1	0	0.3044	0.5573	0.7652	0.7673	0.8336	**1**
0.1379	1	2	0.9982	0.9638	0.9866	0.9505	0.9658	**3**
0.1379	3	0	0.9917	0.9765	0.9882	0.9644	0.9762	**3**
0.1380	2	1	0.9997	0.9612	0.9841	0.9546	0.9694	**3**
0.1386	3	3	0.7851	0.8985	0.9863	0.9879	0.9966	**6**
0.1386	4	2	0.9322	0.9907	0.9991	0.9963	0.9989	**6**
0.1392	3	4	0.9848	0.995	0.999	0.9947	0.9984	**7**
0.1394	5	2	0.9524	0.9956	0.9969	0.9943	0.9985	**7**
0.1395	1	3	0.9981	0.9987	0.9972	0.9746	0.9805	**4**
0.1397	2	2	0.9975	0.9892	0.9922	0.958	0.9692	**4**
0.1398	3	1	0.9974	0.9812	0.9888	0.9635	0.9737	**4**
0.1398	4	0	0.9994	0.9908	0.9905	0.9652	0.9755	**4**
0.1399	4	3	0.8529	0.9685	0.9958	0.9928	0.9979	**7**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 2, 4, 8, 10, 12: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

APPENDIX F:

RESULTS FROM THE ARMA MODEL SELECTION FOR COFFEE PRICES

Table F.1 Best 15 ARMA weekly models sort by AIC

AIC[1]	P[2]	Q[3]	24[4]	48[4]	96[4]	240[4]	600[4]	P+Q[5]
-6.6732	22	24	1.0000	1.0000	1.0000	0.2795	1.0000	46
-6.6702	24	24	1.0000	1.0000	0.9999	0.4045	1.0000	48
-6.6699	24	21	1.0000	1.0000	0.9998	0.4569	1.0000	45
-6.6692	21	24	1.0000	1.0000	0.9996	0.2730	1.0000	45
-6.6692	22	22	1.0000	1.0000	0.9998	0.3148	1.0000	44
-6.6692	23	21	1.0000	1.0000	0.9998	0.3147	1.0000	44
-6.6684	19	20	1.0000	0.9997	0.9992	0.2191	1.0000	39
-6.6678	**18**	**16**	**0.9999**	**0.9919**	**0.9600**	**0.0553**	**0.9997**	**34**
-6.6677	21	19	1.0000	1.0000	0.9984	0.1926	1.0000	40
-6.6674	17	17	1.0000	0.9931	0.9560	0.0563	0.9997	34
-6.6673	22	23	1.0000	1.0000	0.9999	0.3011	1.0000	45
-6.6671	19	21	1.0000	1.0000	0.9998	0.2125	1.0000	40
-6.6668	22	19	1.0000	1.0000	0.9995	0.2127	1.0000	41
-6.6668	22	20	1.0000	0.9999	0.9972	0.2094	1.0000	42
-6.6667	21	20	1.0000	1.0000	0.9995	0.2094	1.0000	41

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 24, 48, 96, 240, 600: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table F.2 Best 15 ARMA monthly models sort by AIC criterion

AIC[1]	P[2]	Q[3]	24[4]	48[4]	72[4]	120[4]	144[4]	P+Q[5]
-0.5298	9	15	1.0000	1.0000	0.9947	0.9998	0.9995	24
-0.5261	10	7	1.0000	0.9935	0.8862	0.9924	0.9875	17
-0.5256	8	9	1.0000	0.9953	0.8965	0.9930	0.9913	17
-0.5247	11	19	1.0000	1.0000	0.9995	1.0000	1.0000	30
-0.5241	10	8	1.0000	0.9944	0.8900	0.9926	0.9879	18
-0.5235	**11**	**7**	**0.9999**	**0.9917**	**0.8772**	**0.9918**	**0.9863**	**18**
-0.5233	10	15	1.0000	1.0000	0.9925	0.9998	0.9997	25
-0.5229	11	8	1.0000	0.9903	0.8836	0.9911	0.9845	19
-0.5227	11	12	1.0000	0.9996	0.9814	0.9992	0.9989	23
-0.5226	10	17	1.0000	1.0000	0.9979	0.9999	0.9998	27
-0.5223	10	9	0.9997	0.9854	0.8729	0.9906	0.9850	19
-0.5222	16	15	0.9999	1.0000	0.9994	1.0000	1.0000	31
-0.5221	12	7	1.0000	0.9935	0.8868	0.9926	0.9884	19
-0.5218	10	16	1.0000	0.9999	0.9981	0.9999	0.9998	26
-0.5217	7	11	1.0000	0.9998	0.9349	0.9970	0.9960	18

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 12, 24, 72, 120, 144: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table F.3 Best 15 ARMA quarterly models sort by AIC criterion

AIC[1]	P[2]	Q[3]	4[4]	8[4]	12[4]	24[4]	60[4]	P+Q[5]
0.1401	**1**	**11**	**0.9975**	**1.0000**	**0.9998**	**0.9973**	**0.9999**	**12**
0.1404	3	12	0.9999	1.0000	1.0000	1.0000	1.0000	**15**
0.1405	3	11	0.9985	1.0000	1.0000	1.0000	1.0000	**14**
0.1406	2	11	0.9986	1.0000	1.0000	0.9996	0.9999	**13**
0.1406	4	11	0.9995	1.0000	1.0000	1.0000	1.0000	**15**
0.1412	1	13	0.9971	1.0000	1.0000	0.9999	1.0000	**14**
0.1418	1	12	0.9977	1.0000	1.0000	0.9983	0.9999	**13**
0.1418	2	12	0.9995	1.0000	1.0000	0.9998	1.0000	**14**
0.1419	2	13	0.9993	1.0000	1.0000	0.9999	1.0000	**15**
0.1423	2	14	0.9978	1.0000	1.0000	0.9999	1.0000	**16**
0.1424	3	13	0.9999	1.0000	1.0000	1.0000	1.0000	**16**
0.1424	4	12	0.9999	1.0000	1.0000	1.0000	1.0000	**16**
0.1425	5	11	0.9998	1.0000	1.0000	1.0000	1.0000	**16**
0.1428	5	13	0.9945	1.0000	1.0000	1.0000	1.0000	**18**
0.1432	1	14	0.9972	1.0000	1.0000	0.9999	1.0000	**15**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 4, 8, 12, 24, 60: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table F.4 Best 15 ARMA annual models sort by AIC criterion

AIC[1]	P[2]	Q[3]	2[4]	4[4]	8[4]	10[4]	12[4]	P+Q[5]
0.1102	4	0	0.9982	0.9997	0.9619	0.9300	0.8947	**4**
0.1110	**1**	**1**	**0.9421**	**0.5766**	**0.6554**	**0.6133**	**0.5968**	**2**
0.1113	2	1	0.9991	0.8698	0.8218	0.7802	0.8116	**3**
0.1116	2	3	0.9399	0.9622	0.9964	0.9944	0.9669	**5**
0.1117	1	2	0.9558	0.8715	0.8033	0.7592	0.7926	**3**
0.1120	4	1	0.9964	0.9979	0.9779	0.9404	0.9054	**5**
0.1120	5	0	0.9964	0.9977	0.9767	0.9393	0.8994	**5**
0.1124	1	4	0.9760	0.9948	0.9845	0.9720	0.9754	**5**
0.1124	6	3	0.9903	0.9938	0.9986	0.9982	0.9973	**9**
0.1125	1	3	0.9433	0.9054	0.8768	0.8493	0.8800	**4**
0.1127	1	5	0.9915	0.9972	0.9997	0.9848	0.9752	**6**
0.1129	6	2	0.8378	0.9629	0.9950	0.9951	0.9944	**8**
0.1130	2	4	0.9955	0.9994	0.9984	0.9953	0.9828	**6**
0.1131	3	3	0.9919	0.9985	0.9981	0.9941	0.9838	**6**
0.1132	3	1	0.9646	0.9259	0.8357	0.7986	0.8405	**4**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 2, 4, 8, 10, 12: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

APPENDIX G:

RESULTS OF THE ARMA MODELS FOR COTTON PRICES

Table F.1 Best 15 ARMA weekly models sort by AIC

AIC[1]	P[2]	Q[3]	24[4]	48[4]	96[4]	300[4]	600[4]	P+Q[5]
-2.0411	6	16	1.0000	0.9997	0.9994	0.9999	1.0000	**22**
-2.0401	17	5	1.0000	0.9993	0.9984	0.9999	1.0000	**22**
-2.0398	7	16	1.0000	0.9998	0.9995	0.9999	1.0000	**23**
-2.0395	7	17	1.0000	0.9999	0.9996	1.0000	1.0000	**24**
-2.0393	5	18	1.0000	0.9997	0.9993	0.9999	1.0000	**23**
-2.0392	5	17	1.0000	0.9989	0.9980	0.9999	1.0000	**22**
-2.0384	8	16	1.0000	0.9998	0.9997	1.0000	1.0000	**24**
-2.0383	12	14	1.0000	0.9834	0.9887	0.9992	1.0000	**26**
-2.0383	17	6	1.0000	0.9993	0.9986	0.9999	1.0000	**23**
-2.0381	19	8	1.0000	1.0000	0.9998	1.0000	1.0000	**27**
-2.0367	5	6	0.9855	0.8711	0.9272	0.9993	1.0000	**11**
-2.0367	**6**	**4**	**0.9871**	**0.9051**	**0.9414**	**0.9990**	**1.0000**	**10**
-2.0364	9	16	1.0000	0.9998	0.9997	1.0000	1.0000	**25**
-2.0363	16	11	1.0000	0.9901	0.9925	0.9994	1.0000	**27**
-2.0361	11	6	0.9969	0.9903	0.9929	0.9998	1.0000	**17**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 24, 48, 96, 240, 600: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table G.2 Best 15 ARMA monthly models sort by AIC criterion

AIC[1]	P[2]	Q[3]	12[4]	24[4]	72[4]	120[4]	144[4]	P+Q[5]
0.0046	**2**	**4**	**0.9071**	**0.9772**	**0.9839**	**0.9845**	**0.9996**	**6**
0.0048	4	4	0.9988	0.9956	0.9915	0.9936	0.9999	**8**
0.0048	7	6	0.9962	0.9990	0.9984	0.9986	1.0000	**13**
0.0060	6	1	0.9789	0.9908	0.9893	0.9908	0.9998	**7**
0.0062	7	3	0.9993	0.9985	0.9913	0.9927	0.9999	**10**
0.0068	4	5	0.9990	0.9958	0.9918	0.9939	0.9999	**9**
0.0068	5	4	0.9990	0.9960	0.9919	0.9940	0.9999	**9**
0.0071	9	8	1.0000	1.0000	0.9999	0.9999	1.0000	**17**
0.0074	6	4	0.9985	0.9988	0.9963	0.9961	1.0000	**10**
0.0076	3	5	0.9773	0.9924	0.9899	0.9908	0.9998	**8**
0.0077	6	2	0.9886	0.9918	0.9922	0.9939	0.9999	**8**
0.0078	7	1	0.9868	0.9917	0.9914	0.9935	0.9999	**8**
0.0082	8	3	0.9988	0.9988	0.9947	0.9952	0.9999	**11**
0.0083	8	6	0.9963	0.9965	0.9975	0.9961	1.0000	**14**
0.0084	7	7	0.9982	0.9937	0.9952	0.9964	1.0000	**14**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 12, 24, 72, 120, 144: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table G.3 Best 15 ARMA quarterly models sort by AIC criterion

AIC[1]	P[2]	Q[3]	4[4]	8[4]	12[4]	24[4]	60[4]	P+Q[5]
0.1467	2	2	0.887	0.8502	0.677	0.8887	0.982	**4**
0.1487	2	3	0.889	0.8553	0.6837	0.8927	0.9826	**5**
0.1487	3	2	0.8884	0.8558	0.6863	0.894	0.983	**5**
0.1493	1	1	0.6281	0.4737	0.3496	0.692	0.9106	**2**
0.1498	3	3	0.9379	0.7694	0.7196	0.9589	0.9863	**6**
0.1500	7	3	0.8489	0.9799	0.9984	0.9995	0.9999	**10**
0.1504	4	2	0.9938	0.8746	0.8614	0.9786	0.9923	**6**
0.1507	4	5	0.9944	0.954	0.95	0.996	0.9985	**9**
0.1510	**3**	**0**	**0.8875**	**0.5708**	**0.3967**	**0.7675**	**0.9319**	**3**
0.1511	1	2	0.6813	0.5317	0.366	0.7136	0.9127	**3**
0.1511	5	4	0.9953	0.9445	0.9479	0.9951	0.9977	**9**
0.1512	2	1	0.6541	0.5059	0.3574	0.7025	0.911	**3**
0.1513	7	7	0.9963	0.9986	0.9714	0.978	0.9993	**14**
0.1514	3	4	0.9906	0.8191	0.8305	0.9754	0.9919	**7**
0.1514	6	6	0.9998	0.9997	0.9773	0.9814	0.9948	**12**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 4, 8, 12, 24, 60: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

Table G.4 Best 15 ARMA annual models sort by AIC criterion

AIC[1]	P[2]	Q[3]	2[4]	4[4]	6[4]	10[4]	12[4]	P+Q[5]
0.0743	**1**	**1**	**0.9977**	**0.9847**	**0.9965**	**0.9884**	**0.9851**	**2**
0.0762	1	2	0.9607	0.9847	0.9963	0.9808	0.9720	**3**
0.0763	2	1	0.9830	0.9858	0.9966	0.9843	0.9791	**3**
0.0777	3	1	0.8618	0.9864	0.9982	0.9643	0.9235	**4**
0.0782	1	3	0.9809	0.9864	0.9969	0.9854	0.9785	**4**
0.0782	2	2	0.9513	0.9841	0.9961	0.9793	0.9697	**4**
0.0786	4	0	0.9993	0.9364	0.9791	0.9323	0.9066	**4**
0.0796	3	0	0.8854	0.6767	0.8860	0.8893	0.8756	**3**
0.0796	4	1	0.8861	0.9931	0.9992	0.9884	0.9731	**5**
0.0797	3	2	0.8644	0.9865	0.9982	0.9688	0.9315	**5**
0.0799	1	4	1.0000	0.9866	0.9978	0.9944	0.9856	**5**
0.0799	3	3	0.9623	0.9992	0.9999	0.9970	0.9783	**6**
0.0801	2	4	0.9181	0.9829	0.9968	0.9879	0.9729	**6**
0.0802	2	3	0.7741	0.9367	0.9861	0.9810	0.9600	**5**
0.0806	4	2	0.7011	0.9350	0.9893	0.9628	0.8949	**6**

[1] AIC = Akaike Criterion
[2] P = Autoregressive component
[3] Q = Moving average component
[4] 2, 4, 8, 10, 12: P-value for Box-Pierce autocorrelation test at the correspondent lag.
[5] P+Q = Parsimony criterion

APPENDIX H:

COEFFICIENTS OF THE ARMA MODELS SELECTED FOR LIVE CATTLE PRICES

Table H.1 Coefficients for ARMA(12,18) weekly model for live cattle prices

0.21090	0.94829	0.88023	-0.06075	-0.41248	-0.71331	-0.61708	-0.38344
0.59765	0.92047	0.42649	-0.80093	-0.94567	0.02082	1.04250	1.09046
0.70619	0.00730	-0.72141	-1.23570	-0.72880	0.28477	0.83660	0.11611
0.04782	0.06469	0.00793	-0.02184	0.01750	0.06130		

Table H.2 Coefficients for ARMA (12, 6) monthly model for live cattle prices

1.43036	-1.99514	2.00964	-2.03475	2.07870	-1.70565	1.19984	-0.37632
0.12697	-0.02761	0.01855	0.11498	0.11954	-1.44265	0.09370	-1.28256
0.32845	-0.76380						

Table H.3 Coefficients for AR (5) quarterly model for live cattle prices

0.88569	-0.15988	0.07280	0.26394	-0.21461

Table H.4 Coefficients for AR (2) annually model for live cattle prices

0.84439	-0.22036

APPENDIX I:

COEFFICIENTS OF THE ARMA MODELS SELECTED FOR COFFEE PRICES

Table I.1 Coefficients for ARMA (18, 16) weekly model for coffee prices

2.37945	-2.07158	1.06972	-1.09025	1.79101	-2.02812	1.77859	-1.76174
1.69573	-1.76837	2.39848	-2.24059	1.04359	-0.50882	1.04529	-1.44243
0.81777	-0.10977	1.08907	-0.34662	0.24725	-0.60462	0.85613	-0.68650
0.66856	-0.79787	0.56498	-0.86558	1.10750	-0.48971	0.06688	-0.30393
0.71580	-0.61615						

Table I.2 Coefficients for ARMA (11, 7) monthly model for coffee prices

1.33255	-0.82757	0.31853	-0.09480	0.13425	-0.10974	-0.28331	0.46471
0.13717	-0.15257	0.01318	0.03549	-0.47810	-0.36209	-0.29524	-0.13951
-0.22840	-0.59982						

Table I.3 Coefficients for ARMA (1, 11) quarterly model for coffee prices

0.89791	-0.44984	0.18741	-0.14198	-0.10659	0.01820	0.16039	-0.10424
0.11277	0.18204	-0.18221	-0.26137				

Table I.4 Coefficients for ARMA (1, 1) annually model for coffee prices

0.57745	-0.56190

APPENDIX J:

COEFFICIENTS OF THE ARMA MODELS SELECTED FOR COTTON PRICES

Table J.1 Coefficients for ARMA (6, 4) weekly model for cotton prices

1.98029	-2.14503	1.94738	-1.75930	1.16509	-0.20221	0.80029	-0.99711
0.55334	-0.77903						

Table J.2 Coefficients for ARMA (2, 4) monthly model for cotton prices

-0.01749	0.89530	-1.30934	-0.39270	-0.14033	-0.13339

Table J.3 Coefficients for AR (3) quarterly model for cotton prices

1.27822	-0.56897	0.18787

Table J.4 Coefficients for ARMA (1, 1) annually model for cotton prices

0.24132	-0.92998