INTERNATIONAL BLACK TEA MARKET INTEGRATION AND PRICE DISCOVERY

A Thesis

by

KALU ARACHCHILLAGE SENARATH DHANANJAYA BANDARA DHARMASENA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2003

Major Subject: Agricultural Economics

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Approved as to style and content by:

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ABSTRACT

International Black Tea Market Integration and Price Discovery.

(December 2003)

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In this thesis we study three basic issues related to international black tea markets: Are black tea markets integrated? Where is the price of black tea discovered? Are there leaders and followers in black tea markets? We use two statistical techniques as engines of analysis. First, we use time series methods to capture regularities in time lags among price series. Second, we use directed acyclic graphs to discover how surprises (innovations) in prices from each market are communicated to other markets in contemporaneous time.

Weekly time series data on black tea prices from seven markets around the world are studied using time series methods. The study follows two paths. We study these prices in a common currency, the US dollar. We also study prices in each country's local currency. Results from unit root tests suggest that prices from three Indian markets are not generated through random walk-like behavior. We conclude that the Indian markets are not weak form efficient. However, prices from all non-Indian markets cannot be distinguished from random walk-like behavior. These latter markets are weak form efficient. Further analysis on these latter markets is conducted to determine whether information among the markets is shared. Vector Autoregressions (VARs) on the non-Indian markets are studied using directed acyclic graphs, impulse response functions and forecast error decomposition analyses. In both local currencies and dollar-converted series, the Sri Lankan and Indonesian markets are price leaders in contemporaneous time. Kenya is an information sink. It is endogenous in current time. Malawi is an exogenous price leader in dollar terms, but it is endogenous in local currency in contemporaneous time.

In the long run, Sri Lanka, Indonesia and Malawi are price leaders in US dollar terms. In local currency series, Indonesia, Kenya and Malawi are price leaders in the long run. We use Theil's U-statistic to test the forecasting ability of the VAR models. We find for most markets in either dollars or on local currencies that a random walk forecast outperforms the VAR generated forecasts. This last result suggests the non-Indian markets are both weak form and semi-strong form efficient.

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TABLE OF CONTENTS

TABLE OF CONTENTS (CONTINUED)

LIST OF FIGURES

LIST OF FIGURES (CONTINUED)

LIST OF TABLES

LIST OF TABLES (CONTINUED)

CHAPTER I

INTRODUCTION

1.1 Problem Statement and Justification

Black tea is traded primarily (about 80%) in spot markets. These markets are located mainly in the following countries: Sri Lanka (Colombo), India (Calcutta, Coimbatore, Cochin, Guwahati, Coonoor, and Siliguri), Bangladesh (Chittagong), Indonesia (Jakarta), Kenya (Mombasa) and Malawi (Limbe)[1]. Tea prices are quoted in each of these markets on at least a weekly basis. These quotes are prices per kilogram. They reflect demand for and supply of tea and different quality characteristics. Prices may also reflect government interventions. Governments use trade policy instruments such as export taxes, import tariffs, and import quotas in apparent attempts to influence the price and/or consumption of tea. Such regulations may introduce inefficiencies into the tea market, which in turn may give false signals to producers in future periods.

1.2 Objectives

Due to the above disparity in prices and the possible absence of an efficient market for tea (tea trade is influenced by government trade policy in importing/exporting countries) tea producers and consumers may be adversely affected. The general problem addressed in this study is to determine how black tea markets are integrated across the world and

This thesis follows the style and format of the *American Journal of Agricultural Economics.*

[1] Auction centers are located in cities in parentheses in the respective country.

where the price of black tea is discovered. This information may contribute to an improved marketing strategy for black tea in respective countries. Specific objectives are to determine whether there are leaders and followers in world black tea markets. And if so, which markets, in particular, serve as leaders or followers.

In this thesis we seek to answer questions of price discovery among 7 black tea auction markets in the world. The study considers weekly prices over the period December 1999 through June 2002. We use two statistical methods as dual engines of analysis. First, we use time series methods to capture regularities in time lags among the 7 price series. Second, we use directed acyclic graphs to study the contemporaneous relation among the 7 markets. Here we try to find out how surprises (innovations) in price from each market are communicated to other markets in current (contemporaneous) time. This type of analysis is done through recent developments in the artificial intelligence literature (see Pearl, 2000). The technique is called Directed Acyclic Graphs (DAG).

1.3 Organization of the Thesis

This thesis is organized as follows. Chapter I provides an introduction to the study with a justification and a statement of objectives. It also identifies the analytical tools used in the study. In Chapter II we explain the demand, supply, exports and imports of black tea, a description of the status of the black tea price today and brief discussion of the auction centers considered in the thesis. Chapter II also reviews other studies done in market integration. Chapter III explains the modeling framework used and offers a description of the data used in the study. In Chapter IV we present results from the analysis and model validation. Chapter V is devoted to a discussion on findings and their implications on black tea auctions markets.

CHAPTER II

WORLD BLACK TEA ECONOMY

This chapter begins with a brief description of what black tea is and how it is processed. This description is followed by an overview of the world black tea trade, with special reference to demand, supply, imports and exports. Markets where the black tea is traded are also discussed. A map of the study area is provided with specific auction markets placed on it. Then we follow with a discussion of each selected auction market. For each market we consider specific features such as market volume, trading partners, etc. The final part of the chapter is devoted to the discussion of the current status of the black tea price.

2.1 Black Tea Processing

Tea (*Camellia sinensis*) is an evergreen plant. If allowed to grow, it grows as a normal evergreen tree. But it may also be cultivated and pruned to be a short bush, harvested for its young leaves and leaf buds. The plants are initially raised in nurseries to produce healthy plants. When the nursery seedlings are about one to one and a half years old they are planted in a regular field prepared for tea planting. Tea plants mature in three to five years and produces a flush, the growth of new shoots. These flush must be hand picked to secure the quality and flavor of tea processed. As a result, tea production is a highly labor intensive practice. Once planted and well looked after through proper cultivation practices, tea plant can produce yield up to about 40 years. Tea is also a beverage produced by brewing dried and processed leaves in hot water. If the leaves go through a special oxidation procedure they are transformed into black brittle leaves that can be brewed in hot water. Tender tea leaves and buds are plucked (hand or machinery plucked) and withered in cool dry air. Then they are rolled through a rolling machine and followed by oxidization. Then the leaves are dried using a furnace to arrest the oxidization process and to dehydrate them so they can be stored. Once completely dried, black tea is sorted by size using a sorting machine, and is then ready to go to market. This description is the orthodox way of processing black tea. Some processors adopt other methods such as cut-tear-curl (CTC) for special tea markets such as "tea bags". In the CTC manufacture, fairly withered tea leaves are crushed to force out most of the sap and followed by tearing them. Then they are curled tightly into balls. Tea, once processed into its final form, easily absorbs moisture and odors. Therefore, it is a requirement that tea must be stored in a cool dry place and away from any strong odorous items. Further, tea must be stored in airtight containers and not exposed to light and should be used within a reasonable time.

2.2 World Black Tea Trade

There are seven major black tea producing countries in the world. They are: Sri Lanka, India, Malawi, Kenya, Indonesia, Tanzania and Zimbabwe. Turkey, Argentina, Iran, Nepal and Bangladesh also produce black tea, but in smaller numbers relative to the major countries. Black tea is traded in several auction centers located in different parts of the world. They are Sri Lanka (Colombo), India (Calcutta, Coimbatore, Cochin, Guwahati, Coonoor, and Siliguri), Bangladesh (Chittagong), Indonesia (Jakarta), Kenya (Mombasa) and Malawi (Limbe).

The Food and Agricultural Organization (FAO) of the United Nations has projected demand, supply and trade of black tea for the year 2005 based on the most recent data available on black tea production, consumption, population and income growth, and trade. Projections on production are based on linear trend analysis and extrapolations for the year 2005. Consumption was projected using past trends estimates on population and income growth and assumed constant real prices (FAO, 2000). These projections are summarized below.

2.2.1 Supply, Demand, Imports and Exports of Black Tea

World black tea production is projected to increase from the 1993-95 average of 1.97 million mt to 2.7 million mt in 2005, an annual average growth rate of 2.8%. Production in India is estimated at 1.02 million mt in 2005, an average annual growth of 2.8% from the 1993-95 base. Most of the envisaged production expansion in Sri Lanka should result from recent economic reforms and the national plan for tea production expansion (FAO, 2000). In Sri Lanka, production is projected to grow 1.6% annually from the 1993-95 base of 240,000 mt to 285,000 mt in 2005. Significant growth in production is also projected for other major tea-producing countries. Indonesia is projected to increase black tea production from 105,100 mt to 160,000 mt. Output of black tea in Bangladesh is projected to grow only moderately from 49,000 mt in 1993-95 to 55,000 mt in 2005. Output in Kenya is expected to increase at an average annual rate of 2.8% to 300,000 mt in 2005. Malawi, Tanzania and Zimbabwe are also expected to increase production significantly. Production and yield of tea produced by small growers in Africa is likely to continue to increase rapidly (FAO, 2000).

In 1999 the world black tea supply moved well ahead of demand for the first time since 1993, which created an obvious potential for an impact on tea prices. Sri Lanka and Kenya continue to lead the black tea export market. The total export tonnage in 1998 was 265,308 mt from Sri Lanka and 263,402 mt from Kenya (FAO, 2000).

World black tea consumption is projected to increase from 1.97 million mt in 1993-95 to 2.67 million mt by 2005, an annual growth rate of 2.8% (FAO, 2000). Developing countries should account for the largest part of the potential increase, with consumption rising from the 1993-95 average of 1.41 million mt to 1.95 million mt by 2005, an annual growth rate of 3%. The reduction of import tariffs by these countries and declining prices as a result could have a more noticeable positive effect on consumption (FAO, 2000).

In developed countries, including countries in transition, black tea consumption is expected to increase more moderately. Consumption in the European community is projected to increase only slightly in the next decade. Consumption in the United States is projected to increase, though at a relatively slow rate of less than one percent (FAO, 2000). Since many developed countries impose no, or only slight, restrictions on bulk and packaged black tea imports, the effect of trade liberalization on their consumption is expected to be negligible (FAO, 2000). Black tea consumption in the countries of the former USSR is projected to increase from 154,000 mt in 1993-95 to 250,000 mt in 2005, equivalent to an annual growth rate of 4.5% over the period (FAO, 2000).

Import requirements in 2005 are projected at 1.27 million mt, an average annual increase of 2.3% from average annual imports in the 1993-95 base period. Import requirements by developing countries are expected to increase more rapidly, while import demand in developed countries is projected to increase by about 1.6% annually (FAO 2000). Major importers of black tea are expected to be the Commonwealth of Independent States (CIS), Pakistan, the United Kingdom, Egypt and the United States. These countries are expected to account for 51% (FAO, 2000) of total import requirements.

Net export availabilities are projected to reach 1.292 million mt in 2005, an average annual increase of 2.5% from the actual exports of 985,000 mt during the base period (FAO, 2000). India, Indonesia, Sri Lanka, and Kenya are expected to account for more than 50% of the total projected export availabilities. Other black tea producers who are expected to increase their exports are Bangladesh, Malawi, Tanzania, Turkey, and Zimbabwe. Sri Lanka currently exports the largest amount of black tea and is expected to see its exports grow by 1.6% annually to 263,000 mt in 2005 (FAO, 2000). Significant growth in black tea exports is also projected for African tea exporting countries. Kenya, which currently accounts for 70% of African tea exports, is expected to increase its availability from 203,000 mt (1993-95 average) to 276,000 mt in 2005, an average annual growth rate of 2.8% (FAO, 2000).

Projections by the FAO suggest that there will be an imbalance in the international black tea demand and supply at current prices. That is, the FAO projects a surplus of exports at current prices. This will result in downward pressure on price that all bulk tea exporters have to face, as there is little product differentiation that exists among exporters products.

2.2.2 Influence of Regional Blocs on World Black Tea Markets

There are several regional entities in different parts of the world that affect tea trade. They are South Asian Association for Regional Cooperation (SAARC), Indo-Lanka Free Trade Agreement (FTA), East African Tea Trade Association (EATTA) and Common Market for Eastern and Southern Africa (COMESA). They have varying degree of influence for world tea trade.

The regional entity with the most potential for impact on the black tea trade today is the SAARC. SAARC consists of major tea producing countries today, such as India and Sri Lanka (other SAARC members are Bangladesh, Nepal, Bhutan, Pakistan and Maldives). Tea trade is expected to be negotiated under the South Asian Preferential Trading Agreement (SAPTA), which is signed by SAARC member countries. But SAPTA has failed to promote tea trade among the signatories (Ranaweera, 1999). In the mean time, India and Sri Lanka signed a bi-lateral agreement to promote trade between two countries, which is Indo-Lanka FTA. Indo-Lanka FTA has influenced the tea trade in the region far better than SAPTA. According to FTA, tea is in Sri Lanka's Negative

List[2]. India has given a 50% duty reduction for Sri Lankan tea subject to an annual quota of 15 million kg. Sri Lanka would continue to enjoy a 7.5% duty rate for tea under the FTA irrespective of the recent increase in Indian tariff rates for tea from 15% to 35% (Indo-Lanka FTA, 2000).

The East African Tea Trade Association (EATTA) is a voluntary organization of tea producers, buyers (exporters), brokers, tea packers and warehousemen, all working together to promote the best interests of the tea trade in Africa.

Common Market for Eastern and Southern Africa (COMESA), which Kenya belongs to, is another regional group established to promote tea trade in Africa. Due to this, Kenyan tea will be given a preferential tariff by Egypt. Because of this, tea from Sri Lanka or India will be subject to a higher tariff. This reduces the Sri Lankan and Indian tea shares in Egypt. At a global level, the World Trade Organization/General Agreement on Tariff and Trade (WTO/GATT) is the ultimate authority, with decision-making power that already influences nation's tea tariffs, import/export rules, subsidies and quotas (Altman, 2000). WTO requires member nations to reduce import duties by 24% from the existing rates by the year 2005. Developed nations such as UK and USA are already having nil duty and will not be affected under the WTO requirements. Compliance with tariff reduction is likely to cause higher imports by Pakistan, Iran, Iraq and Egypt. India, Sri Lanka, Kenya and other exporting countries will benefit from freer trade and lower tariff barriers (India-Infoline, 2002).

[2] Negative List: Sri Lanka does not grant any tariff concessions to India with respect to tea, but does for other products.

2.3 Tea Industry in Each Country and Tea Auction Markets

There are several tea auction markets around the world. They are primarily located in major cities of tea growing countries. Following are the tea markets addressed in this study. They are, Sri Lanka (Colombo), three auctions in India (Calcutta, Cochin, Guwahati), Indonesia (Jakarta), Kenya (Mombasa) and Malawi (Limbe).

2.3.1 Sri Lankan Tea Industry and Colombo Tea Auction

According to Sri Lanka Tea Board (SLTB), Sri Lanka is the third largest tea producing country in the world as of today (SLTB, 2003). It has a 9% share of world production. It is one of the world's leading exporters with a share of 19% of world export volume (SLTB, 2003). Sri Lanka has the capacity to produce tea throughout the year. Production is mainly concentrated in the central and southern inland areas of the country and grouped as high, mid and low grown tea according to the elevation. Sri Lanka mainly produces orthodox tea (traditional processing technique). But now it also produces cut-tear-curl (commonly known as CTC tea), bio-tea, instant tea and flavored tea. This diversification was done to compete in the international markets with other tea-producing competitors. Tea is mainly exported to the Commonwealth of Independent States (CIS), Middle Eastern countries, Western Asia, Australia, Europe, Japan and North America. According to the Central Bank of Sri Lanka (CBSL), the annual average tea price in the Colombo tea auction increased in Sri Lankan Rupee terms but declined in US dollar terms (US$ 1.50 per kilogram of tea) (CBSL, 2002).

Sri Lankan tea is sold through different marketing channels. They are the Colombo tea auction, private sales, forward contracts and direct sales. But almost 95% of tea is sold through the Colombo tea auction. Other channels are used in special circumstances, such as to accommodate any quick requests from buyers (SLTB, 2003). The Colombo tea auction dates back to 1883 when the first tea auction was held on the island. Today the Colombo tea auction is the world's largest tea auction center with almost 200 companies vying with each other on behalf of principals from all over the world (SLTB, 2003). Auctions are held weekly (two days per week, Tuesday and Wednesday). Weekly quantity offered varies from 3-7 million kilograms (SLTB, 2003). The Colombo Tea Traders Association conducts auctions under the guidance of the chamber of commerce (SLTB, 2003). According to SLTB, government has no influence in the price discovery in the auction center. The Sri Lankan government does not restrict the amount of tea entering the auction center. There is a tax called *cess* charged by the SLTB for every kilogram of tea exported. It is 2.50 rupees per kilogram (US$ 0.025 per kilogram of tea).

2.3.2 Indian Tea Industry and Tea Auctions

According to the India Tea Board, India is the world's largest tea producer and consumer. It produced 870 million kilograms in 1998 (ITB, 2003). Indian tea production is about 30% of world production. The major portion is consumed domestically (India-Infoline, 2002). The export market share is about 17% globally (India-Infoline, 2002). In India today, over 80% of tea production is of the CTC type, amounting approximately to

650 million kilograms. Other than this, India produces the traditional orthodox tea as well (ITB, 2003). There are three distinctly different varieties of tea grown in 3 different tea growing areas in India. They are Darjeeling tea, Assam tea and Nilgiri tea. All these are named according to the area grown. Each type has special quality characteristics unique to the area grown. The Indian export markets of tea are CIS, Europe, North America and Middle Eastern countries.

There are six auctions markets for tea in India. They are Calcutta, Coimbatore, Cochin, Guwahati, Coonoor and Siliguri. Established in 1861, the Calcutta auction is the world's oldest tea auction. It handles about 95 million kilograms of tea annually (CTTAa, 2003). The Tea Trade Association of Coimbatore controls the tea auction in Coimbatore. Its market turn over was about 32 million kilograms in 2000-2001 (The Hindu, 2001). Coonoor Tea Trade Association (CTTA) is the principle entity that has control over the Coonoor tea auction. It is the biggest auction center in south India. The market capitalization is 71 million kilograms of tea in 2000 (CTTAb, 2003). Guwahati Tea Auction Center (GTAC) has about 135 million kilogram market sales in a year (GTAC, 2003). It is the second largest tea auction center, only second to the Colombo tea auction (GTAC, 2003).

Even though the Indian government does not directly influence the price in auction centers, the tea marketing control order requires all the manufacturers to sell 75% of their tea (excluding exports and packet sales) through auction houses. This guarantees the supply of tea to auction centers. This supply of tea is not exactly what the buyers need and this can have an impact on the price of tea. Furthermore, imports are not allowed for domestic consumption (India-Infoline, 2002).

2.3.3 Indonesian Tea Industry and Jakarta Tea Auction

In the Indonesian tea industry, the main product is black tea and about 80% is exported (Tea Auction Ltd, 2003). Java and Sumatra, two of the largest islands, are the main growing areas. Tea had been a way of life with the Indonesian people, but after World War II the Indonesian tea industry was neglected and in a very poor state. After the rejuvenation of the industry, by 1984, Indonesia started exporting tea. In 1994, Indonesia exported about 80,000 mt of tea, accounting for over 8% of world exports (The Tea Council Ltd, 2003). Major importers of Indonesian tea are Russia, Pakistan, M.E. and UK/Europe. The Joint Marketing Office or Kantor Pemasaran Bersama conducts Indonesian tea auctions.

2.3.4 Kenyan Tea Industry and Mombasa Tea Auction

Tea is a major foreign exchange earner in Kenya. In 1995, the tea industry brought US $342 million into the country and Kenya became the largest exporter of black tea in Africa and the third largest in the world. (Tea Auction Ltd, 2003) The majority of the Kenyan tea production is sold through the Mombassa auction. The biggest importers are Pakistan, the UK and Egypt. Tea production in Kenya is almost exclusively CTC manufactured. This type of manufacturing produces strong-liquoring teas, which yield a high number of cups per kilo when brewed both loose and in teabags. The share of production is about 8% globally and the share of exports is about 15% (Tea Auction Ltd, 2003). Africa Tea Brokers (ATB) monitors the sales in the Mombasa tea auction. The Kenyan government does not interfere with the price discovery process in the Mombasa auction. However, there are taxes on tea planted acreage and manufacturing. There is no export duty for tea exports. According to the tea board of Kenya, producers have the choice of selling the produce through either the auction center or through private treaty agreements.

2.3.5 Malawi Tea Industry and Limbe Tea Auction

Malawi started growing tea commercially in the 1880s. Now exporting over 35,000 mt annually, Malawi has a 4% share of world exports (The Tea Council Ltd, 2003). The export earning from tea is about 19% (NSOM, 1999). Tea trading is done through the auction market in Limbe an annual capitalization is about 35 million kilograms. Figure 2.1 shows the location of each tea auction in respective countries under this study.

2.4 World Tea Price

The world market for tea has experienced marginal over-supply during the last decade (1990 through 2000). This has resulted in a declining price in real terms over the period. In addition to the traditional supply and demand side variations, the global tea market has been confronted by increasing uncertainties, as economic and market conditions of participants have become more changeable and unpredictable. These uncertainties have led to increasing price volatility. This is the fundamental problem faced by the tea producers and exporters. Therefore, it is important to find out the price dynamics of the tea market and the degree to which the tea markets are integrated.

2.5 Review of Other Studies on Market Integration

In this section we review studies on price discovery and market integration. They concentrate on discovering market efficiency and integration in different commodity markets.

Mjelde and Paggi (1989) used the vector auto regression (VAR) method to cast light on the relationship among domestic corn prices in Texas and Illinois and an export corn price in New Orleans. Decomposition of the error variance gave them the result that there is an increasing exogeneity between the export prices and Texas and Illinois prices. The results further show that the export price influences price in the two domestic markets.

Ardeni (1989) used unit root tests (Dickey Fuller test) and co-integration analysis in several commodity markets (Wheat, Tea, Beef, Sugar, Wool, Zinc and Tin) in four countries (Australia, Britain, Canada and USA) to show how the Law of One Price fails as a long run relationship and that deviations from the historical mean are permanent.

Samarendu, Smith, and Peterson (1996) studied time series evidence of relationships between U.S. and Canadian wheat prices. They examined price relationships using co-integration and an error correction model. They found both U.S. durum and hard spring wheat prices respond to restore the equilibrium relationship.

However, the corresponding Canadian price does not respond to restore equilibrium. So price of Canadian wheat was leading US wheat under their period of study.

Yang, Bessler and Leatham (2000) considered the Law of One Price which rejects the hypothesis that one price prevails in developed countries and another single price in developing countries, thereby segmenting the north-south markets. They used cointegration to reach the conclusion that the north-south markets are integrated.

Kadyrkanova, Bessler and Nichols (2000) considered price relationships among three milk markets in Kyrgyzstan. They used cointegration analysis to see if milk market prices of two private sector and one government sector markets are integrated. They concluded that two private sector markets are integrated with each other and the government market is not integrated with private sector milk markets.

Gonzalez-Rivera and Helfand (2001) examined the extent, pattern and degree of market integration using data from the Brazilian rice market. They used a multivariate system with co-integrating restrictions. They concluded that bi-variate models are inadequate for capturing the spatial dynamics of price adjustment.

Goodwin, Grennes and Craig (2002) examined the economic impact of mechanical refrigeration and spatial and temporal aspects of market integration in the United States. Specifically, they studied the markets for butter, in particular the seasonal fluctuations in prices and the degree of regional integration. They found that the adoption of mechanical refrigeration in the United States reduced the seasonal fluctuations of butter prices. They further concluded that mechanical refrigeration in the

United States had a significant impact on both temporal and spatial butter price relationships.

Bessler and Kergna (2003) studied monthly millet prices in 12 markets in Bamako, Mali. They used an error correction model to consider whether the prices from these market are integrated. They used directed acyclic graphs to study contemporaneous correlation among markets. They found that prices are discovered in the primary wholesale market, where farmers meet retailers and other middle persons. The retail markets did not serve well as points of price discovery.

Finally, Asche, Gjolberg and Volker (2003) studied price relationships between crude oil and refined products (gas oil, kerosene, naphtha, heavy fuel oil) in the North West European market. They developed an error-correction model and found that the crude oil price is weakly exogenous, meaning that crude oil prices are fundamental in understanding prices of refined products. Furthermore, they showed that crude oil and refined product markets are integrated.

Similar tools will be used in this black tea market study. A VAR model or an error correction model will be developed for black tea auction market prices. More emphasis will be given to the use of the directed acyclic graph approach to direct the edges between tea markets in contemporaneous time, as there has been little empirical work using these new methods.

CHAPTER III

CONCEPTUAL FRAMEWORK AND APPLICATION

3.1 Conceptual Framework

This thesis primarily focuses on the use of time series techniques in understanding the time related properties of tea auction market prices around the world. Traditional econometric techniques are found to be inadequate when trying to make inferences with time ordered observational data. Prior theory traditionally suggests the explanatory variables that should go into a model. However, theory is developed using the *cetris-paribus* assumption. When "all other things" are not fixed, as is the case with experimental data, researchers must rely on less "structured" models. Here we use prior theory to suggest variables to be studied, but we rely on empirical patterns in their time sequence to specify explicit relationships among each variable.

In this chapter we first discuss the theoretical properties of univariate and multivariate time series models. Then we explain unit root tests for testing the non-stationary property of a time ordered data series. Next we discuss the properties of directed graphs followed by an explanation of innovation accounting. We explain the properties of impulse response functions and error decompositions in the innovation accounting section. Finally, we give an account of the data we used in the study.

3.1.1 Univariate Time Series Model

Time Series Analysis (TSA) studies data observed over a period of time. Each observation is indexed by t in order to keep track of the order of its observation. A key idea behind all time series modeling is that order of observation matters. As an example let us say that we are observing prices of tea over a period of time. When a new piece of information hits the market in the current time, it moves price away from the most recent price value. This new piece of information is not well defined as a random draw from the historical mean price. Therefore, the historical mean is not a good measure of forecasting the effect of the shock. Analysis of a single series of data and its movement through time is called univariate analysis. Let X_t be a random variable whose value only depend on the past lag values of itself, and values of an error term (this is known as the innovation term in the time series literature). A simple univariate model can be defined as follows:

(1) $$X_t = \alpha + \beta_1 X_{t-1} + \beta_2 X_{t-2} + ... + \beta_p X_{t-p} + e_t$$

Where α is the intercept term and the β's are unknown parameters. The term e is the uncorrelated error term. This is assumed to have a zero mean and a variance of σ_e^2. We just defined in equation (1) an autoregressive model of order p, where p is the number of lags in the model. Stationarity is an important property in time series processes. In general, a time series process is stationary if the mean, variance and co-variance of the series are finite and constant. But if we consider a random walk model: $Y_t = Y_{t-1} + e_t$, the variance of the series is infinite and the series is not stationary (say Y_t is today's price and Y_{t-1} is yesterday's price in the market and the e_t is the white noise term). Such series can be differenced once or many times to make them stationary. If the series is differenced once, it is said to be integrated to order 1. That means, $\Delta Y_t = (Y_t - Y_{t-1})$ is a stationary series and integrated of order one; here Y_t is an $I(1)$ series.

3.1.2 Vector Autoregressive Model

Constraining oneself to univariate models is generally overly restrictive, as the real world is often times viewed (theoretically) as a set of interacting variables. This leads us to multivariate models, where many variables and their interactions are considered. Thus vector auto regression (VAR) models have become popular. The VAR is an atheoretic analysis (non-structural analysis) that summarizes the regularities in a set of variables which theory suggests as important (Bessler, 1984). These models are useful in the analysis of observational data; i.e. data that are collected without experimental controls. In structural modeling, we use a pre-determined model suggested through the knowledge of the prior theory and structure. But in VAR modeling the choice of variables studied does not depend on the pre-determined structure, rather on the problem under study and theory, which will be used to study regularities of data. Say we have *m* variables, $X_1, X_2, X_3 \ldots X_m$ under study. All variables are endogenous. The unrestricted VAR can be written as follows:

$$\begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1m} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_{m1} & \alpha_{m2} & \cdots & \alpha_{mm} \end{bmatrix} \begin{bmatrix} X_{1t} \\ X_{2t} \\ \vdots \\ X_{mt} \end{bmatrix} = \begin{bmatrix} \delta_{1t} \\ \delta_{2t} \\ \vdots \\ \delta_{mt} \end{bmatrix} \tag{2}$$

Where;

$$\alpha_{ij} = 1 - \alpha_{ij}(1)B^{1} - \alpha_{ij}(2)B^{2} - \cdots\cdots - \alpha_{ij}(k)B^{k}; i = j$$

$$\alpha_{ij} = -\alpha_{ij}(1)B^{1} - \alpha_{ij}(2)B^{2} - \cdots\cdots - \alpha_{ij}(k)B^{k}; i \neq j$$

Here B is the lag operator, such that $B^{k}X_{t} = X_{t-k}$. The α_{ij} are parameters, unknown, in our case, and to be estimated from observed data. The term δ_{it} is the innovation term (error), which is uncorrelated through time but generally correlated in contemporaneous time. That is to say, $E(\delta_{it}\delta_{it-k}) = 0; k \neq 0$ and $E(\delta_{it}\delta_{it-k}) = \sigma^{2}_{ij}; k = 0$. Lag length, k, in equation (2) may be known from prior theory or determined through statistical analysis. The latter usually involves hypothesis testing on lag length, a likelihood ratio test (Sims, 1980) or statistical loss functions (Geweke and Meese, 1981). VAR can be re-written with lags on the right hand on condensed matrix form as:

(3) $$X_{t} = \sum_{k=1}^{k} \alpha(k) X_{t-k} + \delta_{t}$$

Here $\alpha(k)$ is merely a re-write of the α matrix given in equation (2) without the diagonal element. Ones (1) and lag operator (B) is not used. In the last representation (equation (3)), X_t is of dimension *(mx1),* $\alpha(k)$ is *(mxm)* and δ_t is *(mx1).*In constructing the VAR, stationarity of X_t's is assumed. If a series is non-stationary, we have to take differences to make it stationary, $\Delta X_{t} = (X_{t} - X_{t-1})$.

3.1.3 Tests of Nonstationary

A series is said to be mean non-stationary if the data points are moving away from its historical mean for a long periods of time. In other words, the data are non-mean reverting. Granger and Newbold (1974) used Monte Carlo simulations to show that results from regressions that use such data could be spurious. Non-stationary data have an infinite variance. This may lead to improper inferences based on the *t*-statistic in estimation and hypothesis testing. Further studies have proved that other traditional statistics such as F distribution and the R^2 statistic do not have the correct properties in the presence of non-stationary data (Phillips, 1986).

A formal test on non-stationary is the Dickey-Fuller test (DF). Here we regress the $\Delta X_t=(X_t-X_{t-1})$ on a constant plus levels lagged period one: x_{t-1}.

$$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} \tag{4}$$

Our null hypothesis is that the series is non-stationary (α_1=0). When the ordinary least squares (OLS) estimate of α_1 in equation (4) is significantly negative, we reject the null of series non-stationary (this means the series is stationary in levels). The *t*-statistic[3] is the test statistic used in the DF test. The approximate 5% critical value estimated using Monte Carlo simulation is –2.89 (say we get a critical value calculated as –4.85, then we reject the null and conclude that the series is stationary in levels). But sometimes the DF test may suffer from problems of autocorrelation in the estimated residuals (Granger and Newbold, 1986). Then we can use an augmented DF test (ADF) to sufficiently whiten

[3] *t*-statistic is calculated as the ratio between estimated coefficient and standard error of the estimated coefficient.

the residuals. The ADF test has the same null hypothesis and the critical value on estimated α_1 value in the equation (5) below, but it has an additional set of terms.

(5) $$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \sum_{i=1}^{k} \beta_i \Delta X_{t-i}$$

In equation (5), *k* is the lag length selected in order to whiten residuals. We use a loss metric such as Schwarz Loss function to determine *k*.

3.1.4 Innovation Accounting

Analysis and interpretation of the individual elements, $\alpha_{ij}(k)$ in equation (3), of the VAR is difficult and generally not practically informative (Sims, 1980). Accordingly, analysts prefer to study the moving average representation of the VAR. In simple terms the VAR of equation (3) is written as equation (6):

(6) $$\alpha(B)x_t = \delta_t$$

We can multiply both sides by $(\alpha(B))^{-1}$ to find the moving average representation of the VAR (equation (2)). This is give as equation (7):

(7) $$(\alpha(B))^{-1}\alpha(B)X_t = (\alpha(B))^{-1}\delta_t$$

This last equation expresses the current values of the *x* vector, x_t, as an infinite sum of past innovations in each series:

(8) $$X_t = (\alpha(B))^{-1}\delta_t = \theta(B)\delta_t$$

Equation (8) is an infinite summation, which shows how the current position of the vector *x* depend on historical innovations (shocks) in each individual series. We can carefully decompose each series into each series historical shocks or simulated each series response to a particular shock over time. Analysis of these decompositions of equation (8) is labeled innovation accounting. It is the basic to analysis of the VAR.

3.1.5 Impulse Response Function

Based on equation (8), we can simulate how the *x* vector responds over time to a one time only shock in a particular element of δ_t, say δ_{it}=1 all other δ_{it}=0; *j* is not same as *i*. That is to say, we study how x_{t+k} evolve.

(9) $$X^*_{t+k} = \theta(B)\delta^*_{t+k}$$

Where: $\delta^*_{t+k} = (0,0,\cdots\cdots,0); k \neq 0$ and $\delta^*_{t+k} = (0,0,\cdots,1,0,\cdots,0); k = 0$, where here just the *i*th element of $\delta^*_{t+k} = 1$.

Equation (9) is known as the impulse response function. In theory it could be calculated analytically from any estimated VAR (equation 6). However, the inverse operation for equation (7) is generally complicated and thus equation (9) is generally studied using computer (0,1) simulation. We can derive the θ(B) elements of equation (8) by simulating the estimated VAR to a series of one time only shocks in each series' innovation term. Details of this process are given in Bessler (1984).

3.1.6 Forecast Error Decompositions

Again based on equation (8) one can forecast the *X* vector ahead to any desired horizon *t+h*. If we are currently at time *t*, the expectation of all future innovations (the entire vector) is the zero vector: $E\{\delta_{t+h})$=0, *h>0*. Call this expectation $\hat{X}_{t+h}$:

(10) $\hat{X}_{t+h} = \theta_0 \hat{\delta}_{t+h} + \theta_1 \hat{\delta}_{t+h-1} + \theta_2 \hat{\delta}_{t+h-1} + \cdots + \theta_{h-1} \hat{\delta}_{t+1} + \theta_h \delta_t + \theta_{h+1} \delta_{t-1} + \cdots$

The expectation of the future innovations $\delta_{t+1}, \delta_{t+2}, \cdots, \delta_{t+h}$ all have a "hat" on their symbols to indicate that we do not know their values. These will be set equal to zero. The actual x_{t+h} will be given as:

(11) $X_{t+h} = \theta_0 \delta_{t+h} + \theta_1 \delta_{t+h-1} + \theta_2 \delta_{t+h-2} + \cdots + \theta_{h-1} \delta_{t+1} + \theta_h \delta_t + \theta_{h+1} \delta_{t-1} + \cdots$

Subtracting equation (10) from equation (11) gives us the forecast error at horizon h periods ahead.

(12) $\varepsilon_{t+h} = \theta_0 \delta_{t+h} + \theta_1 \delta_{t+h-1} + \cdots + \theta_{h-1} \delta_{t+1}$

Recall ε_{t+h} and δ_{t+h} are vectors representing the forecast error and innovations at horizon h periods ahead respectively. Further $\theta_0, \theta_2, \cdots, \theta_{h-1}$ are each *mxm* matrices. Each element of i,j θ_{h-k} will tell us how the forecast error h periods ahead on series i depends on innovation in series j, k periods previous.

Using the property that these innovations (δ_t's) are not correlated through time and have a contemporaneous time stationary variance covariance, we can write the forecast error variance at h steps ahead for a particular series as:

(13) $$\begin{aligned} &V(FE_{t+h}) = V(\delta_{1t+h}) + \theta_{11}^2(1)V(\delta_{1t+h-1}) + \theta_{12}^2(1)V(\delta_{2t+h-1}) + \cdots \\ &\cdots + \theta_{11}^2(h+1)V(\delta_{1t+1}) + \theta_{12}^2(h+1)V\delta_{2t+1} \end{aligned}$$

Note that V is the variance and FE is the forecast error. For any particular element of the vector ε_{t+h} say, $\varepsilon_{i,t+h}$ we can see its variance is composed of the corresponding elements of each θ matrix and each variance term. For $h=2$, we can partition this variance into series one and two as follows. Percentage of variation in series one due to historical shocks in series one is as follows:

$$\frac{V(\delta_1) + \theta_{11}^2(1)V(\delta_1) + \theta_{12}^2(1)V(\delta_1)}{V(\delta_1) + \theta_{11}^2(1)V(\delta_1) + \theta_{12}^2(1)V(\delta_2) + \theta_{11}^2(2)V(\delta_1) + \theta_{12}^2(2)V(\delta_2)}$$

Percentage of variation in series one due to historical shocks in series two is as follows:

$$\frac{+\theta_{21}^2(1)V(\delta_2) + \theta_{22}^2(1)V(\delta_2)}{V(\delta_1) + \theta_{11}^2(1)V(\delta_1) + \theta_{12}^2(1)V(\delta_2) + \theta_{11}^2(2)V(\delta_1) + \theta_{12}^2(2)V(\delta_2)}$$

This partition can be carried out at any horizon for all variables in our VAR. Again, to calculate these analytically would require considerable effort. However, the computer does it vary quickly using current technology. Individual elements of equation (13) are calculated and discussed in our next chapter. These help us summarize the relative influence each series has on every series of the VAR.

3.1.7 Contemporaneous (Current) Time

In both impulse response function equation (9) and the forecast error variance decomposition we have the matrix $\theta_{0,}$ the moving average matrix at lag zero. The matrix summarizes how series *i* and *j* are related in current time (non-lagged relationship). From the VAR all we know about this contemporaneous relationship is that the series are correlated by the *i,j* element of $\sum$, where $\sum$ is the variance covariance matrix. This correlation may be descriptive of a causal relationship between series *i* and *j* or it may be because series *i* and *j* are related to series *k*. A priori we do not know whether a non-zero element of Σ arise because the corresponding series are causally related to one another, say $X_i \rightarrow X_j$ or because both are causally related to another series; $X_j \leftarrow X_k \rightarrow X_i$.

The early research workers on VARs followed Sims (1980) and applied a Choleski factorization of Σ to give a recursive causal structure in contemporaneous time. Since Σ is positive definite, $\Sigma = P'P$. So that: $(P')\Sigma(P)^{-1} = P^{-1}P'PP^{-1} = I$. So if we pre multiply each element of the VAR equation (2) by P^{-1}, we have an identity variance covariance matrix. This Choleski factorization results in the orthogonalized VAR.

(14) $$P^{-1}x_t = P^{-1}\phi_1 x_{t-1} + P^{-1}\phi_2 x_{t-2} + \cdots + P^{-1}\phi_k x_{t-k} + P^{-1}\delta_t$$

Equation (14) requires the analyst know the causal structure in contemporaneous time as P^{-1} will be lower triangular (see Bessler, 1984). For a 3 variable VAR, P^{-1} will be as follows:

(15) $$P^{-1} = \begin{bmatrix} p_{11} & 0 & 0 \\ p_{21} & p_{22} & 0 \\ p_{31} & p_{32} & p_{33} \end{bmatrix}$$

Applying equation (15) in equation (14) gives us a clear indication of what the Choleski solution to contemporaneous correlation does for us. Whatever series is given first in the x vector (X_{1t}) will cause the variable listed second X_{2t} with the coefficient p_{21}. And the first and second variables will affect variable X_{3t} with coefficient p_{31} and p_{32}, respectively. This recursive causal ordering required knowledge, which many researchers did not have in particular applications.

Recently, research workers have begun to investigate the causal structure embedded in $\sum$ using the directed graph methods of Pearl (2000) and Spirtes, Glymour and Scheines (1993). Below we summarize DAGs and their use in solving the contemporaneous time problem in VARs.

3.1.8 Directed Acyclic Graphs

Traditional econometric literature is heavily dependent on the assumption that the system under consideration is *ceteris-paribus*. However, there is a problem with this assumption. Most of the economic data colleted are not generated in an experimental setting. In the experimental setting we can have *ceteris-paribus* assumption. Also in an experimental setting we can deal with the omitted variables through random assignment of treatments to variables. The basic issue is that data used in economic studies are not generated in an experimental setting (they are generated as time evolves). Therefore, the ceteris paribus condition is not appropriate with such data, because there are many unknown (omitted) variables affecting the system. Also, one cannot do random assignment of treatments to variables to deal with omitted variables. The bottom line is we do not know the variables that should go into right and left hand sides of a function that explains the relationship among variables. Traditional econometric theory could do it, because there was a structure defined for a relationship. Directed acyclic graphs (DAG) are used to find the causal relationship among a set of variables that data or theory suggest should be related. Directed graphs work off of the variance-covariance matrix from a set of variables.

The following discussion on DAGs is heavily borrowed from the work of Bessler and Loper (2001) and Bessler and Kergna (2003). A Directed graph is a picture, which can be represented as an ordered triple **<V,M,**E> where **V** is a non-empty set of vertices (variables), **M** is a non-empty set of marks (symbols attached to the end of undirected edges), and **E** is a set of ordered pairs. Each member of **E** is called an edge (line). Vertices (variables) connected by an edge are said to be adjacent. A directed acyclic graph is a directed graph that contains no directed cyclic paths (an acyclic graph contains no vertex more than once).

Directed acyclic graphs are designs for representing conditional independence as implied by the recursive product decomposition:

(16) $$\Pr(X_1, X_2, X_3 \ldots.. X_n) = \prod_{i=1}^{n} \Pr(X_i \mid P_{ai})$$

Pr is the probability of vertices $X_1, X_2, X_3, \ldots X_n$ and P_{ai} the realization of some subset of the variables that precede (come before in a causal sense) X_i in order ($X_1, X_2, \ldots, X_n$).

Pearl (1995) proposes d-separation as a graphical characterization of conditional independence. That is, *d*-separation characterizes the conditional independence relations given by the above equation. If we formulate a directed acyclic graph in which the variables corresponding to Pa_i are represented as the parents (direct causes) of X_i, then the independencies implied by the equation can be read off the graph using the notion of *d*-separation [4] According to Pearl (see Pearl 2000), the fundamental notion which allows us to assign direction of causal flow to a set of variables is the screening off phenomena. If we have three variables, *X, Y* and *Z*, and if *X* is a common cause for both *Y* and *Z*, it forms a causal fork. See Figure 3.1. The unconditional correlation between *Y* and *Z* are nonzero. If one conditions on *X* (having the knowledge of *X*), the correlation between *Y* and *Z* is zero. This is the way that the common cause screens off the association between joint effects. Now say the variables are related as follows. There is a common effect (say *X*) and joint causes (say *Y* and *Z*). See Figure 3.2 for an inverted causal fork. The unconditional correlation between *Y* and *Z* is zero. However, if one conditions on the *X* (knowing information about *X*) the correlation between *Y* and *Z* becomes nonzero. Common effects do not screen off association between their joint causes.

Sprites, Glymour and Schines (1993) incorporated the notion of *d*-separation into "PC Algorithm" for building DAGs using the idea of sepset. PC Algorithm starts from a complete undirected graph of the desired set of variables and removes edges between vertices based on zero order correlation and conditional correlation. We use the Fisher's *z* statistic to test whether conditional correlations are significantly different from zero. The *z* statistic is given as follows:

(17) $$z(\rho(i,j\mid k)n) = 1/2(n-|k|-3)^{1/2} x \ln\{(|1+\rho(i,j\mid k)|) x (|1-\rho(i,j\mid k)|)^{-1}\}$$

[4] Definition: Let X,Y and Z be three disjoint subsets of vertices in a directed acylic graph G, and let p be any path between a vertices in X and a vertices in Y, where by 'path' we mean any succession of edges, regardless of their directions. Z is said to block p if there is a vertex w on p satisfying one of the following: (i) w has converging arrows along p, and neither w nor any of its descendants are on Z, or, (ii) w does not have converging arrows along p, and w is in Z. Further, Z is said to d-separate X from Y on graph G, written (X ml Y | Z)G , if and only if Z blocks every path from a vertex in X to a vertex in Y. (Pearl 1995).

In equation (17), n is the number of observations used to estimate correlations, $\rho(i,j|k)$ is the population correlation between series i and j conditional on series k and k is the number of variables in k that we condition on . If i, j and k are normally distributed and $r(i,j|k)$ is the sample conditional correlation of i and j given k, then the distribution of $z(\rho(i,j|k)n) - z(r(i,j|k)n)$ is standard normal. TETRAD II software (Scheines et al. 1994) is used to direct edges.

There are three assumptions that we need to be careful in deciding the edges using the PC algorithm. They are:

1. *Causal sufficiency condition*: This means that we assume that we have included all the variables that are in the system to the model and there is no omitted variable that causes any two or more of the included variables under study.
2. *Causal Markov condition*: If one needs to find out the probability distribution generating any variable under study, we need only to condition on its parents to fully capture the probability distribution of the variable. That is to say, if X causes Y and Y causes Z, we can factor the underlying probability distribution on X, Y and Z as Pr(X,Y,Z)=Pr(X)Pr(Y|X)Pr(Z|Y).
3. *Faithfulness condition*: Say we have two variables X and Y. We say that X and Y are dependent if and only if there is an edge between X and Y. Thereby we assume that unique parameter a value between variables are not canceling and if the correlation happens to be zero that is only because the correlation coefficients are not significantly different from zero.

Failure of any of these conditions is possible. Thus, interpretation of results based on TETRAD must be done with caution. Spirtes, Glymour and Scheines (1993) considered Monte Carlo results with TETRAD and note it performs well in a rich variety of "known" models.

Applications of directed graphs to VAR model identification are not commonplace. Swanson and Granger (1997) suggested a similar procedure. They considered only first order conditional correlation and involve more subjective insight by the researcher to achieve a "structural recursive ordering". This method of analysis has the advantage of comparing results based on properties of data with a priori knowledge of a structural model suggested by economic theory or subjective intuition.

3.2 Description of Data

We study weekly prices from December 1999 through June 2002 (a total of 133 data points) for each of the tea auction markets (see Appendix for the data). The data source for tea auction prices is the International Tea Committee (ITC), internet address: http://www.intteacomm.co.uk (Accessed on June 27, 2003) web summary weekly tea auction data. Prices are quoted in each auction market in different currency denominations. They are as follows:

1. All Indian markets are in Indian rupees.
2. Sri Lankan market is in Sri Lankan rupees.
3. Kenyan, Malawi and Indonesian markets are in US cents.

The study focuses the analysis in two directions, they are, US dollar as the common currency denominator and the other with local currencies of each country as the base. For that exchange daily averages of exchange rate data were gathered from different sources. Exchange rate data for Sri Lanka, India, Kenya and Indonesia are taken from Oanda Corporation. [Internet address http://www.oanda.com (accessed on July 17, 2003)]. Malawi exchange rate data were gathered from the Reserve Bank of Malawi monthly economic review.

Missing auction price data were fixed with data points assuming that they are the same as previous week's data (assumed a random walk model[5] for the auction market). Regression Analysis for Time Series (RATS) (Doan, 1996) and TETRAD II Version 3.1 Scheines et al. (1994) software are used in all analysis discussed in Chapter IV of the thesis

[5] Random walk model assumes the current price is only a function of previous period's price and a white noise term i.e $p_t = p_{t-1} + e_t$.

CHAPTER IV

ANALYSIS AND RESULTS

4.1 Discussion Using Summary Statistics

In Table 4.1 we discuss the behavior of each price using the mean, standard deviation and the coefficient of variation. We have ranked prices from each auction market over the entire sample period (December 1999 through June 2002).

First we discuss the analysis based on the US dollar as the common currency denominator. Notice that the mean price is highest in the Mombasa (Kenya) market. The lowest is the Limbe (Malawi) market price. Kenya produces a considerable amount of CTC tea that directly goes into the tea bag industry. Other markets produce relatively less CTC tea compared to Kenya. Also, it is a known fact that CTC receives a premium price in the world market due to heavy demand for the tea bags (instant tea). That may be a reason why the average price in Kenya is higher than other markets. In terms of the standard deviation (SD) of price, the Kenyan market ranks number one. With respect to the coefficient of variation (CV) it ranks third. This shows how volatile the Kenyan market price is relative to other markets. The Limbe (Malawi) market for tea is a small market and its contribution to world tea exports is very low (please see section under the Literature Review). That may be a reason why the price is low in this market. The Malawi market has a considerable degree of volatility too. It ranks 4th for SD and 1st for CV. This shows that the Malawi market is the most volatile in terms of CV.

According to the mean, SD and CV ranks, the Calcutta tea auction has the second highest variation in the prices. The Colombo tea auction ranks third in terms of the mean tea auction price. According to the SD rank (5^{th} position), the Colombo tea auction has moderately volatile prices. The Jakarta tea auction has moderate price volatility in terms of all statistics concerned.

Now we look at the price variation in each market when prices are considered in local currency terms. In this case mean and SD are not very good measures to compare markets for price volatility, because now we have different currency bases for each market. The CV is a better measure in this case. The Malawi market ranks number one in price volatility and The Sri Lankan market has the least price volatility in terms of CV. Kenya ranks number three in volatility with respect to local currency analysis.

The weakness of using the above summary statistics in the analysis is that they neither incorporate the time series properties of market data or possible interactions among different markets.

4.2 Time Series Properties

In the following section we discuss the time related properties of the black tea auction price data from 7 auction markets. First, data are plotted to see time trends, followed by unit root tests. Then we discuss tests performed to discover co-integration. The next section explains the vector auto regression analysis followed by a narrative on contemporaneous and long run behavior of prices.

4.2.1 Plots of Black Tea Price in Seven Auction Markets

Here we explain two sets of graphs (see Figure 4.1 and Figure 4.2) drawn for price in levels of each tea auction market. In Figure 4.1 we have shown the price movement in each market taking the US dollar as the currency denominator. In Figure 4.2 we have drawn the graphs considering the local currency in each country.

The visual observation of each market reveals the following information. In Figure 4.2 two of the Indian markets, namely Calcutta and Guwahati, do not have any noticeable time trend. It appears as if prices from these two markets are bouncing around their historical means. The Cochin market has a little time trend, but it is minor when compared to the time trending in other markets. Even in the dollar-converted graph, Indian markets show a similar movement of prices. Since there is no big difference in those two graphs in the Indian market we tentatively infer that the Indian Rupee might have been stable with respect to the US dollar at least in the time period concerned in this study. That is why whether we measure in Rupee or in dollar terms, we observe a similar movement in prices.

The Sri Lankan tea price (Colombo auction market) has an upward trend in the local currency (the Sri Lankan local currency is the Rupee). We observe a downward trend in the Colombo auction price in terms of the US dollar. The Sri Lankan Rupee appears to have devaluated against the US dollar faster toward the latter part of the sample period. The Sri Lankan Rupee is free floated against the US dollar and the monetary authority has allowed it to devaluate to promote exports. Within the sample period concerned the rupee has devaluated considerably. That may be the reason that in terms of the US dollar the Colombo auction market has a downward trend toward the end of the sample period.

Tea prices in Indonesia (Jakarta) show a downward trend in terms of the US dollar (note that the Jakarta tea auction trades in US dollars). The graph shows that the tea prices in Jakarta are decreasing in dollar terms. In the local currency terms, tea prices in Jakarta have an upward trend. This shows that the Indonesian Rupiah has devaluated against the US dollar over the sample period. Even though the Indonesian tea producer gets a lower price for tea in terms of US dollars, once converted into Rupiah they get a high price.

The Kenyan auction market price has a similar downward trend in both the dollar and local currency (Kenyan Shillings are the local currency) graphs (there are small differences in peaks and troughs). This shows that the Kenyan currency has not changed much during the sample period. However, it is worth showing that price at the Kenyan auction center decreases over the time period and hits a very low level towards the end of the sample period. This means that the Kenyan tea grower is not experiencing a lucrative period as prices are falling considerably.

Tea prices in Malawi (Limbe auction center) increased up until the middle of the sample period and then started to fall both in US dollar terms and Malawi Kwacha terms. The decrease in price in US dollar terms is more intense than the local currency terms. This shows that the Kwacha is devaluating against the dollar, but at a slower rate. The money that the local farmer earns in terms of Kwacha is decreasing and this discourages the Malawi tea growers.

Note that there is no exchange rate risk in price discovery in Jakarta, Kenya and Malawi markets, as these markets are held in US dollar terms. Nevertheless, the local producer gets paid in local currency to their hand. Whether this amount is increasing or decreasing over time is determined through the purchasing power of each currency.

Except from the plots from three Indian markets, we suspect the mean non-stationary property in prices in all other auction markets. A more rigorous analysis of the time series properties is given below. We offer tests on unit root behavior for each market in the following section.

4.2.2 Stationary: Results from Dickey-Fuller and Augmented Dickey Fuller Tests

Table 4.2 gives the result from the Dickey-Fuller (DF) and the Augmented Dickey Fuller (ADF) tests for dollar converted and local currency data on each series. The null hypothesis is that prices from all tea auction markets are mean non-stationary. The statistics presented on the table have a 5% critical value of –2.89. Under both the DF and ADF tests, we reject the null for calculated statistics less than this 5% level.

In the dollar-converted analysis, the DF test tells us that all but the Cochin market is mean non-stationary in levels. The ADF shows that all Indian markets are mean stationary in levels and the remainder of the markets are mean non-stationary in levels. In the local currency analysis, all but the Indonesian market is mean non-stationary in levels. The ADF shows that all Indian markets again are mean stationary in levels and the rest of the markets are mean non-stationary in levels. As residuals from these markets are better behaved under the ADF (we have made the residuals white by augmenting the DF test with lags of the dependent variable), we suggest the use of results from augmented tests. The tests suggest that price in the non-Indian markets behave as a random walk: $P_t = P_{t-1} + e_t$, where e_t is a white noise (uncorrelated) innovation.

As we are studying the prices as they evolve in the market through time, we fully expect that they will individually look much like a random walk (Samuelson, 1965). That is, from the results on the Table 4.2, each non-Indian market behaves such that new information perturbs price away from the most recent value and not as a perturbation from the historical mean. This is not true with respect to the 3 Indian markets. In levels, all prices from the Indian markets are mean stationary. That means the new information perturbs price away from the historical mean and not from the most recent value. Prices in the 3 Indian markets are not generated through random walk-like behavior. The other 4 markets are mean non-stationary according to the unit root tests. The 3 Indian markets are taken out of the analysis of market integration as the unit root tests indicated that price from these markets are not efficient. The word "efficient" is used to suggest that the best prediction of price in India in period *t+1* is something different from the price in period t (its historical mean price is a useful statistic for next period's price). This result appears not to hold for the four non-Indian markets. Here we cannot reject the random walk hypothesis. Following Fama (1970), we say these four non-Indian markets are efficient in terms of price discovery. We continue to concentrate on these four markets to find out more about market integrations.

4.2.3 Tests of Cointegration Results

From the results of the ADF tests above we conclude that four tea auctions, Sri Lanka (Colombo), Indonesia (Jakarta), Kenya (Mombasa) and Malawi (Limbe) are individually non-stationary in both dollar and local currency analysis. Our next step is to find out whether the data are co-integrated. If they are co-integrated, then we will develop an error correction model. If they are not co-integrated then a VAR will be developed by making the data stationary.

According to Table 4.3 and Table 4.4, we reject the null hypothesis of the presence of any co-integrating vectors. Therefore, there is no co-integration in dollar converted and local currency data. Now we concentrate on building a VAR for the auction market price.

4.2.4 Estimated Vector Autoregressions for Dollar Converted and Local Currency Data Series

From the DF and ADF analysis of dollar converted and local currency data, we found that auction price data in the 3 Indian markets are stationary in levels and the rest of the markets are non-stationary in levels. To develop the VAR and to identify the time series properties, first we need to make the data series stationary (the need for making the data series stationary is discussed extensively in the methodology section). For that we take the first differences of each data series. We develop two VARs, one for each dollar converted series and local currency series.

Then we want to find out how many lags of each series we should have in each VAR. We used the Schwarz Loss (SL)[6] function to determine the number of lags in the VAR (see Appendix C for the RATS input program). The results are shown in Table 4.5.

We select the lag length that gives the minimum SL value. According to that the lag length in our VAR in dollar converted series and local currency data series is one. Therefore, we take one lag of first differenced data. The following abbreviations are used for each market: Colombo (Sri Lanka) (SLA), Jakarta (Indonesia) (INA), Mombasa (Kenya) (KEN), and Limbe (Malawi) (MAL). The Δ refers to the first difference of a series, such as $\Delta SLA_t = (SLA_t - SLA_{t-1})$. Lagged one period of first differences is shown in the 3rd matrix from the left. The final matrix after the plus sign from left shows the innovation term for each series.

The estimated VAR model for dollar converted data series is as follows[7]:

$$\begin{bmatrix} \Delta SLA \\ \Delta INA \\ \Delta KEN \\ \Delta MAL \end{bmatrix} = \begin{bmatrix} -0.00054 & 0.119 & 0.103 & 0.069 & -0.031 \\ (-0.128) & (1.179) & (1.118) & (0.783) & (-0.469) \\ -0.0013 & 0.339 & -0.279 & 0.049 & -0.036 \\ (-0.297) & (3.232) & (-2.909) & (0.534) & (-0.523) \\ -0.0036 & -0.008 & -0.119 & 0.229 & 0.118 \\ (-0.735) & (-0.064) & (-1.104) & (2.241) & (1.515) \\ 0.00023 & -0.116 & -0.113 & 0.152 & -0.034 \\ (0.036) & (-0.754) & (-0.802) & (1.139) & (-0.339) \end{bmatrix} \begin{bmatrix} 1 \\ \Delta SLA_{t-1} \\ \Delta INA_{t-1} \\ \Delta KEN_{t-1} \\ \Delta MAL_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}$$

6 $SL = \ln|\Gamma| + (mxk)(\ln T)T$ Where Γ is the error covariance matrix estimated with k repressors in each equation, T is the total number of observations on each series, | | denotes the determinant operator, and ln is the natural logarithm (Geweke and Meese, 1981).

7 *t*-statistics are in parenthesis. The constant is in the autoregressive matrix (it is the first column of the autoregressive matrix).

The estimated VAR model for local currency data series is as follows:

$$\begin{bmatrix} \Delta SLA \\ \Delta INA \\ \Delta KEN \\ \Delta MAL \end{bmatrix} = \begin{bmatrix} 0.253 & 0.097 & 0.00027 & 0.043 & -0.0031 \\ (0.729) & (0.959) & (0.385) & (0.529) & (-0.037) \\ 21.608 & 15.836 & -0.282 & -0.778 & -6.533 \\ (0.439) & (1.111) & (-2.816) & (-0.068) & (-0.546) \\ -0.227 & -0.075 & -0.00039 & 0.181 & 0.220 \\ (-0.529) & (-0.602) & (-0.453) & (1.806) & (2.112) \\ 0.195 & -0.102 & -0.00032 & 0.051 & 0.016 \\ (0.458) & (-0.820) & (-0.369) & (0.513) & (0.152) \end{bmatrix} \begin{bmatrix} 1 \\ \Delta SLA_{t-1} \\ \Delta INA_{t-1} \\ \Delta KEN_{t-1} \\ \Delta MAL_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}$$

Most of the coefficients are statistically not significant at 95% confidence level (according to the *t*-statistics in parentheses) for both analyses. However, in the dollar-converted data series, coefficients associated with INA on INA and SLA lagged one period are statistically significant at the 95% level (*t*-statistics –2.909 and 3.232 respectively). This shows that the information (price) discovered in IND today is primarily affected by its own lag one period and lag one period price of the Sri Lankan market. New information discovered in the Kenyan market today is mainly affected by the Kenyan market price last period (lagged one period) (see the t-statistic is 2.241). In the local currency data series only the coefficient associated with the Indonesian market on its own lag one period is statistically significant at the 95% level (the t-statistic is –2.816).

Up until now we examined lagged relationships among our 4 series of dollar converted and local currency data. Now it is time to find out how each market is related to other markets in contemporaneous time (current time). This is done through the analysis of directed acyclic graphs.

4.2.5 Contemporaneous and Long Run Behavior of Four Auction Markets

We apply the directed graphs to the innovations from the VAR models developed above. For that we need to work with the correlation matrix of innovations (error terms) from each VAR model. Table 4.17 shows the correlation matrix of innovations generated for dollar converted data series.

We applied the Tetrad II Version 3.1 software (Scheines et al., and Sprites et al., 1993) to this correlation matrix with PC algorithm (explained in the methodology section) to determine the contemporaneous causal relationship between market prices when the data are in dollar terms. Several things should be noted from the correlation matrix. The Sri Lankan market is not highly correlated with other markets. The highest being with Kenya (14%) and Malawi (only 11%). The Sri Lankan market is negatively correlated with the Kenyan and Malawi markets. That means surprises (errors) in the Sri Lankan price are related negatively to surprises (errors) in the Indonesian and Kenyan prices. The Indonesian errors are positively correlated more with Kenyan market errors (23%) and negatively correlated with Malawi market errors. That means new information discovered in the Indonesian market today is positively related to new information in the Kenyan market, yet at this moment the exact causal flow is not known. Malawi and Kenyan markets are positively correlated with each other at 21%. Yet again, the causal pattern in the current time is not known.

Table 4.18 shows the correlation of innovations in the local currency data series. Then we applied the Tetrad II Version 3.1 software (Scheines et al., and Sprites et al., 1993) to this correlation matrix and ran the PC algorithm (explained in the methodology section) to find out the contemporaneous causal relationship between auction market prices when the data are used in local currency terms.

The Sri Lankan market is negatively correlated with Indonesian and Kenyan markets. That means the perturbations in the Sri Lankan price negatively affect the Indonesian and Kenyan price. It is almost not correlated with the Kenyan market in local currency terms. The Indonesian market is correlated 20% with the Malawi market and 14% with the Kenyan market. Again, two African markets, Kenya and Malawi are correlated by 21% to each other. This is just the correlation. Correlation does not necessarily imply causation. The causal pattern is not known.

Here we discuss the contemporaneous relation among the four tea markets. We begin by presenting a complete undirected graph connecting all markets from each VAR model. We then remove edges based on a correlation test. The null hypothesis for the test is that there is no correlation (edge) between markets (or the correlation coefficient is zero). If one fails to reject the null, we remove the edge. Removal of edges is done the following way. First we investigate the zero order correlation between edges, that is to say, we look at the correlation coefficients based on no conditioning information. For example, if we have three variables, A, B, and C, first we look at the correlation between A and B, A and C and B and C. After removing edges based on zero order correlation, we investigate the correlation based on the first order correlation. That is to say, we look at the correlation between A and B given C. We go on removing the edges until we reject the null hypothesis for all remaining edges. This is the process programmed in PC algorithm. Tetrad II software is used to run the PC algorithm. Tetrad II allows us to impose knowledge of time ordering. Here we use time ordering based on the day the markets are open given a working week starting Monday. All markets are closed on Mondays and are open on Tuesdays. The Indonesian market opens on Wednesday. In the Figure 4.3 we exhibit the times the auction markets are open in a given a week.

Given a Tuesday, the first market to open is the Sri Lankan market followed by the Mombasa (Kenya) and Limbe (Malawi) markets. On the African continent, Kenya is the first market to open and then the Malawi market. The last market to close on Tuesday is the Malawi market. Then on Wednesday, the first market to open is the Indonesian market followed by the Sri Lankan market.

The Sri Lankan market is open from 8:00 am through 6 pm on Tuesdays and opens at 8:00 am on Wednesdays. No specific ending time is given for Wednesdays and the auction lasts as long as supply is available. Kenyan markets opens only on Tuesdays and trade from 8:30 am through 2:30 pm or until the supply runs out. The Limbe market opens on every Tuesday at 8:30 am and closes at noon. The Indonesian market opens at 8:30 am and no specific closing time is given.

Figure 4.3 shows the complete undirected graph we start with. All markets are connected with each other with an undirected edge. Then, as explained in the methodology section, we remove edges based on the significance of correlation between edges. When we apply the PC algorithm to the correlation matrix it gives us the directed graph based on the significance level we specify. Here we use 10% and 20% significance levels for the edge removal. Table 4.6 shows the edges removed, correlations, and *p*-values for each correlation for dollar converted data series at 10% and 20% significance levels respectively. Table 4.7 shows the edges removed, correlations and *p*-values for local currency data series at 10% and 20% significance levels.

A note on the selection of edges and significance level is worth discussing at this moment. The PC algorithm can commit type I and type II errors on edge existence. That is to say, it can fail to include and edge when it should have and it can include an edge when it should not have (Awokuse and Bessler, 2003). The same types of errors are possible even with the edge direction. Thus, it may fail to put an arrowhead when it should have and it may put an arrowhead when it should not have. (Awokuse and Bessler, 2003). Spirtes, Glymour and Scheines (1993) have done extensive simulations into errors on both edge inclusion and direction. They conclude that there is little chance of the algorithm including an edge that is not in the "true" model. However, they further explain that with samples that are less than 200 observations, there is a considerable chance that the algorithm will omit an edge that belongs in the model. Accordingly, the authors conclude: "In order for the method to converge to correct decisions with probability one, the significance level used in making decisions should decrease as the sample size increases, and the use of higher significance levels (e.g. 0.20 at sample sizes less than 100, and 0.10 at sample sizes between 100 and 300) may improve the performance at small sample sizes"(Spirtes, Glymour and Scheines, 1993, p. 161).

Once the algorithm identifies the edges that should be in the model our next step is to direct the edges. To do this we use the concepts developed by Spirtes, Glymour and Scheines (1993). They incorporated the notion of *d*-separation as discussed in the methodology section. They use the notion of *sep-set* to direct edges. They define the *sep-set* as: "The conditioning variable(s) on removed edges between two variables is called the *sep-set* of the variables whose edge has been removed (for vanishing zero order conditioning information the *sep-set* is the empty set)". In other words, if we remove the edge based on the zero order correlation, since there is no conditioning variable, there is no *sep-set*. Edges are directed by considering triplets X—Y—Z, such that X and Y are adjacent as are Y and Z, but X and Z are not adjacent. Direct the edges between triplets: X→Y←Z if Y is not in the sep-set of X and Z. Therefore, there is no edge between X and Z. If X→Y and Y and Z are adjacent, X and Z are not adjacent, and there is no arrowhead at Y, then orient Y—Z as Y→Z (Bessler, 2002). See the Appendix C for the Tetrad II program and its output. We have taken 10% and 20% significant levels to reject or fail to reject the hypothesis.

First we discuss the edge removal done on US dollar converted data series. According to Table 4.6, the edge between Sri Lanka and Indonesia is removed since it is not significantly different from zero at the 10% level (see the *p-value* is 0.7955). Also, at the 20% level we reject the null hypothesis that there is no edge between Sri Lanka and Kenya. In other words, there is an edge between Sri Lanka and Kenya at the 20% level (see the *p-value* is 0.1538). Likewise, all of the above edges are removed based on the 10% and 20% significance levels (note the p-values for all removed edges are greater than 0.10 if we choose the 10% significance level and greater than 0.20 if we choose the 20% significance level).

Table 4.7 presents results for the local currency. At a 10% level, the following edges are statistically not different from zero: Sri Lanka-Indonesia, Sri Lanka-Malawi and Indonesia-Kenya. Therefore, these edges are removed. Note that at the 20% level the only extra edge that we could remove is Indonesia-Kenya. The DAG is constructed using all edges that are not removed.

Now we discuss the DAGs that are constructed for dollar converted data series and local currency data series. Figure 4.5 and Figure 4.6 give the DAG developed for dollar converted series when edges are removed at 10% and 20% significance levels respectively. Sri Lanka, Indonesia and Malawi are exogenous in contemporaneous time. Sri Lanka is a relatively large market with more trade volume than Indonesian and Malawi markets. But both small markets appear to be exogenous as well. At the 20% level directed arrows emanate from these markets and no arrows are directed toward them. Therefore, we can interpret this result as indicating that new information originates in the Indonesian, Sri Lankan and Malawi markets in contemporaneous time. The Kenyan market is endogenous. All arrows are directed to it. We say that Kenya is an information sink as no arrows are directed out from it. We interpret this result as indicating that this market is a receiver of information in contemporaneous time.

Figure 4.6 and Figure 4.7 explain the DAG developed for local currency series when edges are removed at 10% and 20% significance levels respectively. According to Figure 4.6, Indonesia and Sri Lanka are exogenous in contemporaneous time. There are no arrows pointing toward them. The interesting thing here is the bi-directed edge between Malawi and Kenya. At the 10% significance level the algorithm fails to remove the bi-directed edge. This shows that information flows in both directions between these two markets. This indicates the presence of an omitted variable (Spirtes et al., 2000). Besides that, Malawi receives information from Indonesia directly and Kenya receives the information inflow from Sri Lanka. At the 10% level both African markets are endogenous and information sinks. At the 20% level of significance, again, Sri Lanka, Indonesia and Malawi markets are exogenous and Kenya is endogenous. Again, Kenya is an information sink in contemporaneous time. There is an edge between Indonesian and Malawi that the algorithm fails to direct at the 20% level.

When we consider all DAGs from the above analysis several factors are clear and common between them. They are as follows. Sri Lanka and Indonesia are always exogenous in contemporaneous time. Kenya is always endogenous in contemporaneous time. Malawi is exogenous in dollar-converted analysis but endogenous in the 10% local currency analysis.

Deeper questions related to the relative size of these influences on other markets, both in contemporaneous time and lagged time, need to be addressed to make strong statements on price discovery and price leadership. To accomplish the above, we study the error decompositions[8] and impulse responses[9] of each market relative to other markets.

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[8] Impulse responses show how each series responds to a one-time only shock in every series.
[9] Error decompositions show how the error for each series is decomposed into shocks in each series.

Table 4.8 gives a measure of uncertainty in each market and rankings based on the VAR and the directed graph of markets in the US dollar converted analysis. This modeled uncertainty is associated with predicting each series into the future (zero, one and twenty three weeks ahead).

For example, if a tea buyer in the current period (period *t*) plans to buy tea from an auction in the next period (period *t+1*), the uncertainty he would face, if he used our VAR model as a basis for decision making, can be measured in terms of standard deviation as; 0.0434 US$/kg in the Jakarta (Indonesia) market. The uncertainties of the rest of the markets can also be expressed in the same way. The uncertainty increases up to 0.0471 US$/kg if one looks at 2 weeks ahead and to 0.0475 US$/kg at 23 weeks (6 months). The Limbe (Malawi) market demonstrates both short run and long run uncertainty that is greater than the other markets. It is interesting to compare the results in Table 4.8 and Table 4.1. In Table 4.1 we ranked the markets based on their risk in price in each market (standard deviation). According to Table 4.1 (excluding all Indian markets), the most risky market was the Kenyan (Mombasa) market (here we have not taken the efficient adjustments due to time and across markets). After we take into account the interrelationships through time and across markets, Malawi is the most risky market. Furthermore, the Indonesian market ranks least risky if we look at only the standard deviation of the price. According to the time series analysis we find that the Indonesian market is the third most risky market, Sri Lanka being the least risky. According to Table 4.9, we can see that the risk in each market increases as we move into longer time horizons. For example, the Sri Lankan market has a risk of 3.24 rupees per kilogram of black tea in the current time and it increases up to 6.84 rupees per kilogram in the 23^{rd} week.

Table 4.8 and Table 4.9 indicate that some markets are more risky while others are not. How much the new information discovered in one market is influenced by other markets can be studied by building the forecast error decomposition model for all markets under both US dollar converted and local currency scenarios. To develop forecast error decomposition and impulse response model, we use the causal ordering suggested by the DAG analyses. See Appendix C for the RATS programs for the impulse response and error decompositions.

Tables 4.10 through 4.14 give an overall summary of the relationships between each market under dollar converted and local currency scenarios. They explain the percentage of error accounted by each market on a given market. They assist in determining whether markets are exogenous or endogenous relative to each other at different forecast horizons. Horizon zero represents contemporaneous time. Horizon one is the short run and horizon 23 is the long run.

In the US dollar converted analysis, Table 4.10 and Table 4.11 show that Sri Lanka, Indonesia and Malawi markets are exogenous in contemporaneous time. That is to say, in horizon zero 100% of innovation in each market is explained through each market and no influences from other markets are seen. This result confirms the outcome of the directed graph drawn for 10% and 20% significance levels for dollar converted data series.

When we look into the forecast error decomposition results from the 4 auction markets with the causal ordering based on the 10% significance level, in the short run, almost 97% of the innovation in the Sri Lankan market is explained by itself, so too in the long run (horizon 23). In the short run, 98% of the innovation is explained by itself in the Malawi market. In the short and long run, almost 90% of the Indonesian market is explained by itself and only a 10% contribution is from the Sri Lankan market. This may be due to the fact that the Sri Lankan market opens on Tuesday and the Indonesian market opens on Wednesday. Therefore, information discovered in the Sri Lankan market in the previous day does influence the Indonesian market the next day. The Kenyan market is endogenous in contemporaneous time (again, this confirms the result of the DAG). That is to say, in contemporaneous time, 87% of innovations are explained by the Kenyan market itself and 6% each through the innovations from the Indonesian and the Malawi markets. The influence from the Malawi market on the Kenyan market is 9.5% in the long run.

Now we look into the forecast error decomposition developed when causal ordering is based on a 20% significance level. Here again, Sri Lanka, Indonesia and Malawi are exogenous in contemporaneous time (this confirms the result of the DAG at the 20% level). In the short run and in the long run almost 97% of the innovations in the Sri Lankan market are explained by itself. About 90% of the Indonesian market is explained by itself in the short and long run. The rest of the contribution comes from the Sri Lankan market. Innovations in the Malawi market in the short and long run is mainly explained by itself. The Kenyan market is endogenous in contemporaneous time (again, this confirms the result from the DAG). Only 84% of its forecast uncertainty is explained by itself in contemporaneous time: the Sri Lankan market accounts for 2.75%, the Indonesian market accounts for 6.5% and the Malawi market accounts for 6.75% in contemporaneous time. In the long run, contributions from the Sri Lankan and Malawi markets on the Kenyan market increases and there is a slight decrease in the influence from the Indonesian market.

Here we discuss the forecast error decompositions developed by considering the local currency data with causal ordering based on 10% and 20% significance levels. One must remember that we had a bi-directed edge between Kenya and Malawi at the 10% level of significance. When we take the causal ordering as Malawi→Kenya, we observe that Sri Lankan and Indonesian markets are exogenous in contemporaneous time. This is true even when one assumes that Kenya→Malawi. The only difference lies in the percentage explanation in the Malawi and Kenyan market innovation by each other in both cases. When we consider Malawi→Kenya edge analysis, 43% of the innovations in the Kenyan market are explained by the Indonesian market, and 41% through the Malawi market in contemporaneous time. Contributions from these two markets on the Kenyan market increases toward the long run (in the long run, 48% explanation through Indonesian markets and 45% through the Malawi market). Once we consider the Malawi→Kenya edge, according to the DAG we see that Indonesian information comes through Malawi to Kenya (a causal chain). Therefore, activity in the Malawi market is important for the information transfer from Indonesia to Kenya. According to the DAG, Indonesia causes Malawi in contemporaneous time. Only 50% of innovations of the

Malawi market are explained by itself in contemporaneous time and the rest comes from the Indonesian market. This result holds even in the long run. Even though the Indonesian market is exogenous in contemporaneous time, nearly 20% of that is explained by the Malawi market in the long run. When we consider the Kenya→Malawi edge, we see a causal chain as follows: Sri Lanka→Kenya→Malawi. In contemporaneous time, nearly 99% of innovations in the Kenyan market are explained by itself. But in the long run, nearly 50% is explained by the Indonesian market and 45% by the Malawi market. This shows the importance of the Indonesian market in determining the Kenyan market price. The Malawi market is endogenous in contemporaneous time. About 50% of innovations are explained through the Indonesian market. This result holds even in the long run.

Now we offer a discussion on forecast error decompositions in the local currency analysis with causal ordering based on a 20% significance level. In contemporaneous time, Sri Lanka, Indonesia and Malawi are exogenous and Kenya is endogenous. In the short run and long run, about 95% of innovations in the Indonesian market are explained by itself and only a slight contribution from Sri Lanka and Kenya (about 1% from Sri Lanka and 3% from Kenya). In the short and long run, about 37% of the innovations in the Malawi market are explained by the Indonesian market and about 35% by the Kenyan market. Even though the Sri Lankan market is exogenous in contemporaneous time, in the short and long run about 35% is explained through the Indonesian market and another 38% from the Kenyan market.

Figures 4.9 through 4.13 give the dynamic response of each series to a one-time-only shock in each series. To compare the responses across markets, the responses are normalized by dividing each response by the historical standard deviation of innovation in each series. Our purpose of impulse response analysis is not to convey explicit numerical responses, but to give the reader a feeling of responses by observing the pattern in each graph. Note that we had developed the VAR in first differences. Then our impulse responses tell us how the differenced series is changing to a one time only shock in the other differenced series. In these figures, columns shows the innovations in each market and the rows indicate how each market responds to that innovation in each market.

According to Figure 4.9 and Figure 4.10 (US dollar converted data series), Indonesia, Kenya and Malawi markets respond to one-time-only shocks in the Sri Lankan market. The Indonesian response is larger than the other two markets. However, they reach stability within a few periods. Shocks in the Indonesian market move the Sri Lankan and Kenyan markets. Sri Lankan, Indonesian and Malawi markets respond to shocks in the Kenyan market. Finally, shocks in the Malawi market basically affect the Kenyan market price. Overall, we can see that auction markets in Sri Lanka, Indonesia, Kenya and Malawi are highly integrated with each other, responding to shocks in each market.

According to Figures 4.11, 4.12 and 4.13 (local currency data series), the Sri Lankan market does not have much influence in other markets. Shocks in the Indonesian market moves African markets away from stability. The Kenyan market does not have any noticeable influence on other markets. Shocks in Malawi markets moves Indonesian and Kenyan markets.

Unlike in the dollar-converted series, once the local currencies are considered, Indonesian, Kenyan and Malawi markets show more integration with other markets in the long run. That is to say, in the local currency scenario, Indonesia, Kenya and Malawi dominate in the long run. However, in contemporaneous time Sri Lanka too acts as an exogenous price leader. In the dollar-converted series, Sri Lanka, Indonesia and Malawi dominate in the long run. This is true even in contemporaneous time. That is to say, Sri Lanka, Indonesia and Malawi are price leaders in contemporaneous time as well as in the long run.

4.2.6 Model Validation through Forecasts

We initially collected 133 weekly data points (December 1999 through June 2002). For the purpose of model estimation we used only 100 data points and saved the remainder of our sample (33 weekly data points) to validate the model though forecasting. We compared the forecasting ability of the model using the Theil's U-statistic (Doan, 1996). See Appendix C for the RATS program for the computation of the Theil's U-statistic. Based on the models discussed above we forecast the final 33 data points. Our forecasting operation is recursive for one-period, two-periods, up to five periods ahead. At each origin, we re-estimate the model and forecast up to five steps ahead. From these and actual data (data we saved without using to estimate the VAR), we compute several error statistics.

1. Calculate the Sum of Squared Forecast Errors (SSE): $SSE_t = \sum_{i=1}^{N_t} e_{it}^2$. Where e_{it} is the actual value minus the predicted value for the dependent variable.
2. Root Mean Error (RME) is calculated: $RME_t = \sqrt{SSE_t / N_t}$
3. Sum of Squared Error No-Change Forecasts (SSENCF): $SSENCF_t = \sum_{i=1}^{N_t} \eta_{it}^2$ where η_{it} is the forecast error if we assume the difference between the dependent variable value assuming the random walk model and the actual observed value.
4. Root Mean Square of the SSENCF: $RMSNCF_t = \sqrt{SSENCF_t / N_t}$ where N_t is the total number of sample observations.
5. Theil U: $U_t = {RMS_t}/{RMSNCF_t}$

By calculating the Theil U-statistic, we compare our VAR model forecasts against the forecasts generated assuming a random walk model (efficient markets are assumed to have a random walk type of behavior). The statistic in excess of one means our model did not forecast well compared to the random walk model (the naïve forecast). Tables 4.15 and 4.16 explain the forecast performance of VAR models for each market.

According to the Theil U-statistic, the VAR model developed using the dollar-converted data forecasts relatively well for Sri Lankan and Malawi markets for two steps ahead forecasts. Forecast errors from the VAR are larger relative to the random walk model for rest of the markets. In the local currency series, the VAR model forecasts relatively well for the Malawi market for one step ahead. For the rest of the markets, the forecast errors from the VAR are large relative to the naïve model forecasts.

CHAPTER V

DISCUSSION AND CONCLUSIONS

In this chapter we discuss the results obtained in the study. Here we explain the importance of price discovery and price leadership in the international tea auction markets and possible policy measures.

We have studied weekly black tea auction prices from eight auction markets over the period December 1999 through June 2002. We performed the analysis in two ways; we used the US dollar as the common currency denominator and we used the local currencies in each country. Our results show for both sets of analyses, prices from three Indian markets (Calcutta, Guwahati and Cochin) are stationary and prices from other markets (Sri Lanka, Indonesia, Kenya and Malawi) are non-stationary. Therefore, prices from Indian auction markets are tied to a particular historical mean and prices from the other markets are not tied to any historical mean. We conclude that the three Indian markets are not efficient in terms of price discovery. That is to say, if a market is efficient, any new information discovered in the market perturbs price from its most recent level and not a random draw from its historical mean. This is the efficient market hypothesis. Since Indian market prices are tied to their historical means, according to the efficient market hypothesis, they are not efficient in terms of price discovery. This takes us to the conclusion that the rest of the markets may be efficient, as their prices are not tied to their historical means. We continued the study of market prices from Sri Lanka, Indonesia, Kenya and Malawi. Our results, from both dollar terms and local currency terms, show that these four markets are not tied together in any long run co-integration relationship. This means that there is no “long run” predictable relationship holding these four markets together. In terms of efficiency, such a finding is supportive of pricing efficiency, since it would not be possible to generate predictable returns from knowledge of these “public prices”.

In terms of market integration in the dollar-converted series, the DAG analysis of the four markets shows that in contemporaneous time these markets are related to each other (at the 20% significance level). Sri Lankan and Malawi and Indonesian markets cause the Kenyan market price. Kenya is an information sink. It gathers information from Sri Lankan, Indonesia and Malawi markets. In contemporaneous time no information passes out of this market. According to DAG analysis, Sri Lankan, Indonesian and Malawi markets are exogenous price leaders. Black tea price is primarily discovered in Sri Lanka, Indonesia and Malawi markets. It is then passed to the Kenyan market. Therefore, the Kenyan market acts as a follower of price. Given an auction week, Sri Lanka, Kenya and Malawi markets open trade on Tuesday. Obviously Kenya and Malawi markets open at the closure of the Sri Lankan market. Therefore, there is a good chance that the auctioneers in the Kenyan and Malawi markets look at the price discovered in the Sri Lankan market. But that price information is not the only factor that is going to determine the tea price in Kenya and Malawi. The quality of their tea too should meet the quality of tea produced in preceding markets. That is one of the primary problems faced by the sellers in tea auctions as tea quality changes considerably across countries due to weather and the method of processing. If they do not meet the quality standard of a market with high price, they are not in a position to get that premium price. Thus, our results in contemporaneous time suggest that there are information flows among our four markets. However, these flows are short-lived.

In the local currency analysis, again, Sri Lanka, Indonesia and Malawi act as exogenous price leaders in contemporaneous time when we consider the 20% significance level. Kenya is again an information sink and no information is passed out of it in contemporaneous time. In the 10% level of significance analysis we find that Sri Lanka and Indonesia are exogenous price leaders in contemporaneous time. Malawi and Kenya are highly endogenous and act as information sinks receiving information from the other markets, but not passing information in to other markets.

We studied the market interdependence in the long run by looking at the error decompositions developed. Our results in the dollar base analysis show that Sri Lanka, Malawi and Indonesian markets are exogenous in contemporaneous time as well as in the long run. Almost 96% of each market's innovations are explained by each market's past innovations and much less from other markets. These results support the outcome from DAG in contemporaneous time, as Sri Lanka, Indonesia and Malawi markets are exogenous price leaders. The Kenyan market is endogenous in contemporaneous time; some of the price movement in this market is explained through the innovations in Sri Lankan, Indonesian and Malawi markets. We find similar results for the local currency analysis. The impulse responses developed through dollar base data also confirms the interaction between Sri Lanka, Indonesia, Kenya and Malawi. In the local currency analysis, impulse response functions show a slightly different story. A Shock in the Sri

Lankan market has negligible effect on other markets. The other three markets act as price leaders in the long run.

We can draw several implications out of our study for different markets participating in black tea trade. The Indian markets show clear evidence of market inefficiency. Thus, we do not look to these markets for long-run price discovery. Tea producers in other producing countries can receive new and valuable information on tea prices in these other markets. The models developed here can be used to forecast the tea prices reasonably well. Theil's U-statistic for several markets is found to be below 1.0 for 32 one-step-ahead forecasts. This suggests only small gains relative to the most recent observed price. Buyers (exporters) at the auctions can obtain relevant information coming from other tea markets to the respective price in the auction that they intend buying tea. Implications related to diversification in buying have not been explored, but do seem to be non trivial. Since the tea markets are efficient (at least the four markets under study), government policy maker need not do much here; rather they should not intervene in the market and distort the price.

Tea is a commodity where the quality changes drastically across the producers and over time with storage. Therefore, price in each market not only communicates the supply-demand balance but also the quality characteristics. Quality characteristics are not incorporated into this study. To extend this study, one can incorporate the price structure based on different quality of tea traded in each market. The price we used in this study is an average overall weekly price for tea in each auction centre.

Finally, the empirical regularities discovered in this study are expected to motivate similar work on price discovery and price leadership studies in commodity trading to uncover potential strategic behavior among markets.

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APPENDIX A

FIGURES

Figure 2.1. Tea auction markets in Asia and South East Asia

Figure 2.2. Tea auction markets in East Africa

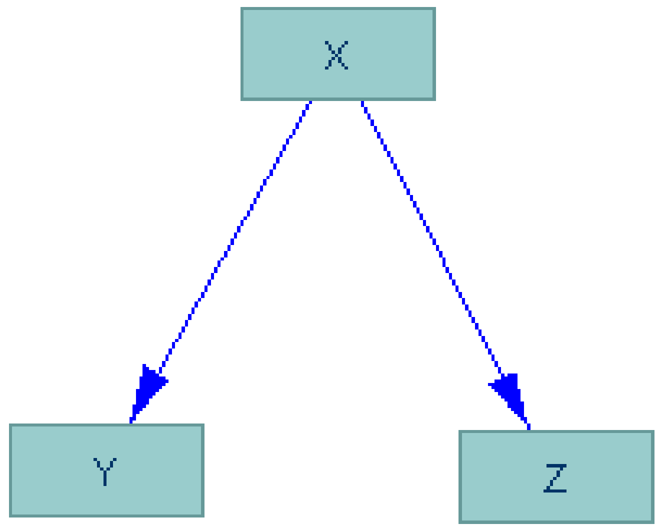

Figure 3.1. A causal fork

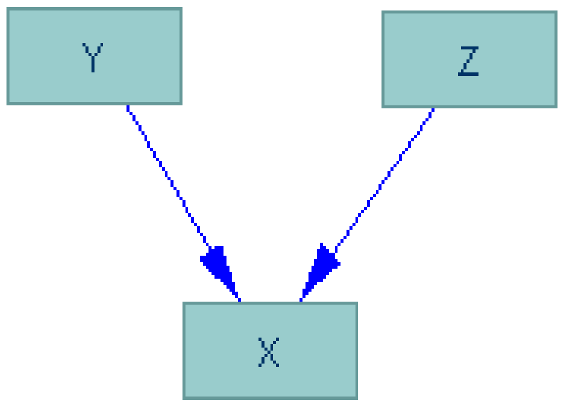

Figure 3.2. Inverted causal fork

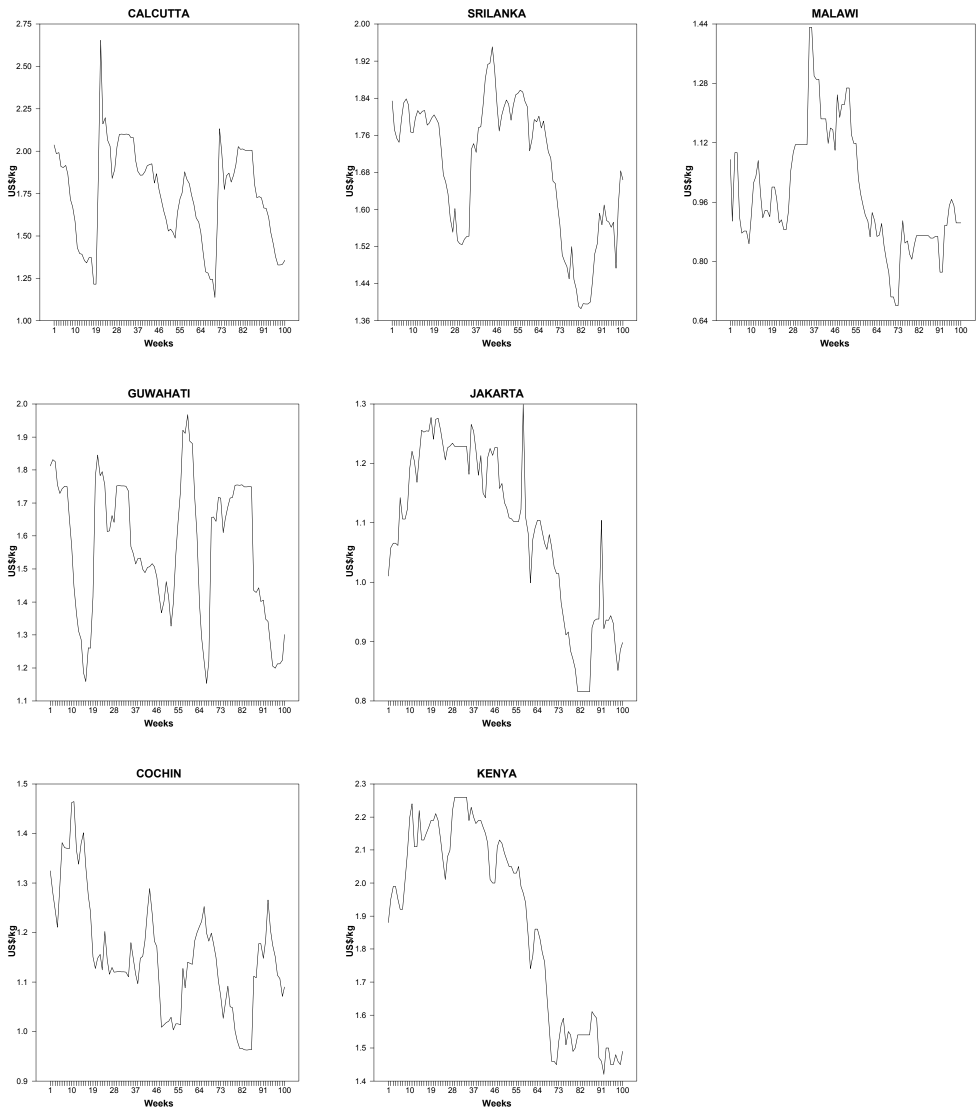

Figure 4.1. Black tea auction price in levels in seven world auction centers (December 1999 through June 2002) in US dollar terms [10]

[10] Note that auction centers in Jakarta, Kenya and Malawi trades in US dollar terms. Rests of the markets do trade in their local currencies. In this plot all prices are converted into US dollar terms. Note that horizontal axis in all graphs are number of weeks and vertical axis in all graphs are in US$/kg.

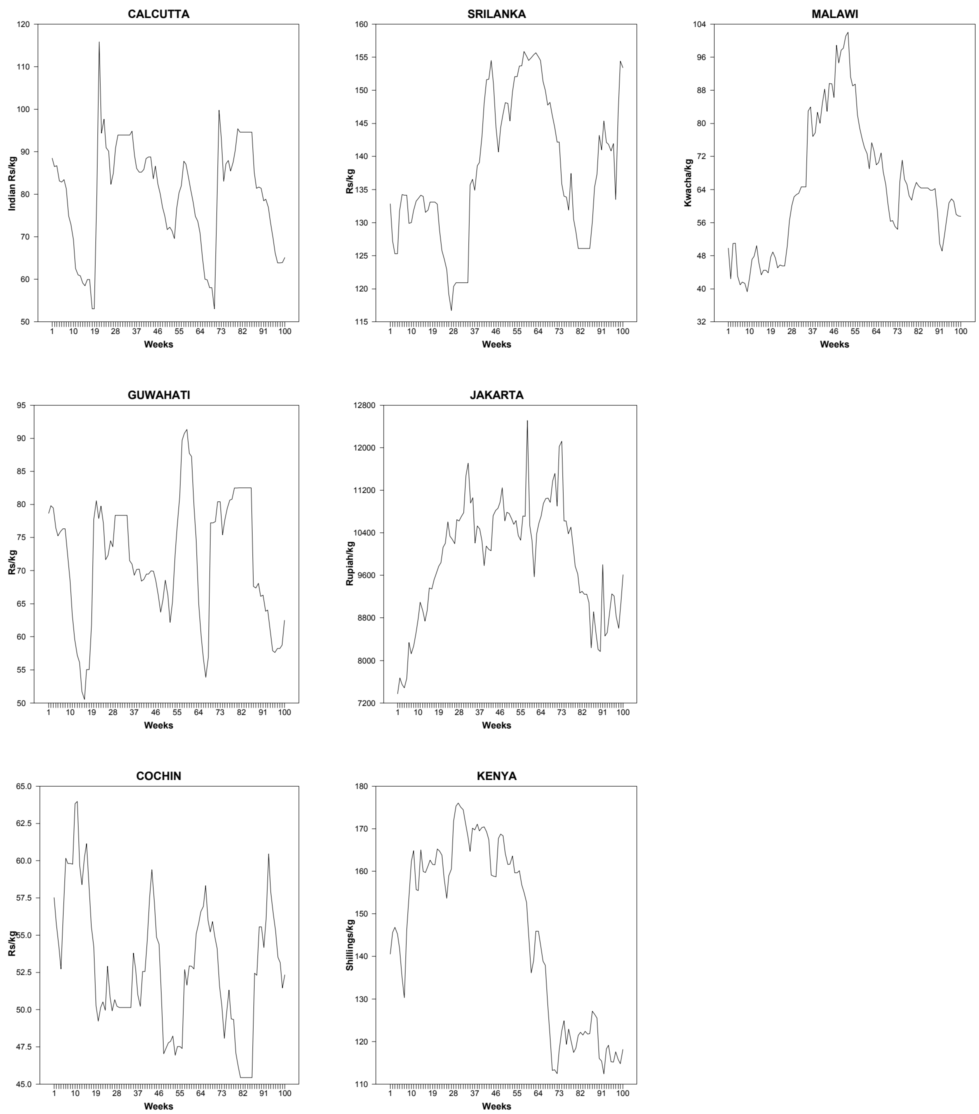

Figure 4.2. Black tea auction price in levels in seven world auction centers (December 1999 through June 2002) in local currencies [11]

[11] Note that India trade in Indian rupees, Sri Lanka in Sri Lankan rupees. Indonesian market price is converted into Indonesian Rupeih, Kenyan market price is converted to Kenyan Shillings and Malawi market price is converted into Malawi Kwacha. Note that all horizontal axis are in Weeks. Vertical axis for Calcutta, Guwahati and Cochin are in Rs/kg, for Sri Lanka in Rs/kg, Jakarta in Rupiah/kg, Kenya in Shillings/kg and Malawi in Kwacha/kg.

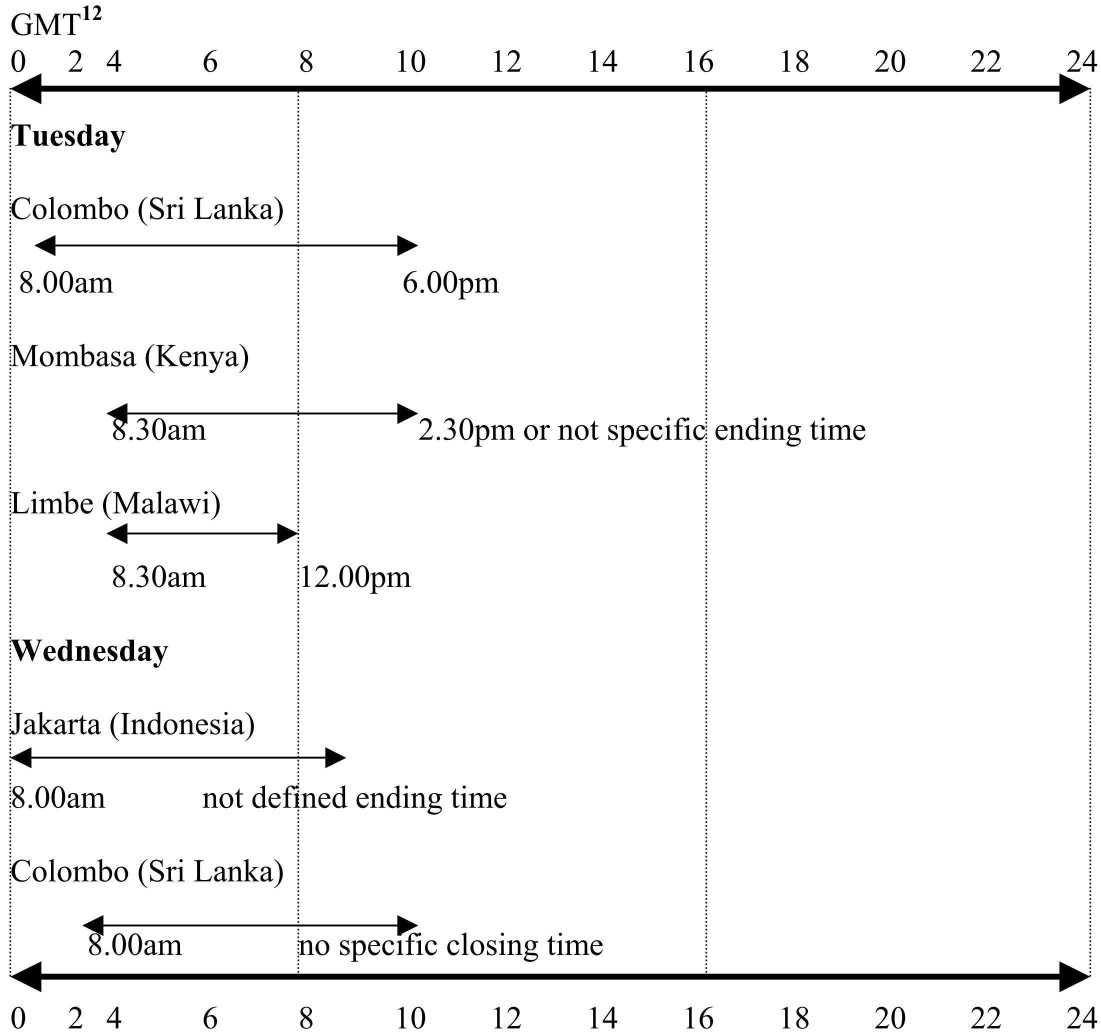

Figure 4.3. Regular trading hours in four tea auction markets on Tuesday and Monday in a regular week

[12] GMT is the Greenwich Mean Time.

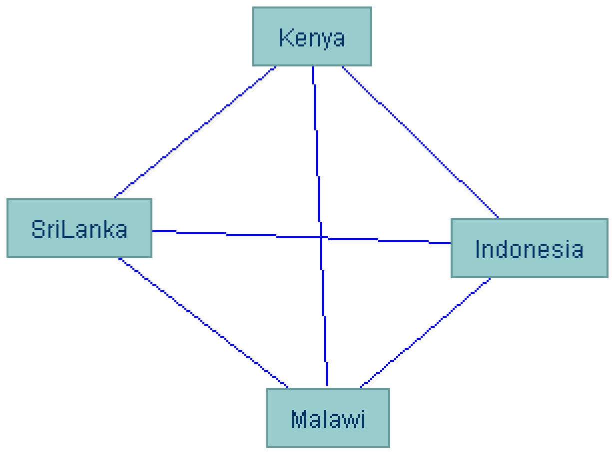

Figure 4.4. Complete undirected graph with edges connecting all markets

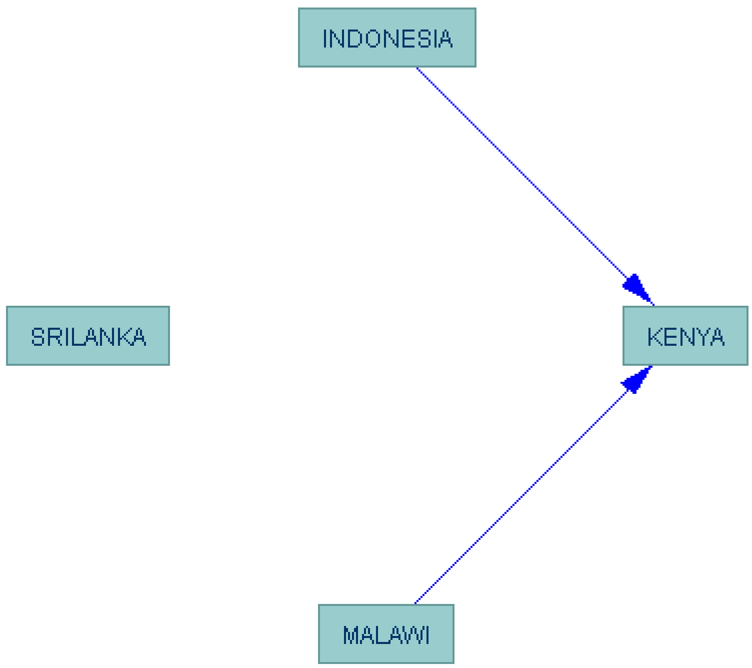

Figure 4.5. Complete directed graph on innovations from the VAR, US dollar converted data and 10% significance level of edge removal

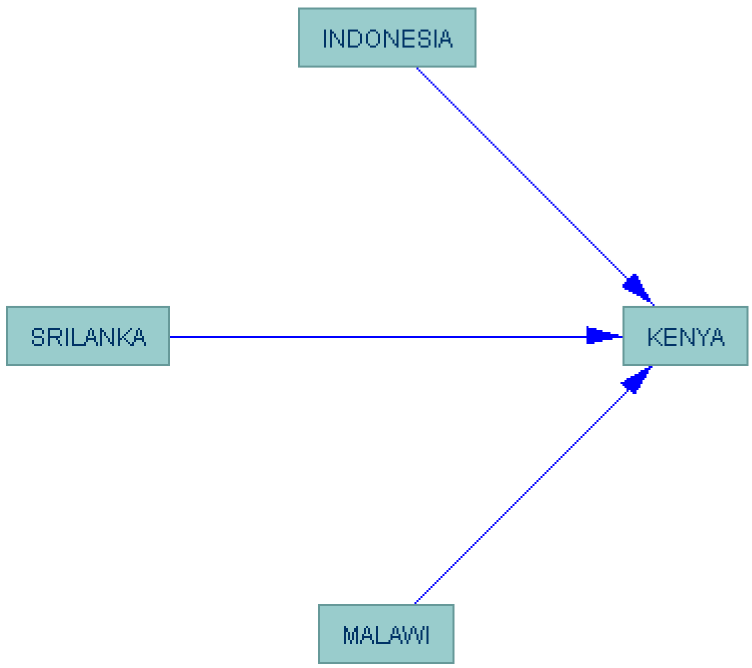

Figure 4.6. Complete directed graph on innovations from the VAR, US dollar converted data and 20% significance level of edge removal

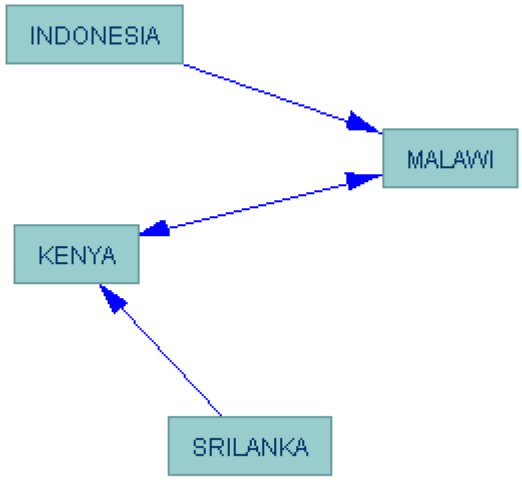

Figure 4.7. Complete directed graph on innovations from the VAR, local currency data and 10% significance level of edge removal

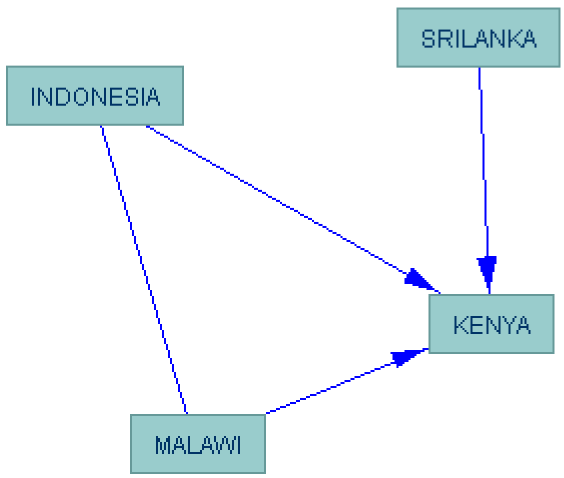

Figure 4.8. Complete directed graph on innovations from the VAR, local currency data and 20% significance level of edge removal

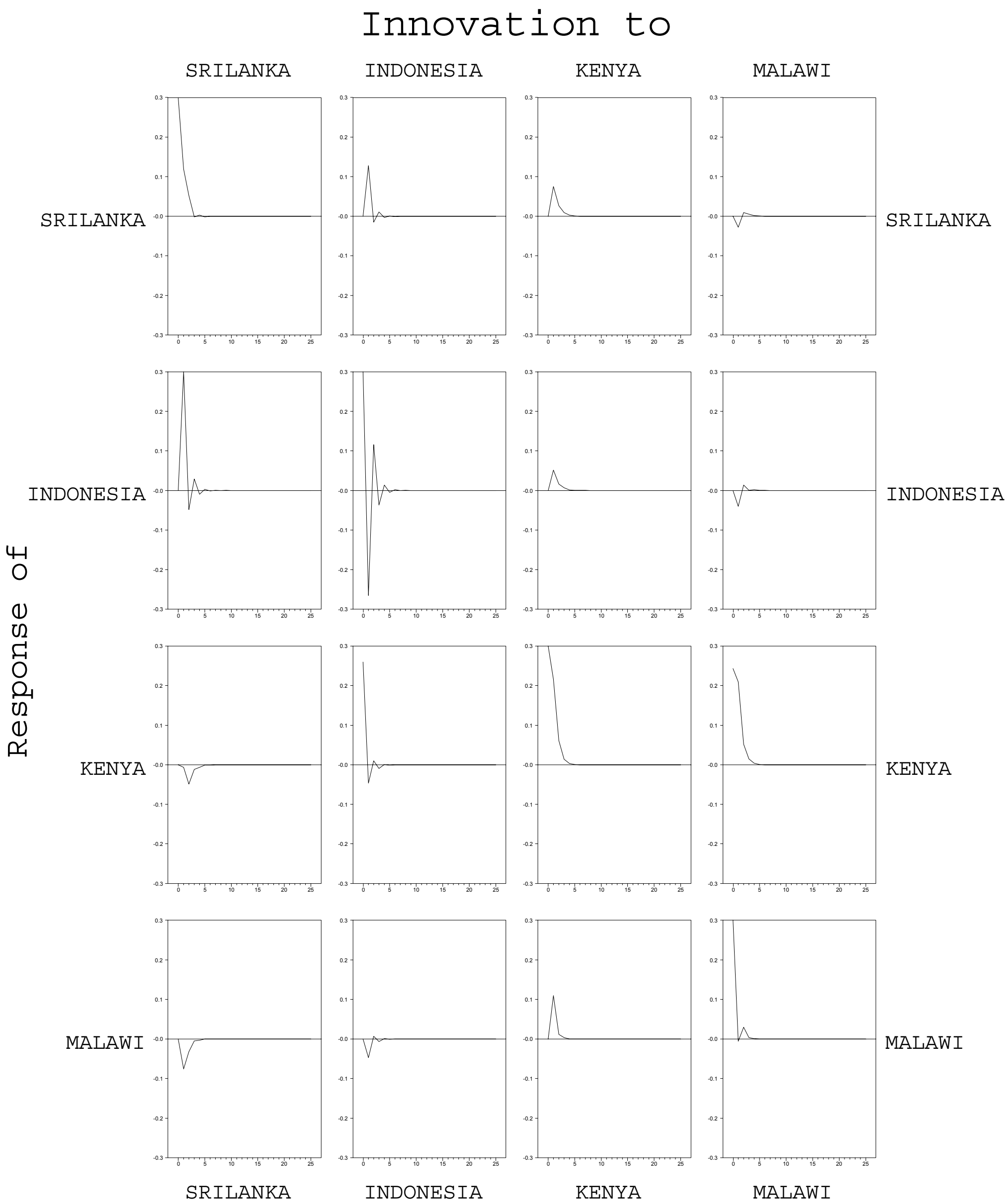

Figure 4.9. Responses of each market to a one-time only shock in each series based on lagged relation and contemporaneous relation, dollar converted data and causal pattern from the DAG at 10% significant level[13]

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[13] Note that the horizontal axis shows the number of periods in weeks that a markets takes to stabilizes due to a shock in each market, they are 5, 10, 15, 20 and 25 weeks. The vertical axis shows the size of the shock ranging 0.3 through –0.3.

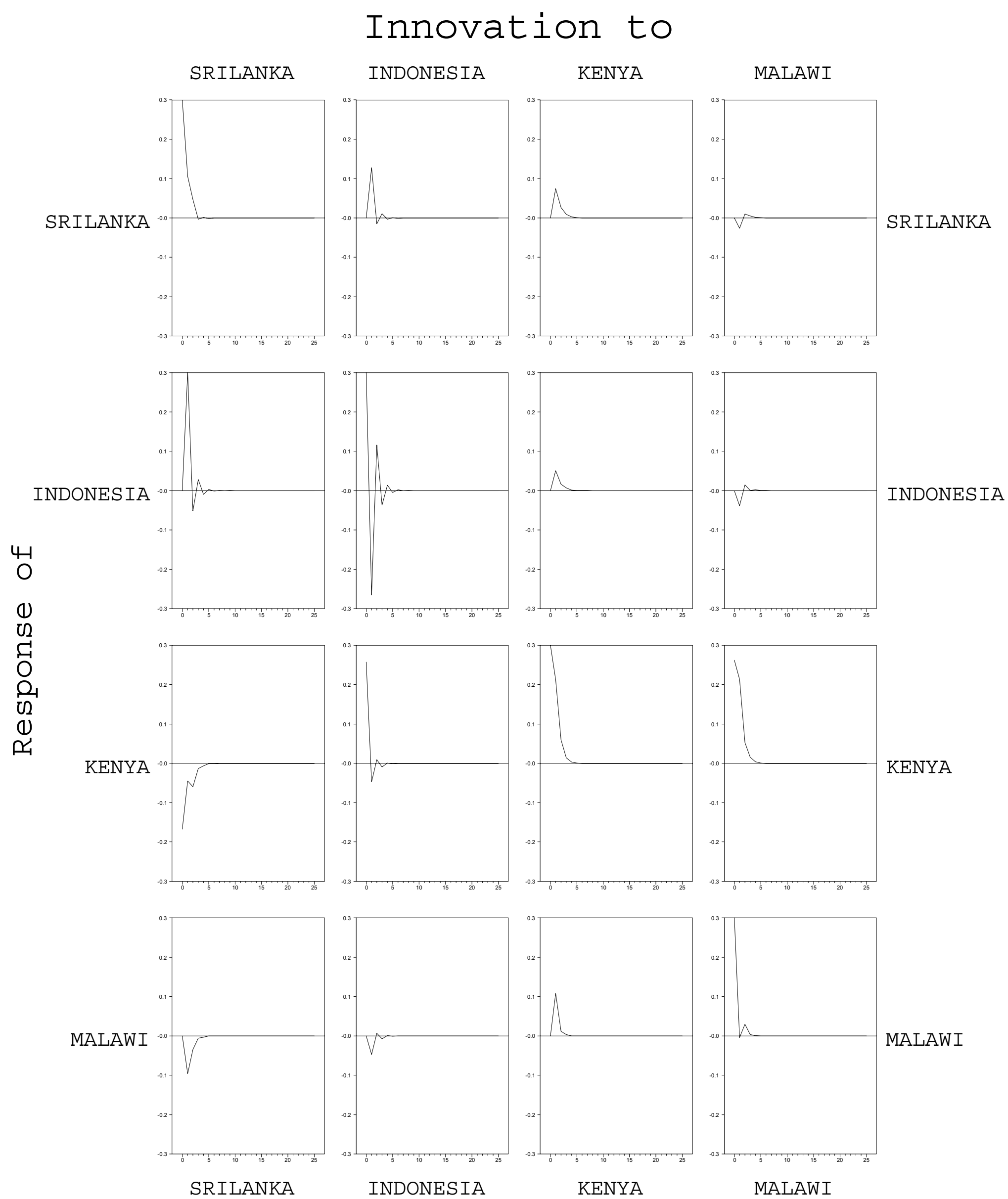

Figure 4.10. Responses of each market to a one-time only shock in each series based on lagged relation and contemporaneous relation, dollar converted data and causal pattern from the DAG at 20% significant level[14]

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[14] Note that the horizontal axis shows the number of periods in weeks that a markets takes to stabilizes due to a shock in each market, they are 5, 10, 15, 20 and 25 weeks. The vertical axis shows the size of the shock ranging 0.3 through –0.3.

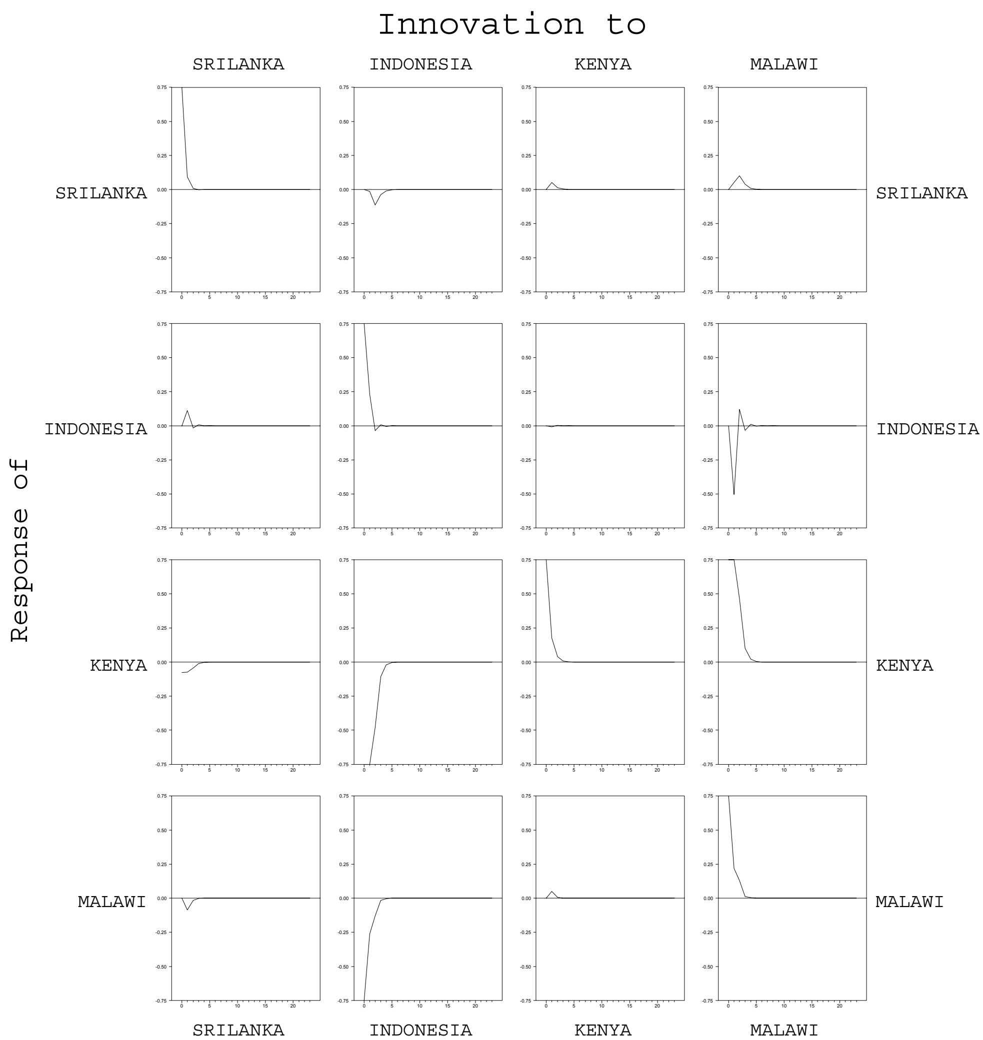

Figure 4.11. Responses of each market to a one-time only shock in each series based on lagged relation and contemporaneous relation, local currencies and causal pattern from the DAG at 10% significant level (consider the Malawi→Kenya relationship)[15]

[15] Note that the horizontal axis shows the number of periods in weeks that a markets takes to stabilizes due to a shock in each market, they are 5, 10, 15, 20 and 25 weeks. The vertical axis shows the size of the shock ranging 0.75 through –0.75.

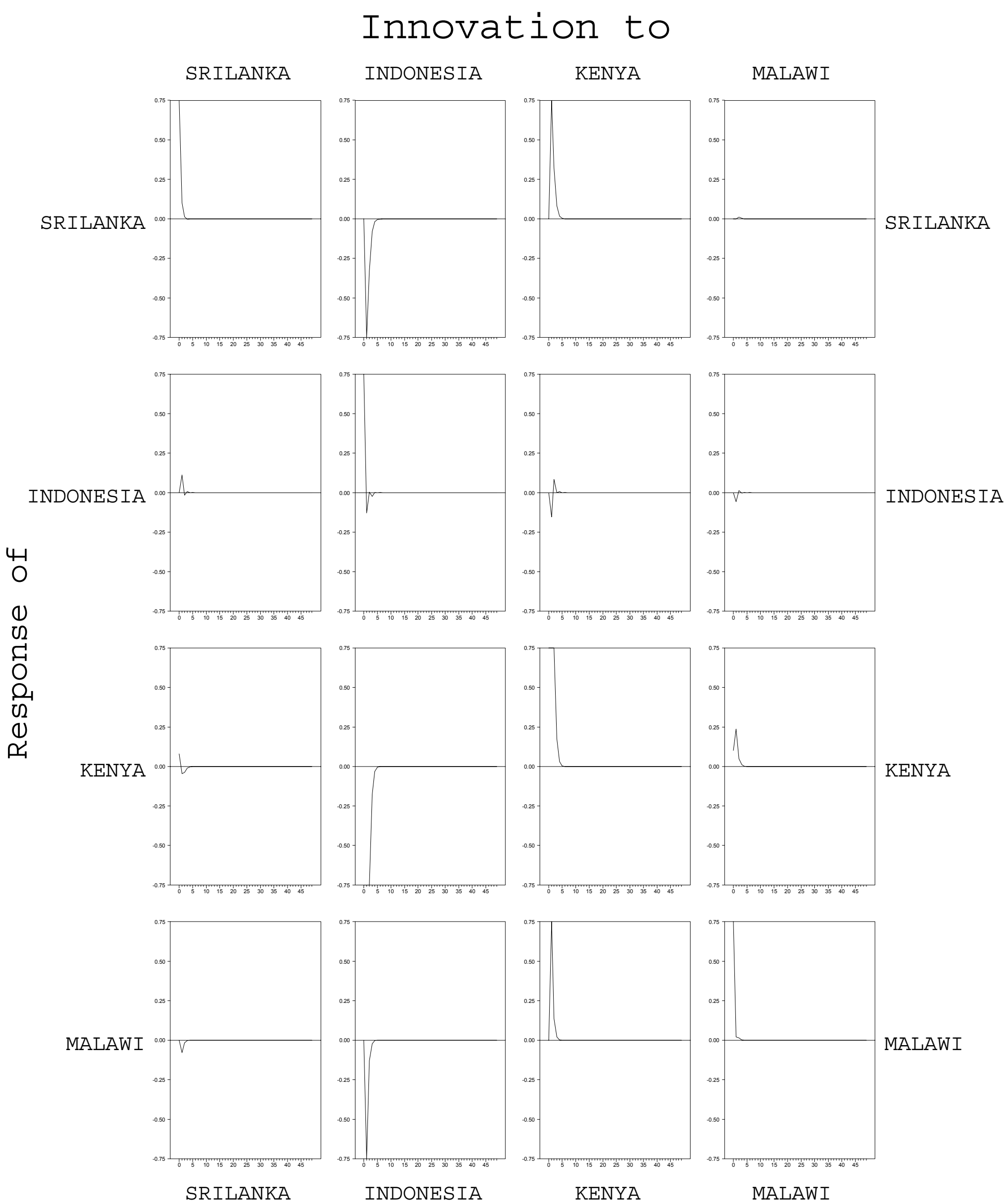

Figure 4.12. Responses of each market to a one-time only shock in each series based on lagged relation and contemporaneous relation, local currencies and causal pattern from the DAG at 10% significant level (consider the Kenya→Malawi relationship)[16]

[16] Note that the horizontal axis shows the number of periods in weeks that a market takes to stabilize due to a shock in each market, they are 5, 10, 15, 20, 25, 30, 35, 40 and 45 weeks. The vertical axis shows the size of the shock ranging 0.75 through –0.75.

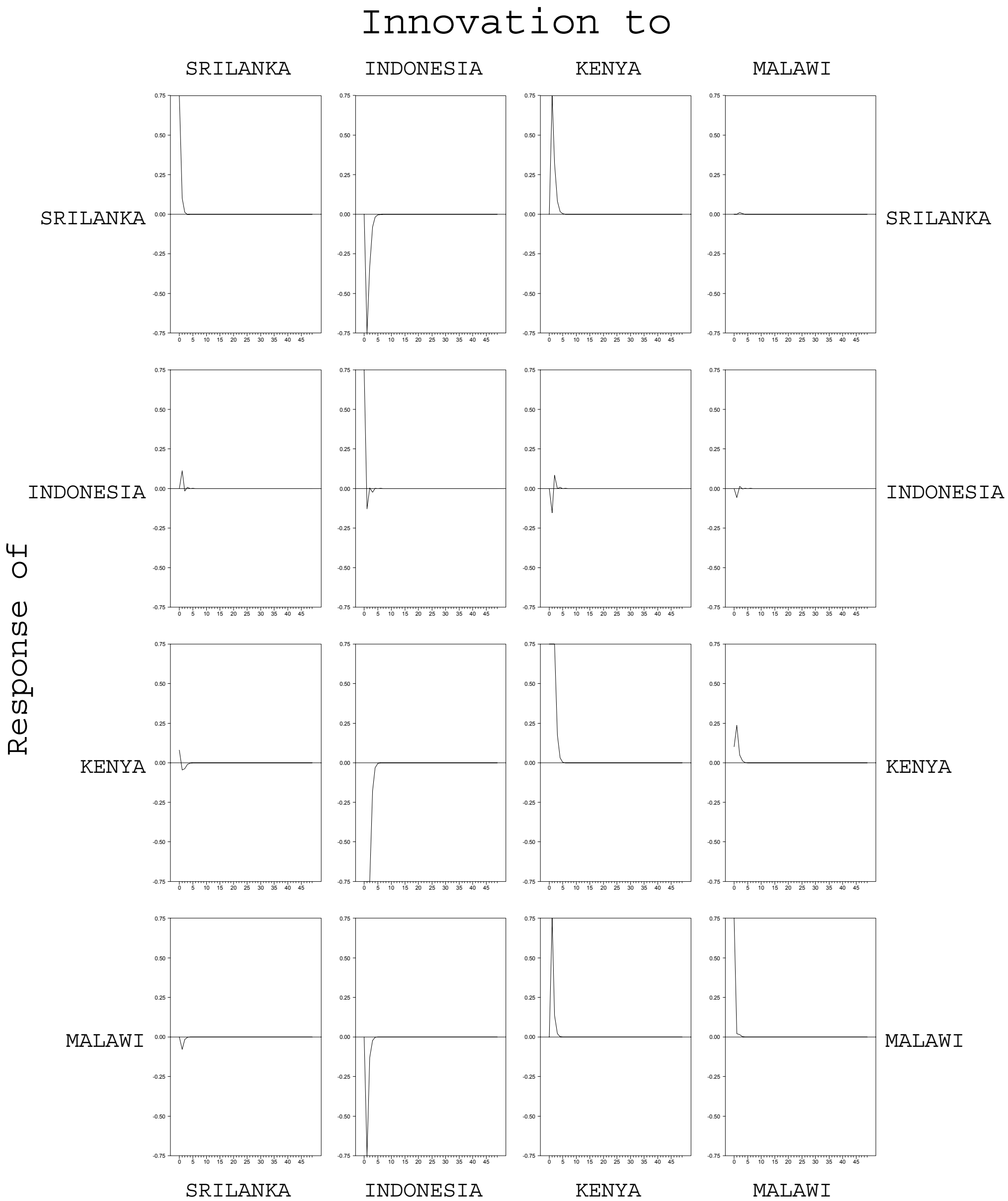

Figure 4.13. Responses of each market to a one-time only shock in each series based on lagged relation and contemporaneous relation, local currencies and causal pattern from the DAG at 20% significant level[17]

[17] Note that the horizontal axis shows the number of periods in weeks that a market takes to stabilize due to a shock in each market, they are 5, 10, 15, 20, 25, 30, 35, 40 and 45 weeks. The vertical axis shows the size of the shock ranging 0.75 through –0.75.

APPENDIX B

TABLES

Table 4.1. Descriptive Statistics on Prices for Black Tea from Seven Auction Markets, December 1999 through June 2002[18]

	US Dollar						Local currency	
Market	Mean $/kg	Mean Rank	SD	SD Rank	CV	CV Rank	CV	CV Rank
Calcutta (India)	1.75	2	0.28	2	0.162	2	0.158	2
Guwahati(India)	1.56	4	0.21	3	0.135	4	0.132	4
Cochin (India)	1.15	5	0.12	7	0.101	6	0.083	6
Colombo (Sri Lanka)	1.69	3	0.15	5	0.088	7	0.079	7
Jakarta (Indonesia)	1.09	6	0.14	6	0.128	5	0.112	5
Mombasa (Kenya)	1.89	1	0.29	1	0.152	3	0.143	3
Limbe (Malawi)	0.98	7	0.16	4	0.163	1	0.250	1

[18] Observed data are weekly average prices received in each tea auction market. On the left hand side of the table we discuss the summary statistics of dollar-converted data (Prices are quoted here in US $/kilogram of black tea, Kenyan, Malawi and Indonesian markets trade in US dollar terms, and other markets are in local currencies). On the right hand side column of the table we discuss the summary statistics from auction prices in local currency terms.

The entry “Mean” refers to the mean price quoted in each market in the sample period. “ Mean Rank” column refers to the ranking based on the mean price in the market. The acronym SD stands for the standard deviation of the prices in each market over the sample period. The term “SD Rank” is the column that ranks the auction market price based on the standard deviation. The column headed CV refers to the coefficient of variation, calculated as the standard deviation divided by the mean for each market price. The CV Rank refers to the ranking based on the coefficient of variation. The highest rank is 1 and the lowest rank is 7.

Table 4.2. Tests of Nonstationary on Price from Seven Tea Auction Markets, December 1999 through June 2002

Tea auction center	US Dollar[19]			Local Currency[20]		
	DF[21] t-statistic	ADF t-statistic	k[22]	DF t-statistic	ADF t-statistic	k
Calcutta (India)	-2.59	-3.23	1	-2.70	-3.30	1
Guwahati (India)	-2.04	-4.20	3	-2.21	-4.24	3
Cochin (India)	-3.42	-3.48	1	-2.39	-3.47	1
Colombo (Sri Lanka)	-1.47	-1.58	1	-1.32	-1.41	1
Jakarta (Indonesia)	-1.42	-0.92	1	-2.94	-2.20	1
Mombasa (Kenya)	-0.72	-0.89	1	-0.67	-0.86	1
Limbe (Malawi)	-1.71	-1.81	1	-1.45	-1.61	1

[19] Original currencies used to trade in auction markets.
1. Indian markets-Indian Rupees.
2. Sri Lankan market-Sri Lankan Rupees.
3. Indonesian, Kenyan and Malawi markets- US dollar.

[20] Local currencies in each market:
1. Indian markets-Indian Rupees.
2 .Sri Lankan market- Sri Lankan Rupees.
3. Indonesian market-Rupiah.
4. Kenyan market-Shillings.
5.Malawi market-Kwacha.

[21] DF is the Dickey Fuller test and ADF is the Augmented Dickey Fuller Test.

[22] Note that *k* is the lag length and is determined through the Schwarz-Loss Metric (we take the lag length that has the minimum Schwarz-Loss value).

Table 4.3. Tests of Cointegration Between Prices from Four Tea Auction Markets (December 1999 through June 2002)[23] Dollar Converted Data

R	T*	C(5%)*	D*	T	C(5%)	D
=0	51.688	53.423	F#	54.516	47.208	R
<=1	19.947	34.795	F	28.006	29.376	F
<=2	5.410	19.993	F	9.836	15.340	F
<=3	0.840	9.113	F	0.947	3.841	F

F# is the first fail to reject situation that suggest the presence of no co-integration among 4 tea auction markets.

[23] R is the number of co-integrating vectors (it runs from being equal to zero through equal or less than 3. T* is the calculated trace test for constant inside the co-integrating space, associated with the number of co-integrating vectors in the left-hand-most column. C(5%)* is the table value of the statistic at 95% significance level. D is the decision to reject or fail to reject the null hypothesis of presence of co-integrating vectors. Following Johansen (1992), we stop testing at the first failure to reject the null, starting at the top of the table and moving sequentially across from left to right and from top to the bottom. R stands for reject the above null hypothesis. T, C(5%) and D without the asterisk means the test results for the discovery of co-integrating vectors where the constant outside the co-integrating space. The critical values are taken from Table B.2 (within) and Table B.3 (outside) in Hansens and Juselius (1995, p. 80-81).

Table 4.4. Tests of Cointegration Between Prices from Four Tea Auction Markets (December 1999 through June 2002)[24] Local Currency Data

R	T*	C(5%)*	D*	T	C(5%)	D
=0	33.313	53.423	F#	44.469	54.516	F
<=1	12.677	34.795	F	23.718	28.006	F
<=2	5.726	19.993	F	11.931	9.836	R
<=3	0.704	9.113	F	3.907	0.947	R

F# is the first fail to reject situation that suggest the presence of no co-integration among 4 tea auction markets.

[24] R is the number of co-integrating vectors (it runs from being equal to zero through equal or less than or equal to 3. T* is the calculated trace test for the constant inside the co-integrating space, associated with the number of co-integrating vectors in the left-hand-most column. C(5%)* is the table value of the statistic at 95% significance level. D is the decision to reject or fail to reject the null hypothesis of presence of co-integrating vectors. Following Johansen (1992), we stop testing at the first failure to reject the null, starting at the top of the table and moving sequentially across from left to right and from top to the bottom. R stands for reject the above null hypothesis. T, C(5%) and D without the asterisk means the test results for the discovery of co-integrating vectors where the constant is outside the co-integrating space. The critical values are taken from Table B.2 (within) and Table B.3 (outside) in Hansens and Juselius (1995, p. 80-81).

Table 4.5. Determination of Number of Lags in the VAR[25]

US dollar converted		Local currency	
Number of Lags	Schwarz loss function value	Number of Lags	Schwarz loss function value
1	-23.0981	1	21.6685
2	-22.4226	2	22.4438
3	-21.5394	3	23.3228
4	-20.6926	4	24.1793
5	-19.7588	5	25.1159

[25] VAR is Vector Autoregression.

Table 4.6. Correlations and *p*-Values for Removed Edges for US Dollar Converted Data Series

10% significance level

Edge Removed	Correlation[26] Zero order	Correlation Coefficient	p-value[27]
Sri Lanka-Indonesia	(SLA,INA)[28]	-0.0263	0.7955
Sri Lanka-Kenya	(SLA,KEN)	-0.1441	0.1538
Sri Lanka-Malawi	(SLA,MAL)	0.1151	0.2551
Indonesia-Malawi	(INA,MAL)	-0.0998	0.3240

20% significance level

Edge Removed	Correlation Zero order	Correlation Coefficient	p-value
Sri Lanka-Indonesia	(SLA,INA)	-0.0263	0.7955
Sri Lanka-Malawi	(SLA,MAL)	0.1151	0.2551
Indonesia-Malawi	(INA,MAL)	-0.0998	0.3240

[26] Here all edges are based on zero order correlation and that gives us the final DAG (we did not want to condition on any other variable to remove the edge).
[27] *p*-value is the probability value.
[28] SLA-Sri Lanka, INA-Indonesia, KEN-Kenya and MAL-Malawi.

Table 4.7. Correlations and *p*-Values for Removed Edges for Local Currency Data Series

10% significance level

Edge Removed	Correlation Zero order	Correlation Coefficient	p-value[29]
Sri Lanka-Indonesia	(SLA,INA)[30]	-0.0403	0.6911
Sri Lanka-Malawi	(SLA,MAL)	0.0042	0.9669
Indonesia-Kenya	(INA,KEN)	0.1456	0.1496

20% significance level

Edge Removed	Correlation Zero order	Correlation Coefficient	p-value
Sri Lanka-Indonesia	(SLA,INA)	-0.0403	0.6911
Sri Lanka-Malawi	(SLA,MAL)	0.0042	0.9669

[29] *p*-value is the probability value.
[30] SLA-Sri Lanka, INA-Indonesia, KEN-Kenya and MAL-Malawi.

Table 4.8. Standard Deviations on Forecast Errors at Horizons of 0, 1 and 23 Weeks Ahead, US Dollar Converted Series

	0 weeks		1 week		23 weeks	
Tea auction center	US$/kg	Rank	US$/kg	Rank	US$/kg	Rank
Colombo (Sri Lanka)	0.0418	4	0.0425	4	0.0426	4
Jakarta (Indonesia)	0.0434	3	0.0471	3	0.0475	3
Kenya (Mombasa)	0.0493	2	0.0516	2	0.0518	2
Limbe (Malawi)	0.0637	1	0.0644	1	0.0645	1

Table 4.9. Standard Deviations on Forecast Errors at Horizons of 0, 1 and 23 Weeks Ahead, Local Currency Series

Tea auction center	0 weeks LC[31]/kg	1 week LC/kg	23 weeks LC/kg
Colombo (Sri Lanka)	3.4215	6.6492	6.8465
Jakarta (Indonesia)	483.8325	497.5382	499.1560
Kenya (Mombasa)	134.7264	136.9485	137.0663
Limbe (Malawi)	4.2038	8.1790	8.2188

[31] LC is the local currency in each country. They are: Sri Lanka-Sri Lankan Rupees, Indonesia-Rupiah, Kenya-Shillings and Malawi-Kwacha.

Table 4.10. Forecast Error Decompositions on Prices from Four Tea Auction Markets, US Dollar Converted Series (Causal Ordering Based on 10% Significance Level)

Horizon	Sri Lanka	Indonesia	Kenya	Malawi
(Sri Lanka-Colombo)				
0	100.00	0.00	0.00	0.00
1	97.79	1.59	0.55	0.08
23	97.68	1.61	0.63	0.09
(Indonesia-Jakarta)				
0	0.00	100.00	0.00	0.00
1	9.01	90.63	0.23	0.13
23	9.14	90.46	0.25	0.15
(Kenya-Mombasa)				
0	0.00	6.67	87.48	5.85
1	0.004	6.31	84.36	9.33
23	0.23	6.27	83.99	9.51
(Malawi-Limbe)				
0	0.00	0.00	0.00	100.00
1	0.57	0.21	1.18	98.04
23	0.67	0.22	1.19	97.91

Table 4.11. Forecast Error Decompositions on Prices from Four Tea Auction Markets, US Dollar Converted Series (Causal Ordering Based on 20% Significance Level)

Horizon	Sri Lanka	Indonesia	Kenya	Malawi
(Sri Lanka-Colombo)				
0	100.00	0.00	0.00	0.00
1	97.81	1.59	0.53	0.07
23	97.70	1.61	0.61	0.08
(Indonesia-Jakarta)				
0	0.00	100.00	0.00	0.00
1	8.55	91.10	0.22	0.13
23	8.71	90.90	0.24	0.14
(Kenya-Mombasa)				
0	2.75	6.49	84.02	6.75
1	2.696	6.13	80.91	10.26
23	3.00	6.09	80.47	10.43
(Malawi-Limbe)				
0	0.00	0.00	0.00	100.00
1	0.89	0.22	1.14	97.75
23	1.01	0.22	1.15	97.61

Table 4.12. Forecast Error Decompositions on Prices from Four Tea Auction Markets, Local Currency Series (Causal Ordering Based on 10% Significance Level and with Malawi→Kenya Edge)

Horizon	Sri Lanka	Indonesia	Kenya	Malawi
		(Sri Lanka-Colombo)		
0	100.00	0.00	0.00	0.00
1	99.45	0.02	0.26	0.27
23	96.95	1.38	0.27	1.40
		(Indonesia-Jakarta)		
0	0.00	100.00	0.00	0.00
1	0.96	79.80	0.003	19.23
23	0.97	78.86	0.004	20.16
		(Kenya-Mombasa)		
0	0.09	43.16	15.03	41.72
1	0.07	48.42	5.93	45.58
23	0.08	48.49	5.77	45.65
		(Malawi-Limbe)		
0	0.00	50.85	0.00	49.15
1	0.01	50.85	0.002	49.14
23	0.01	50.85	0.002	49.14

Table 4.13. Forecast Error Decompositions on Prices from Four Tea Auction Markets, Local Currency Series (Causal Ordering Based on 10% Significance Level and with Kenya→Malawi Edge)

Horizon	Sri Lanka	Indonesia	Kenya	Malawi
		(Sri Lanka-Colombo)		
0	100.00	0.00	0.00	0.00
1	98.83	0.70	0.27	0.20
23	96.08	2.18	0.28	1.47
		(Indonesia-Jakarta)		
0	0.00	100.00	0.00	0.00
1	0.79	71.60	0.01	27.60
23	0.80	70.54	0.01	28.66
		(Kenya-Mombasa)		
0	0.95	0.00	99.05	0.00
1	0.11	48.02	6.87	45.01
23	0.12	48.14	6.60	45.15
		(Malawi-Limbe)		
0	0.00	50.76	0.004	49.24
1	0.003	50.76	0.01	49.24
23	0.003	50.76	0.01	49.24

Table 4.14. Forecast Error Decompositions on Prices from Four Tea Auction Markets, Local Currency Series (Causal Ordering Based on 20% Significance Level)

Horizon	Sri Lanka	Indonesia	Kenya	Malawi
(Sri Lanka-Colombo)				
0	100.00	0.00	0.00	0.00
1	26.75	35.11	38.14	0.00
23	25.23	36.00	38.76	0.003
(Indonesia-Jakarta)				
0	0.00	100.00	0.00	0.00
1	1.18	96.27	2.24	0.31
23	1.19	95.59	2.89	0.33
(Kenya-Mombasa)				
0	0.001	49.58	50.42	0.001
1	0.001	49.59	50.40	0.01
23	0.001	49.59	50.40	0.01
(Malawi-Limbe)				
0	0.00	0.00	0.000	100.00
1	0.16	37.55	35.86	26.43
23	0.17	37.65	36.01	26.18

Table 4.15. Theil's U-Statistic[32] to Compare the Forecast Performance of VAR in Different Markets, US Dollar Converted Data

Step[33]	Sri Lanka	Indonesia	Kenya	Malawi	Number of Observations[34]
1	0.995	0.999	1.051	0.994	32
2	1.003	1.027	1.064	1.005	31
3	0.992	1.032	1.071	1.012	30
4	0.993	1.062	1.083	1.017	29
5	0.989	1.063	1.115	1.022	28

[32] Theil's U-statistic is calculated as the ratio between the root mean square of the errors of forecasts using the vector auto regression model and the root mean square of the errors of forecasts using the random walk model.
[33] Steps: this is the number of steps ahead the model forecasts.
[34] Number of Observations: this is the number of observations available for each step ahead forecast.

Table 4.16. Theil's U-Statistic to Compare the Forecast Performance of VAR in Different Markets, Local Currency Data

Step	Sri Lanka	Indonesia	Kenya	Malawi	Number of Observations
1	1.016	1.033	1.052	1.003	32
2	1.036	1.053	1.062	0.989	31
3	1.041	1.054	1.064	0.994	30
4	1.051	1.073	1.069	0.995	29
5	1.063	1.069	1.099	0.996	28

Table 4.17. Correlation Coefficients of Innovations: US Dollar Converted Data

	Sri Lanka	Indonesia	Kenya	Malawi
Sri Lanka	1			
Indonesia	-0.0263	1		
Kenya	-0.1441	0.2357	1	
Malawi	0.1151	-0.0998	0.2175	1

Table 4.18. Correlation Coefficients of Innovations: Local Currency Data

	Sri Lanka	Indonesia	Kenya	Malawi
Sri Lanka	1			
Indonesia	-0.0403	1		
Kenya	-0.1735	0.1456	1	
Malawi	0.0042	-0.2042	0.2119	1

APPENDIX C

Regression Analysis for Time Series (RATS) Input Programs Used in the Thesis

1. Summery Statistics (Dollar Converted Data)

```
*************** RATS Input Program for summary statistics****************
*************************in 7 tea auctions markets*************************
**************************data converted into US dollars************

calendar 1 1 1
allocate 130 100
eqv 1 to 7
CAL GUW COC SLA JAK KEN MAL
*********
open data s:\tea.txt
data(format=free,org=obs) 1:1 100:1 1 to 7
***************************************************

eqv 8 to 9
SLRS INRS
*************************************************
open data s:\exrate.txt
data(format=free,org=obs) 1:1 100:1 8 to 9
**************************************************

eqv 10 to 16
CALCUTTA GUWAHATI COCHIN SRILANKA JAKARTA KENYA MALAWI

set CALCUTTA 1:1 100:1 = (CAL)*(1/INRS)
set GUWAHATI 1:1 100:1 = (GUW)*(1/INRS)
set COCHIN 1:1 100:1 = (COC)*(1/INRS)
set SRILANKA 1:1 100:1 = (SLA)*(1/SLRS)
set JAKARTA 1:1 100:1 = (JAK)/100
set KENYA 1:1 100:1 =(KEN)/100
set MALAWI 1:1 100:1 =(MAL)/100

Table

EXTREMUM(print) CALCUTTA 1:1 100:1
EXTREMUM(print) GUWAHATI 1:1 100:1
```

```
EXTREMUM(print) COCHIN 1:1 100:1
EXTREMUM(print) SRILANKA 1:1 100:1
EXTREMUM(print) JAKARTA 1:1 100:1
EXTREMUM(print) KENYA 1:1 100:1
EXTREMUM(print) MALAWI 1:1 100:1

STATISTICS(print) CALCUTTA 1:1 100:1
STATISTICS(print) GUWAHATI 1:1 100:1
STATISTICS(print) COCHIN 1:1 100:1
STATISTICS(print) SRILANKA 1:1 100:1
STATISTICS(print) JAKARTA 1:1 100:1
STATISTICS(print) KENYA 1:1 100:1
STATISTICS(print) MALAWI 1:1 100:1

end
```

2. Summary Statistics (Local Currency)

```
*************** RATS Input Program for Summary statistics *****************
************************* 7 tea auctions markets**********
*************************in local currencies**********

calendar 1 1 1
allocate 200 100
eqv 1 to 7
CAL GUW COC SLA JAK KEN MAL
*********
open data s:\tea.txt
data(format=free,org=obs) 1:1 100:1 1 to 7
****************************************************

eqv 8 to 12
SLRS INRS IARH KESH MKAW
**************************************************
open data s:\exrate.txt
data(format=free,org=obs) 1:1 100:1 8 to 12
***************************************************

eqv 13 to 19
CALCUTTA GUWAHATI COCHIN SRILANKA JAKARTA KENYA MALAWI

set CALCUTTA 1:1 100:1 = CAL
set GUWAHATI 1:1 100:1 = GUW
set COCHIN 1:1 100:1 = COC
set SRILANKA 1:1 100:1 = SLA
set JAKARTA 1:1 100:1 = (JAK)/100*(IARH/1)
set KENYA 1:1 100:1 =(KEN)/100*(KESH/1)
set MALAWI 1:1 100:1 =(MAL)/100*(MKAW/1)

Table

EXTREMUM(print) CALCUTTA 1:1 100:1
EXTREMUM(print) GUWAHATI 1:1 100:1
EXTREMUM(print) COCHIN 1:1 100:1
EXTREMUM(print) SRILANKA 1:1 100:1
EXTREMUM(print) JAKARTA 1:1 100:1
EXTREMUM(print) KENYA 1:1 100:1
EXTREMUM(print) MALAWI 1:1 100:1

STATISTICS(print) CALCUTTA 1:1 100:1
```

```
STATISTICS(print) GUWAHATI 1:1 100:1
STATISTICS(print) COCHIN 1:1 100:1
STATISTICS(print) SRILANKA 1:1 100:1
STATISTICS(print) JAKARTA 1:1 100:1
STATISTICS(print) KENYA 1:1 100:1
STATISTICS(print) MALAWI 1:1 100:1

end
```

3. Plot of Dollar Converted Data

```
*************** RATS Input Program for graphs ****************
************************ 7 tea auctions markets***************
************************data converted into US dollars*******

calendar 1 1 1
allocate 130 100
eqv 1 to 7
CAL GUW COC SLA JAK KEN MAL
*********
open data s:\tea.txt
data(format=free,org=obs) 1:1 100:1 1 to 7
**********************************************

eqv 8 to 9
SLRS INRS
**********************************************
open data s:\exrate.txt
data(format=free,org=obs) 1:1 100:1 8 to 9
**********************************************

eqv 10 to 16
CALCUTTA GUWAHATI COCHIN SRILANKA JAKARTA KENYA MALAWI

set CALCUTTA 1:1 100:1 = (CAL)*(1/INRS)
set GUWAHATI 1:1 100:1 = (GUW)*(1/INRS)
set COCHIN 1:1 100:1 = (COC)*(1/INRS)
set SRILANKA 1:1 100:1 = (SLA)*(1/SLRS)
set JAKARTA 1:1 100:1 = (JAK)/100
set KENYA 1:1 100:1 =(KEN)/100
set MALAWI 1:1 100:1 =(MAL)/100

extremum srilanka 1:1 100:1

open plot s:\dollar.rgf

spgraph(vfields=3,hfields=3)
graph(vlable='US$/kg',hlable='Weeks',patterns,header=%label([series] CALCUTTA),$
MAX=2.653,MIN=1.139) 1
# 10 1:1 100:1 1

graph(vlable='US$/kg',hlable='Weeks',patterns,header=%label([series] GUWAHATI),$
MAX=1.967,MIN=1.153) 1
# 11 1:1 100:1 1
```

```
graph(vlable='US$/kg',hlable='Weeks',patterns,header=%label([series] COCHIN),$
MAX=1.465,MIN=0.963) 1
# 12 1:1 100:1 1

graph(vlable='US$/kg',hlable='Weeks',patterns,header=%label([series] SRILANKA),$
MAX=1.950,MIN=1.386) 1
# 13 1:1 100:1 1

graph(vlable='US$/kg',hlable='Weeks',patterns,header=%label([series] JAKARTA),$
MAX=1.2988,MIN=0.8155) 1
# 14 1:1 100:1 1

graph(vlable='US$/kg',hlable='Weeks',patterns,header=%label([series] KENYA),$
MAX=2.26,MIN=1.42) 1
# 15 1:1 100:1 1

graph(vlable='US$/kg',hlable='Weeks',patterns,header=%label([series] MALAWI),$
MAX=1.4307,MIN=0.6811) 1
# 16 1:1 100:1 1

spgraph(done)
end
```

4. Plot of Local Currency Data

```
*************** RATS Input Program for graphs ****************
************************ 7 tea auctions markets**********
************************in local currencies**********

calendar 1 1 1
allocate 200 100
eqv 1 to 7
CAL GUW COC SLA JAK KEN MAL
*********
open data s:\tea.txt
data(format=free,org=obs) 1:1 100:1 1 to 7
***********************************************

eqv 8 to 12
SLRS INRS IARH KESH MKAW
*********************************************
open data s:\exrate.txt
data(format=free,org=obs) 1:1 100:1 8 to 12
**********************************************

eqv 13 to 19
CALCUTTA GUWAHATI COCHIN SRILANKA JAKARTA KENYA MALAWI

set CALCUTTA 1:1 100:1 = CAL
set GUWAHATI 1:1 100:1 = GUW
set COCHIN 1:1 100:1 = COC
set SRILANKA 1:1 100:1 = SLA
set JAKARTA 1:1 100:1 = (JAK)/100*(IARH/1)
set KENYA 1:1 100:1 =(KEN)/100*(KESH/1)
set MALAWI 1:1 100:1 =(MAL)/100*(MKAW/1)

*extremum malawi 1:1 100:1
open plot s:\local.rgf

spgraph(vfields=3,hfields=3)
graph(vlable='Indian Rs/kg',hlable='Weeks',patterns,header=%label([series]
CALCUTTA),$
MAX=115.86,MIN=53.08) 1
# 13 1:1 100:1 1

graph(vlable='Rs/kg',hlable='Weeks',patterns,header=%label([series] GUWAHATI),$
MAX=91.35,MIN=50.56) 1
```

```
# 14 1:1 100:1 1

graph(vlable='Rs/kg',hlable='Weeks',patterns,header=%label([series] COCHIN),$
MAX=63.98,MIN=45.44) 1
# 15 1:1 100:1 1

graph(vlable='Rs/kg',hlable='Weeks',patterns,header=%label([series] SRILANKA),$
MAX=155.87,MIN=116.70) 1
# 16 1:1 100:1 1

graph(vlable='Rupiah/kg',hlable='Weeks',patterns,header=%label([series] JAKARTA),$
MAX=12513.938,MIN=7373.73) 1
# 17 1:1 100:1 1

graph(vlable='Shillings/kg',hlable='Weeks',patterns,header=%label([series] KENYA),$
MAX=176.054,MIN=112.393) 1
# 18 1:1 100:1 1

graph(vlable='Kwacha/kg',hlable='Weeks',patterns,header=%label([series] MALAWI),$
MAX=102.05,MIN=39.32) 1
# 19 1:1 100:1 1

spgraph(done)
end
```

5. DF and ADF for Dollar Converted Data

```
*****RATS input program for dicky-fuller test*****
************and ADF test tea auctions markets******
***************data converted in to US dolars*****

calendar 1900 1 1
allocate 130 2001:1
eqv 1 to 35
CAL GUW COC SLA JAK KEN MAL $
DCAL DGUW DCOC DSLA DJAK DKEN DMAL $
CALCUTTA GUWAHATI COCHIN SRILANKA JAKARTA KENYA MALAWI $
DCALCUTTA DGUWAHATI DCOCHIN DSRILANKA DJAKARTA DKENYA
DMALAWI $
DDCALCUTTA DDGUWAHATI DDCOCHIN DDSRILANKA DDJAKARTA
DDKENYA DDMALAWI
**********************************************
open data d:\tea.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 7
**********************************************
eqv 36 to 37
SLRS INRS
**********************************************
open data d:\exrate.txt
data(format=free,org=obs) 1901:1 2000:1 36 to 37
**********************************************

set CALCUTTA 1901:1 2000:1 = (CAL)*(1/INRS)
set GUWAHATI 1901:1 2000:1 = (GUW)*(1/INRS)
set COCHIN 1901:1 2000:1 = (COC)*(1/INRS)
set SRILANKA 1901:1 2000:1 =(SLA)*(1/SLRS)
set JAKARTA 1901:1 2000:1 = (JAK)/100
set KENYA 1901:1 2000:1 = (KEN)/100
set MALAWI 1901:1 2000:1 = (MAL)/100

*declare symmetric v
do i=15,21
diff i 1902:1 2000:1 i+7 1902:1
end do i

do i=22,28
linreg i 1902:1 2000:1
# constant (i-7){1}
***********************************
```

```
compute schwarz = log((%seesq)) + ((%nreg))*log(%nobs)/%nobs
compute phi = log(%seesq) + ((%nreg))*(2.01)*log(log(%nobs))/%nobs
display @10 ##### %nreg schwarz @+10 ####.####  phi @+10 #####.####
*************************************
end do i
do i=22,28
do j=1,10
linreg i 1912:1 2000:1
# constant (i-7){1} i{1 to j}
*******************************************************
compute schwarz = log(%seesq) + ((%nreg))*log(%nobs)/%nobs
compute phi =  log(%seesq) + ((%nreg))*2.1*log(log(%nobs))/%nobs
display @10  ### %nreg schwarz @+10 ####.### phi @+10 ####.###
end do j
end do i

do i=22,28
diff i 1903:1 2000:1 i+7 1903:1
end do i

do i=29,35
do j=1,10
linreg i 1913:1 2000:1
#constant (i-7){1} i{1 to j}
*******************************************************
compute schwarz = log(%seesq) + ((%nreg))*log(%nobs)/%nobs
compute phi =  log(%seesq) + ((%nreg))*2.1*log(log(%nobs))/%nobs
display @10  ### %nreg schwarz @+10 ####.### phi @+10 ####.###
end do j
end do i

end
```

6. DF and ADF for Local Currency Data

```
*****RATS input program for dicky-fuller test*****
************and ADF test 7 tea auctions markets******
***************data in local currencies*****

calendar 1900 1 1
allocate 130 2001:1
eqv 1 to 35
CAL GUW COC SLA JAK KEN MAL $
DCAL DGUW DCOC DSLA DJAK DKEN DMAL $
CALCUTTA GUWAHATI COCHIN SRILANKA JAKARTA KENYA MALAWI $
DCALCUTTA DGUWAHATI DCOCHIN DSRILANKA DJAKARTA DKENYA
DMALAWI $
DDCALCUTTA DDGUWAHATI DDCOCHIN DDSRILANKA DDJAKARTA
DDKENYA DDMALAWI
**********************************************
open data s:\tea.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 7
***********************************************
eqv 36 to 40
SLRS INRS IARH KESH MKAW
**********************************************
open data s:\exrate.txt
data(format=free,org=obs) 1901:1 2000:1 36 to 40
**********************************************

set CALCUTTA 1901:1 2000:1 = CAL
set GUWAHATI 1901:1 2000:1 = GUW
set COCHIN 1901:1 2000:1 = COC
set SRILANKA 1901:1 2000:1 = SLA
set JAKARTA 1901:1 2000:1 = (JAK)/100*(IARH/1)
set KENYA 1901:1 2000:1 =(KEN)/100*(KESH/1)
set MALAWI 1901:1 2000:1 =(MAL)/100*(MKAW/1)

do i=15,21
diff i 1902:1 2000:1 i+7 1902:1
end do i

do i=22,28
linreg i 1902:1 2000:1
# constant (i-7){1}
*************************************
compute schwarz = log((%seesq)) + ((%nreg))*log(%nobs)/%nobs
```

```
compute phi = log(%seesq) + ((%nreg))*(2.01)*log(log(%nobs))/%nobs
display @10 ##### %nreg schwarz @+10 ####.####  phi @+10 #####.####
************************************
end do i
do i=22,28
do j=1,10
linreg i 1912:1 2000:1
# constant (i-7){1} i{1 to j}
******************************************************
compute schwarz = log(%seesq) + ((%nreg))*log(%nobs)/%nobs
compute phi =  log(%seesq) + ((%nreg))*2.1*log(log(%nobs))/%nobs
display @10  ### %nreg schwarz @+10 ####.### phi @+10 ####.###
end do j
end do i

do i=22,28
diff i 1903:1 2000:1 i+7 1903:1
end do i

do i=29,35
do j=1,10
linreg i 1913:1 2000:1
#constant (i-7){1} i{1 to j}
******************************************************
compute schwarz = log(%seesq) + ((%nreg))*log(%nobs)/%nobs
compute phi =  log(%seesq) + ((%nreg))*2.1*log(log(%nobs))/%nobs
display @10  ### %nreg schwarz @+10 ####.### phi @+10 ####.###
end do j
end do i

end
```

7. Determine the Presence of Co-Integration Dollar Converted

```
*****************Cointegration analysis******
******************in five tea auctions markets***************
**********************dollar converted***************
**
calendar 1900 1 1
allocate 200 2001:1
eqv 1 to 14
CAL GUW COC SLA JAK KEN MAL $
CALCUTTA GUWAHATI COCHIN SRILANKA JAKARTA KENYA MALAWI
**********************************************
open data s:\tea.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 7
************************************************
eqv 15 to 16
SLRS INRS
**********************************************
open data s:\exrate.txt
data(format=free,org=obs) 1901:1 2000:1 15 to 16
***********************************************

set CALCUTTA 1901:1 2000:1 = (CAL)*(1/INRS)
set GUWAHATI 1901:1 2000:1 = (GUW)*(1/INRS)
set COCHIN 1901:1 2000:1 = (COC)*(1/INRS)
set SRILANKA 1901:1 2000:1 =(SLA)*(1/SLRS)
set JAKARTA 1901:1 2000:1 = (JAK)/100
set KENYA 1901:1 2000:1 = (KEN)/100
set MALAWI 1901:1 2000:1 = (MAL)/100

set ser4 = SRILANKA
set ser5 = JAKARTA
set ser9 = KENYA
set ser10 = MALAWI

open copy s:\coin_dollar_out.txt
source c:\rats\CATS\CATSMAIN.SRC
****

@CATS(proc=rank,lags=2,dettrend=cimean,batch) 1901:1 2000:1
# SRILANKA JAKARTA KENYA MALAWI
**
end
```

8. Determine the Presence of Co-Integration Local Currency Data

```
*****************Cointegration analysis******
*******************in five tea auctions markets***************
***********************local currencies***************
**
calendar 1900 1 1
allocate 200 2001:1
eqv 1 to 14
CAL GUW COC SLA JAK KEN MAL $
CALCUTTA GUWAHATI COCHIN SRILANKA JAKARTA KENYA MALAWI
***********************************************
open data s:\tea.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 7
*************************************************
eqv 15 to 19
SLRS INRS IARH KESH MKAW
***********************************************
open data s:\exrate.txt
data(format=free,org=obs) 1901:1 2000:1 15 to 19
************************************************

set CALCUTTA 1901:1 2000:1 = CAL
set GUWAHATI 1901:1 2000:1 = GUW
set COCHIN 1901:1 2000:1 = COC
set SRILANKA 1901:1 2000:1 = SLA
set JAKARTA 1901:1 2000:1 = (JAK)/100*(IARH/1)
set KENYA 1901:1 2000:1 =(KEN)/100*(KESH/1)
set MALAWI 1901:1 2000:1 =(MAL)/100*(MKAW/1)

set ser4 = SRILANKA
set ser5 = JAKARTA
set ser9 = KENYA
set ser10 = MALAWI

open copy s:\coin_local_out.txt
source c:\rats\CATS\CATSMAIN.SRC
****

@CATS(proc=rank,lags=2,dettrend=cimean,batch) 1901:1 2000:1
# SRILANKA JAKARTA KENYA MALAWI

end
```

9. To find out the Number of Lags in the VAR- Dollar Converted Data

```
*****************VAR in first differences identify # of lags***
******************in Four tea auctions markets***************
**********************dollar converted***************

calendar 1900 1 1
allocate 200 2001:1
eqv 1 to 12
SLA JAK KEN MAL $
SRILANKA JAKARTA KENYA MALAWI $
DSRILANKA DJAKARTA DKENYA DMALAWI
**********************************************
open data s:\tea4.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 4
************************************************
eqv 13 to 16
SLRS IARH KESH MKAW
**********************************************
open data s:\exrate4.txt
data(format=free,org=obs) 1901:1 2000:1 13 to 16
***********************************************

set SRILANKA 1901:1 2000:1 = (SLA)*(1/SLRS)
set JAKARTA 1901:1 2000:1 = (JAK)/100
set KENYA 1901:1 2000:1 =(KEN)/100
set MALAWI 1901:1 2000:1 =(MAL)/100

do i=5,8
diff i 1902:1 2000:1 i+4 1902:1
end do i

do k=1,5
system 1 to 4

equation 1 DSRILANKA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

equation 2 DJAKARTA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

equation 3 DKENYA
```

```
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

equation 4 DMALAWI
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

end(system)

estimate(noprint,noftests,outsigma=vsigma) 1901:1 2000:1

compute schwarz = log(%det(vsigma)) + ((%nreg)*8)*log(%nobs)/%nobs
compute phi =  log(%det(vsigma)) + ((%nreg)*8)*(2.01)*log(log(%nobs))/%nobs
display @10  ##### %nreg
display @10 ####.#### schwarz @20  ####.#### phi

end do k

end
```

10. Identify the Number of Lags in the VAR- Local Currency Data

```
*****************VAR in first differences identify # of lags***
******************in Four tea auctions markets***************
*********************Local currencies***************

calendar 1900 1 1
allocate 200 2001:1
eqv 1 to 12
SLA JAK KEN MAL $
SRILANKA JAKARTA KENYA MALAWI $
DSRILANKA DJAKARTA DKENYA DMALAWI
**********************************************
open data s:\tea4.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 4
************************************************
eqv 13 to 16
SLRS IARH KESH MKAW
**********************************************
open data s:\exrate4.txt
data(format=free,org=obs) 1901:1 2000:1 13 to 16
***********************************************

set SRILANKA 1901:1 2000:1 = SLA
set JAKARTA 1901:1 2000:1 = (JAK)/100*(IARH/1)
set KENYA 1901:1 2000:1 =(KEN)/100*(KESH/1)
set MALAWI 1901:1 2000:1 =(MAL)/100*(MKAW/1)

do i=5,8
diff i 1902:1 2000:1 i+4 1902:1
end do i

do k=1,5
system 1 to 4

equation 1 DSRILANKA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

equation 2 DJAKARTA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

equation 3 DKENYA
```

```
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

equation 4 DMALAWI
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

end(system)

estimate(noprint,noftests,outsigma=vsigma) 1901:1 2000:1

compute schwarz = log(%det(vsigma)) + ((%nreg)*8)*log(%nobs)/%nobs
compute phi =  log(%det(vsigma)) + ((%nreg)*8)*(2.01)*log(log(%nobs))/%nobs
display @10  ##### %nreg
display @10 ####.#### schwarz @20  ####.#### phi

end do k

end
```

11. VAR in First Differences and Covariance/Correlation Matrix (Dollar Converted Data)

```
*****************VAR in first differences ***
******************in Four tea auctions markets***************
**********************dollar converted************
***************and variance/correlation matrix******

calendar 1900 1 1
allocate 200 2001:1
eqv 1 to 12
SLA JAK KEN MAL $
SRILANKA JAKARTA KENYA MALAWI $
DSRILANKA DJAKARTA DKENYA DMALAWI
**********************************************
open data s:\tea4.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 4
************************************************
eqv 13 to 16
SLRS IARH KESH MKAW
**********************************************
open data s:\exrate4.txt
data(format=free,org=obs) 1901:1 2000:1 13 to 16
***********************************************

set SRILANKA 1901:1 2000:1 = (SLA)*(1/SLRS)
set JAKARTA 1901:1 2000:1 = (JAK)/100
set KENYA 1901:1 2000:1 =(KEN)/100
set MALAWI 1901:1 2000:1 =(MAL)/100

do i=5,8
diff i 1902:1 2000:1 i+4 1902:1
end do i

do k=1,1
system 1 to 4

equation 1 DSRILANKA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

equation 2 DJAKARTA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}
```

```
equation 3 DKENYA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

equation 4 DMALAWI
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

end(system)

end do k

DECLARE SYMMETRIC V
estimate(print,noftests,outsigma=v) 1901:1 2000:1
vcv 1901:1 2000:1
# 101 102 103 104
end
```

12. VAR in First Differences and Covariance/Correlation Matrix (Local Currency Data)

```
*****************VAR in first differences***
******************in Four tea auctions markets***************
*********************local currencies and**********
**************varaince/correlation matrix***********

calendar 1900 1 1
allocate 200 2001:1
eqv 1 to 12
SLA JAK KEN MAL $
SRILANKA JAKARTA KENYA MALAWI $
DSRILANKA DJAKARTA DKENYA DMALAWI
**********************************************
open data s:\tea4.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 4
***********************************************
eqv 13 to 16
SLRS IARH KESH MKAW
**********************************************
open data s:\exrate4.txt
data(format=free,org=obs) 1901:1 2000:1 13 to 16
**********************************************

set SRILANKA 1901:1 2000:1 = SLA
set JAKARTA 1901:1 2000:1 = (JAK)/100*(IARH/1)
set KENYA 1901:1 2000:1 =(KEN)/100*(KESH/1)
set MALAWI 1901:1 2000:1 =(MAL)/100*(MKAW/1)

do i=5,8
diff i 1902:1 2000:1 i+4 1902:1
end do i

do k=1,1
system 1 to 4

equation 1 DSRILANKA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

equation 2 DJAKARTA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}
```

```
equation 3 DKENYA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

equation 4 DMALAWI
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

end(system)

end do k

DECLARE SYMMETRIC V
estimate(print,noftests,outsigma=v) 1901:1 2000:1
vcv 1901:1 2000:1
# 101 102 103 104

end
```

13. Programs for Impulse Responses and Error Decompositions (Dollar Converted Data)

```
*****************VAR in first differences ***********
******************in Four tea auctions markets*********
*********************dollar converted*************************
**************to get impulse responses and*********************
**************forecast error decompositions in levels************
**************20% dag significance level***********************

***INDONESIA-->KENYA
***MALAWI-->KENYA
***SRILANKA-->KENYA

calendar 1900 1 1
allocate 200 2001:1
eqv 1 to 12
SLA JAK KEN MAL $
SRILANKA JAKARTA KENYA MALAWI $
DSRILANKA DJAKARTA DKENYA DMALAWI
*********************************************
open data s:\tea4.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 4
**********************************************
eqv 13 to 16
SLRS IARH KESH MKAW
*********************************************
open data s:\exrate4.txt
data(format=free,org=obs) 1901:1 2000:1 13 to 16
*********************************************

declare rect[series] impblk(4,4)
declare vect[series] scaled(4)
declare vect[labels] implabel(4)
declare vect[strings] mplabel(4)

source(noecho) c:\rats\bernanke.src

set SRILANKA 1901:1 2000:1 = (SLA)*(1/SLRS)
set JAKARTA 1901:1 2000:1 = (JAK)/100
set KENYA 1901:1 2000:1 =(KEN)/100
set MALAWI 1901:1 2000:1 =(MAL)/100

do i=5,8
```

```
diff i 1902:1 2000:1 i+4 1902:1
end do i

do k=1,1
system 1 to 4

equation 1 DSRILANKA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

equation 2 DJAKARTA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

equation 3 DKENYA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

equation 4 DMALAWI
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k} $
DMALAWI{1 to k}

end(system)

estimate(print,noftests,outsigma=v) 1901:1 2000:1
end do k

***INDONESIA-->KENYA
***MALAWI-->KENYA
***SRILANKA-->KENYA

WRITE v
DECLARE RECT PATTERN(4,4)
INPUT PATTERN
1 0 0 0
0 1 0 0
1 1 1 1
0 0 0 1

nonlin A31 A32 A34

declare rect A
compute A31=.1
compute A32=.1
```

```
compute A34=.1

compute A=%Identity(4)
find min -2*log(%det(A))+%sum(%log(%mqformdiag(v,TR(A)))) {
compute A(3,1)=A31, A(3,2)=A32, A(3,4)=A34
}
end find
@BERNANKE(TEST,PRINT) v PATTERN FACTOR
ERRORS(DECOMP=FACTOR,Impulses) 4 24
# 1
# 2
# 3
# 4

** to plot the impulse response functions of five world markets
***INDONESIA-->KENYA
***MALAWI-->KENYA
***SRILANKA-->KENYA

compute neqn = 4

compute implabel=||'SRILANKA','INDONESIA','KENYA','MALAWI'||
list ieqn = 1 to 4

compute mplabel=||'SRILANKA','INDONESIA','KENYA','MALAWI'||

impluse(noprint,decomp=factor) 4 26 1
 card ieqn impblk(ieqn,1) 1 ieqn

  set scaled(1) = (impblk(1,1))/sqrt(v(1,1))
  set g11 = scaled(1)
  labels scaled(1)
  #implabel(1)

  set scaled(2) = (impblk(2,1))/sqrt(v(2,2))
  set g21 = scaled(2)
  labels scaled(2)
  #implabel(2)


  set scaled(3) = (impblk(3,1))/sqrt(v(3,3))
  set g31 = scaled(3)
  labels scaled(3)
  #implabel(3)
```

```
set scaled(4) = (impblk(4,1))/sqrt(v(4,4))
  set g41 = scaled(4)
  labels scaled(4)
  #implabel(4)

 impluse(noprint,decomp=factor) 4 26 2
 card ieqn impblk(ieqn,2) 1 ieqn

  set scaled(1) = (impblk(1,2))/sqrt(v(1,1))
  set g12 = scaled(1)
  labels scaled(1)
  #implabel(1)

  set scaled(2) = (impblk(2,2))/sqrt(v(2,2))
  set g22 = scaled(2)
  labels scaled(2)
  #implabel(2)

  set scaled(3) = (impblk(3,2))/sqrt(v(3,3))
  set g32 = scaled(3)
  labels scaled(3)
  #implabel(3)

set scaled(4) = (impblk(4,2))/sqrt(v(4,4))
  set g42 = scaled(4)
  labels scaled(4)
  #implabel(4)

 impluse(noprint,decomp=factor) 4 26 3
 card ieqn impblk(ieqn,3) 1 ieqn

  set scaled(1) = (impblk(1,3))/sqrt(v(1,1))
  set g13 = scaled(1)
  labels scaled(1)
  #implabel(1)

  set scaled(2) = (impblk(2,3))/sqrt(v(2,2))
  set g23 = scaled(2)
  labels scaled(2)
  #implabel(2)

  set scaled(3) = (impblk(3,3))/sqrt(v(3,3))
  set g33 = scaled(3)
```

```
  labels scaled(3)
  #implabel(3)

  set scaled(4) = (impblk(4,3))/sqrt(v(4,4))
  set g43 = scaled(4)
  labels scaled(4)
  #implabel(4)

impluse(noprint,decomp=factor) 4 26 4
 card ieqn impblk(ieqn,4) 1 ieqn

  set scaled(1) = (impblk(1,4))/sqrt(v(1,1))
  set g14 = scaled(1)
  labels scaled(1)
  #implabel(1)

  set scaled(2) = (impblk(2,4))/sqrt(v(2,2))
  set g24 = scaled(2)
  labels scaled(2)
  #implabel(2)

  set scaled(3) = (impblk(3,4))/sqrt(v(3,3))
  set g34 = scaled(3)
  labels scaled(3)
  #implabel(3)

  set scaled(4) = (impblk(4,4))/sqrt(v(4,4))
  set g44 = scaled(4)
  labels scaled(4)
  #implabel(4)

grparm(nobold,font='time new roman') hlabel 12 matrixlabels 14 $
                                 header * vlabel *
spgraph(vfields=4,hfields=4,header='Innovation to',$
       xlabels=mplabel,ylabels=mplabel,vlabel='Response of',$
       xpos=both,ypos=both)

dofor i = g11 g21 g31 g41 $
         g12 g22 g32 g42 $
         g13 g23 g33 g43 $
         g14 g24 g34 g44


   open plot s:\imp1st_dollar_20.rgf
```

```
   graph(number=0,min=-0.3,max=0.3) 1
   # i

end dofor i
spgraph(done)
*/

end
```

14. Program for Impulse Responses and Error Decompositions
(Local Currency Data)

```
*******************VAR in first differences ***********
********************in Four tea auctions markets*********
************************local currencies****************************
***************to get impulse responses and************************
***************forecast error decompositions in levels************
***************10% dag significance level*************************

***INDONESIA-->MALAWI
***SRILANKA-->KENYA
***MALAWI-->KENYA

calendar 1900 1 1
allocate 200 2001:1
eqv 1 to 12
SLA JAK KEN MAL $
SRILANKA JAKARTA KENYA MALAWI $
DSRILANKA DJAKARTA DKENYA DMALAWI
***********************************************
open data d:\tea4.txt
data(format=free,org=obs) 1901:1 2000:1 1 to 4
*************************************************
eqv 13 to 16
SLRS IARH KESH MKAW
***********************************************
open data d:\exrate4.txt
data(format=free,org=obs) 1901:1 2000:1 13 to 16
************************************************

declare rect[series] impblk(4,4)
declare vect[series] scaled(4)
declare vect[labels] implabel(4)
declare vect[strings] mplabel(4)

source(noecho) c:\rats\bernanke.src

set SRILANKA 1901:1 2000:1 = SLA
set JAKARTA 1901:1 2000:1 = (JAK)/100*(IARH/1)
set KENYA 1901:1 2000:1 =(KEN)/100*(KESH/1)
set MALAWI 1901:1 2000:1 =(MAL)/100*(MKAW/1)

do i=5,8
```

```
diff i 1902:1 2000:1 i+4 1902:1
end do i

do k=1,1
system 1 to 4

equation 1 DSRILANKA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

equation 2 DJAKARTA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

equation 3 DKENYA
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

equation 4 DMALAWI
# constant DSRILANKA{1 to k} DJAKARTA{1 to k} DKENYA{1 to k}$
DMALAWI{1 to k}

end(system)

estimate(print,noftests,outsigma=v) 1901:1 2000:1

end do k

***INDONESIA-->MALAWI
***SRILANKA-->KENYA
***MALAWI-->KENYA

WRITE v
DECLARE RECT PATTERN(4,4)
INPUT PATTERN
1 0 0 0
0 1 0 0
1 0 1 1
0 1 0 1

nonlin A31 A34 $
    A42

declare rect A
```

```
compute A31=.1
compute A34=.1
compute A42=.1

compute A=%Identity(4)
find min -2*log(%det(A))+%sum(%log(%mqformdiag(v,TR(A)))) {
compute A(3,1)=A31, A(3,4)=A34, A(4,2)=A42
}
end find
@BERNANKE(TEST,PRINT) v PATTERN FACTOR
ERRORS(DECOMP=FACTOR,Impulses) 4 24
# 1
# 2
# 3
# 4

** to plot the impulse response functions of 4 world markets
***INDONESIA-->MALAWI
***SRILANKA-->KENYA
***KENYA-->MALAWI

compute neqn = 4

compute implabel=||'SRILANKA','INDONESIA','KENYA','MALAWI'||
list ieqn = 1 to 4

compute mplabel=||'SRILANKA','INDONESIA','KENYA','MALAWI'||

impluse(noprint,decomp=factor) 4 24 1
 card ieqn impblk(ieqn,1) 1 ieqn

  set scaled(1) = (impblk(1,1))/sqrt(v(1,1))
  set g11 = scaled(1)
  labels scaled(1)
  #implabel(1)

  set scaled(2) = (impblk(2,1))/sqrt(v(2,2))
  set g21 = scaled(2)
  labels scaled(2)
  #implabel(2)

  set scaled(3) = (impblk(3,1))/sqrt(v(3,3))
  set g31 = scaled(3)
  labels scaled(3)
```

```
 #implabel(3)

set scaled(4) = (impblk(4,1))/sqrt(v(4,4))
 set g41 = scaled(4)
 labels scaled(4)
 #implabel(4)

impluse(noprint,decomp=factor) 4 24 2
card ieqn impblk(ieqn,2) 1 ieqn

 set scaled(1) = (impblk(1,2))/sqrt(v(1,1))
 set g12 = scaled(1)
 labels scaled(1)
 #implabel(1)

 set scaled(2) = (impblk(2,2))/sqrt(v(2,2))
 set g22 = scaled(2)
 labels scaled(2)
 #implabel(2)

 set scaled(3) = (impblk(3,2))/sqrt(v(3,3))
 set g32 = scaled(3)
 labels scaled(3)
 #implabel(3)

set scaled(4) = (impblk(4,2))/sqrt(v(4,4))
 set g42 = scaled(4)
 labels scaled(4)
 #implabel(4)

impluse(noprint,decomp=factor) 4 24 3
card ieqn impblk(ieqn,3) 1 ieqn

 set scaled(1) = (impblk(1,3))/sqrt(v(1,1))
 set g13 = scaled(1)
 labels scaled(1)
 #implabel(1)

 set scaled(2) = (impblk(2,3))/sqrt(v(2,2))
 set g23 = scaled(2)
 labels scaled(2)
 #implabel(2)

 set scaled(3) = (impblk(3,3))/sqrt(v(3,3))
```

```
  set g33 = scaled(3)
  labels scaled(3)
  #implabel(3)

  set scaled(4) = (impblk(4,3))/sqrt(v(4,4))
  set g43 = scaled(4)
  labels scaled(4)
  #implabel(4)

impluse(noprint,decomp=factor) 4 24 4
 card ieqn impblk(ieqn,4) 1 ieqn

  set scaled(1) = (impblk(1,4))/sqrt(v(1,1))
  set g14 = scaled(1)
  labels scaled(1)
  #implabel(1)

  set scaled(2) = (impblk(2,4))/sqrt(v(2,2))
  set g24 = scaled(2)
  labels scaled(2)
  #implabel(2)

  set scaled(3) = (impblk(3,4))/sqrt(v(3,3))
  set g34 = scaled(3)
  labels scaled(3)
  #implabel(3)

  set scaled(4) = (impblk(4,4))/sqrt(v(4,4))
  set g44 = scaled(4)
  labels scaled(4)
  #implabel(4)

grparm(nobold,font='time new roman') hlabel 12 matrixlabels 14 $
                                header * vlabel *
spgraph(vfields=4,hfields=4,header='Innovation to',$
        xlabels=mplabel,ylabels=mplabel,vlabel='Response of',$
        xpos=both,ypos=both)

dofor i = g11 g21 g31 g41 $
          g12 g22 g32 g42 $
          g13 g23 g33 g43 $
          g14 g24 g34 g44

   open plot d:\imp1st_local_10_1.rgf
```

```
   graph(number=0,min=-0.75,max=0.75)
   *graph(number=0,min=-0.05,max=0.05) 1
   # i

end dofor i
spgraph(done)
*/

end
```

15. Program for Forecast Using Theil's U-Statistic-Dollar Converted Data

```
*****************Forecast in first differences***************
****************and convert into levels*********************
******************in four tea auctions markets***************
*********************dollar converted**********************
**
calendar 1900 1 1
allocate 300 2033:1
eqv 1 to 12
SLA INA KEN MAL $
SRILANKA INDONESIA KENYA MALAWI $
DSRILANKA DJAKARTA DKENYA DMALAWI
**********************************************
open data s:\tea133.txt
data(format=free,org=obs) 1901:1 2033:1 1 to 4
************************************************
eqv 13 to 16
SLRS IARH KESH MKAW
**********************************************
open data s:\exrate133.txt
data(format=free,org=obs) 1901:1 2033:1 13 to 16
***********************************************

set SRILANKA 1901:1 2033:1 = (SLA)*(1/SLRS)
set INDONESIA 1901:1 2033:1 = (INA)/100
set KENYA 1901:1 2033:1 =(KEN)/100
set MALAWI 1901:1 2033:1 =(MAL)/100

do i=5,8
diff i 1902:1 2033:1 i+20 1902:1
end do i

equation 1 25
# 25 {1} constant
equation 2 26
# 26 {1} constant
equation 3 27
# 27 {1} constant
equation 4 28
# 28 {1} constant

equation 5 5
# 25 5{1}
```

```
associate 5
# 5 1
equation 6 6
# 26 6{1}
associate 6
# 6 1
equation 7 7
# 27 7{1}
associate 7
# 7 1
equation 8 8
# 28 8{1}
associate 8
# 8 1

system 1 to 8
end(system)

Theil(setup) 8 5 2033:1
# 1 to 8
do date=2001:1,2033:1
estimate(noprint) 1902:1 date

forecast 8 5 date+1

# 1  40
# 2  41
# 3  42
# 4  43
# 5  44
# 6  45
# 7  46
# 8  47

Theil date+1
end do date
Theil(dump)

end
```

16. Program for Forecast Using the Theil's U-Statistic-Local Currency Data

```
******************Forecast in first differences***************
*****************and convert into levels**********************
*******************in four tea auctions markets***************
***********************local currencies***********************
**
calendar 1900 1 1
allocate 300 2033:1
eqv 1 to 12
SLA INA KEN MAL $
SRILANKA INDONESIA KENYA MALAWI $
DSRILANKA DJAKARTA DKENYA DMALAWI
*************************************************
open data s:\tea133.txt
data(format=free,org=obs) 1901:1 2033:1 1 to 4
***************************************************
eqv 13 to 16
SLRS IARH KESH MKAW
*************************************************
open data s:\exrate133.txt
data(format=free,org=obs) 1901:1 2033:1 13 to 16
**************************************************

set SRILANKA 1901:1 2033:1 = SLA
set INDONESIA 1901:1 2033:1 = (INA)/100*(IARH/1)
set KENYA 1901:1 2033:1 =(KEN)/100*(KESH/1)
set MALAWI 1901:1 2033:1 =(MAL)/100*(MKAW/1)

do i=5,8
diff i 1902:1 2033:1 i+20 1902:1
end do i

equation 1 25
# 25 {1} constant
equation 2 26
# 26 {1} constant
equation 3 27
# 27 {1} constant
equation 4 28
# 28 {1} constant

equation 5 5
# 25 5{1}
```

```
associate 5
# 5 1
equation 6 6
# 26 6{1}
associate 6
# 6 1
equation 7 7
# 27 7{1}
associate 7
# 7 1
equation 8 8
# 28 8{1}
associate 8
# 8 1

system 1 to 8
end(system)

Theil(setup) 8 5 2033:1
# 1 to 8
do date=2001:1,2033:1
estimate(noprint) 1902:1 date

forecast 8 5 date+1

# 1  40
# 2  41
# 3  42
# 4  43
# 5  44
# 6  45
# 7  46
# 8  47

Theil date+1
end do date
Theil(dump)

end
```

17. Program for the Tetrad II to Run the PC Algorithm and Direct the Edges-Dollar Converted Data

```
/covariance
 100
   x1     x2        x3       x4
   1.0000
  -0.0263        1.0000
  -0.1441        0.2357    1.0000
   0.1151      -0.0998     0.2175   1.0000

/knowledge
significance .05
```

18. Program for the Tetrad II to Run the PC Algorithm and Direct the Edges-Local Currency Data

```
/covariance
 100
   x1       x2        x3        x4
   1.0000
  -0.0403    1.0000
  -0.1735    0.1456     1.0000
   0.0042   -0.2042     0.2119    1.0000

/knowledge
significance .05
```

APPENDIX D

Average Prices of Tea at Weekly Auctions: December 1999 through June 2002 (Sri Lanka in Rupees and Rest are in US cents)

Sri Lanka	Indonesia	Kenya	Malawi
132.84	101.01	188	107.47
127.16	105.77	195	90.87
125.28	106.56	199	109.3
125.28	106.56	199	109.3
131.75	106.22	195	92.07
134.23	114.21	192	87.62
134.14	110.62	192	88.21
134.14	110.62	201	88.21
129.9	112.3	209	84.79
130.03	119.21	220	91.52
131.85	122.02	224	101.26
133.25	120.36	211	102.87
133.62	116.84	211	107.19
134.17	121.25	222	98.32
133.97	125.56	213	91.73
131.57	125.24	213	93.81
131.92	125.46	215	93.71
133.13	125.4	217	92.04
133.13	127.73	219	100.06
133.13	124.05	219	100.06
132.78	127.41	221	96.96
128.85	127.6	219	90.41
125.74	125.52	213	91.26
124.55	123.14	207	88.56
122.92	120.56	201	88.59
119.13	122.6	208	93.65
116.7	122.93	210	104.4
120.38	123.37	222	109.37
120.95	122.88	226	111.52
120.95	122.88	226	111.52
120.95	122.88	226	111.52
120.95	122.88	226	111.52
120.95	122.88	226	111.52
120.95	122.88	226	111.52
135.72	118.18	219	143.07

APPENDIX D (CONTINUED)

Sri Lanka	Indonesia	Kenya	Malawi
136.55	126.58	223	143.07
134.91	125.43	220	129.97
138.59	122.37	218	129.07
139.08	118.01	219	129.07
142.96	121.33	219	118.36
148.1	115.02	217	118.36
151.59	114.22	215	118.36
151.68	121	212	111.85
154.49	122.51	201	115.98
150.99	121.36	200	115.46
144.4	122.65	200	109.94
140.67	122.65	211	124.89
144.38	115.79	213	118.84
146.45	116.6	212	122.31
148.14	113.39	209	122.31
148.02	112.52	207	126.77
145.38	110.83	205	126.77
149.79	110.7	205	114.21
152.09	110.19	203	111.79
152.09	110.19	203	111.79
153.67	110.19	205	102.33
153.72	112.26	199	98.12
155.87	129.88	197	94.91
155.15	110.91	194	92.51
154.5	108.25	184	90.85
154.95	99.89	174	86.61
155.34	107.24	178	93.24
155.68	109.12	186	90.88
155.07	110.39	186	86.68
154.49	110.39	183	87.14
151.3	108.5	179	90.19
150.02	106.51	176	84.3
147.74	105.52	166	80.53
148.18	108.04	156	76.98
146.16	105.97	146	70.45
144.53	102.62	146	70.45
142.19	101.45	145	68.11
142.19	101.45	152	68.11

APPENDIX D (CONTINUED)

Sri Lanka	Indonesia	Kenya	Malawi
135.84	96.56	157	82.9
134.01	94.04	159	90.93
133.88	91.15	151	84.96
131.89	91.6	155	85.55
137.44	88.41	154	81.94
130.5	87.04	149	80.67
128.65	85.38	150	84.61
126.09	81.55	154	86.96
126.09	81.55	154	86.96
126.09	81.55	154	86.96
126.09	81.55	154	86.96
126.09	81.55	154	86.96
126.09	81.55	154	86.96
130.12	92.35	161	86.27
135.39	93.51	160	86.27
137.28	93.79	159	86.76
143.19	93.79	147	86.76
141.01	110.4	146	77.12
145.37	92.18	142	77.12
142.13	93.66	150	89.76
141.84	93.56	150	89.76
140.85	94.36	145	95.02
141.94	93.08	145	96.76
133.5	88.36	148	95.07
146.99	85.13	146	90.36
154.42	88.59	145	90.36
153.43	89.83	149	90.36
157.03	95.65	147	85.21
155.2	90.66	145	85.21
151.84	89	149	93.19
146.2	89.01	146	93.19
149.94	91.56	149	98.2
153.41	91.56	152	98.42
153.41	91.56	152	98.42
154.68	91.56	152	88.38
159.06	92.01	156	92.89
153.84	92.97	151	83.76
151.01	91.63	151	82.76

APPENDIX D (CONTINUED)

Sri Lanka	Indonesia	Kenya	Malawi
154.5	92.89	151	82.44
154.23	93.04	151	83.83
159.58	96.44	154	82.14
162.4	96.95	160	85.18
160.75	102.74	162	83.41
160.75	103.11	163	86.57
162.1	103.9	155	83.2
162.93	105.13	158	77.6
157.71	105.28	160	85.5
155.28	102.52	160	85.5
152.44	104.26	157	88.65
149.36	102.56	159	87.24
154.99	102.96	151	88.62
154.99	102.96	149	89.23
144.13	102.91	145	90.37
144.79	102.92	143	90.17
140.14	101.67	146	88.97
136.44	101.41	151	91.54
137.4	96.84	148	89.65
138.91	98.55	149	83.96
136.3	99.92	153	92.63
136.06	99.92	153	89.2

VITA

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Bachelor of Science in Agriculture, First Class Honors at University of Peradeniya, Sri Lanka, December 1999. Emphasis in Agricultural Economics.

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