Thesis for Master in International Economics and Business Studies

Unraveling the underlying causes of price volatility in world coffee and cocoa commodity markets

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Abstract: In recent years, Commodity Dependent Developing Countries (CDDCs) have faced multiple global food, energy and climate crises, compounded by the recent financial and economic crises which have increased their vulnerability to excessive price volatility in commodity markets. Moreover, structural vulnerabilities in most CDDCs render their economies more vulnerable to increased commodity market turbulence than developed countries, given their comparatively lower income and high dependence on commodity exports. Therefore, this paper empirically examines the patterns and underlying causes of excessive price volatility for two major soft commodities of critical importance to many of the poorest CDDCs: coffee and cocoa. It aims to identify interactions, similarities and causalities between coffee and cocoa prices on the one hand and, oil and futures prices on the other hand. Analyzing coffee and cocoa historical prices proves that, their means and volatilities are time-dependent, hence the use of GARCH type models. It is also found that, coffee's volatility has uneven reactions to markets positive or negative shocks. Oil price spillovers on coffee and cocoa are assessed with cointegration and causality models. Long-run causality is found between oil price, and coffee and cocoa prices but, only cocoa has an equilibrium relationship with oil in the long-term. Despite turmoil in the policies regulating the financial instruments; the speed of adjustment between the cash and the futures markets, measured with cointegration and error correction models, reflects efficiency in cocoa and coffee futures markets. Given the results, this study proposes some policy recommendations to manage price risk in cocoa and coffee exporting countries.

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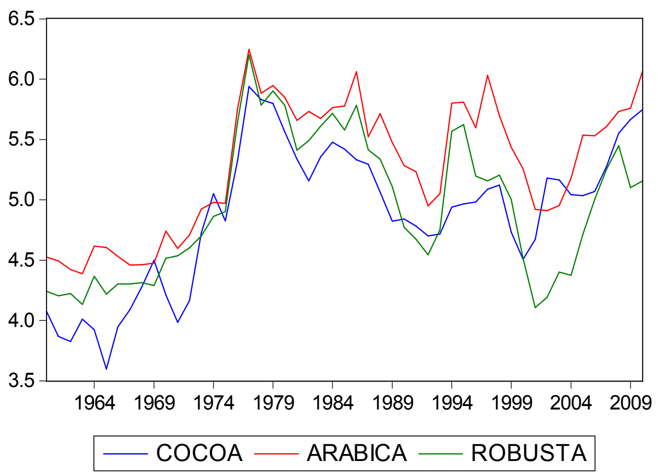
1. Introduction

Since 2000, growing volatility[2] in commodity markets and unpredicted price swings on global food security and welfare for producers, particularly in the Least Developed Countries (LDCs) and commodity-dependent developing countries (CDDCs) has informed the focus of this study. This study intends to explore the gravity of the commodity trade and development problematique vis-à-vis high food and energy prices and volatile markets for the world's most vulnerable CDDCs. It aims to empirically explore underlying price behavior and volatility in the coffee and cocoa markets, and also to identify interactions, similarities and causalities between coffee and cocoa prices on the one hand and, oil and futures prices on the other hand. Coffee and cocoa are both tropical commodities mainly produced in CDDCs and that have experienced extreme variability in their prices over the last 40 years. As beverage-commodities: coffee, cocoa and tea, represent a low percentage of the food price index (about 13%) its impact on the global food price crisis has been neglected. However, coffee and cocoa price variations have proven very large compared to grains or meat. This study will differentiate between arabica and robusta coffee as they are grown on different trees and traded on separate exchange markets. The graph below shows the evolution in arabica, robusta and cocoa logarithmic real prices over the last 50 years.

Graph 1.1 Annual current prices for coffee and cocoa 1960-2010 (in log)



Source*: ICO, ICCO (details in Annexes- Tables*

[2] Volatility is a statistical measure of the tendency of an asset's price to vary over time. It is usually captured in the standard deviation or variance.

A first observation is that coffee and cocoa have similar long-run price trends. Moreover, both commodities' production is mostly located in LDCs and developing countries in Africa, South America and South Asia (Annexes- Doc1). Thus, coffee and cocoa price volatility has an important economic stake in CDDCs whereas the tea trade for instance has no strong impact on its main producers' (China and India) trade balances. Coffee and cocoa are the two major export crops of the Sub-Saharan African region (SSA) hence; they represent a major source of income for many LDCs or developing countries that have strong commodity-export dependence. Cocoa crop exports provide a livelihood for 25 per cent of the Cote d'Ivoire's population (FAO 2006). The share of coffee in total exports represents 79% in Burundi and 64% in Ethiopia (FAO 2006). For coffee and cocoa exporting CDDCs price volatility is a major cause for concern while it is a relatively minor concern for most importing countries. For the former, significant fluctuations in world prices may have dramatic effects both at the national and producer levels by which can impact futures investments decisions economic. For most importing countries, changes in coffee or cocoa prices would probably only result in relatively minor changes in consumption habits.

1.1 Coffee

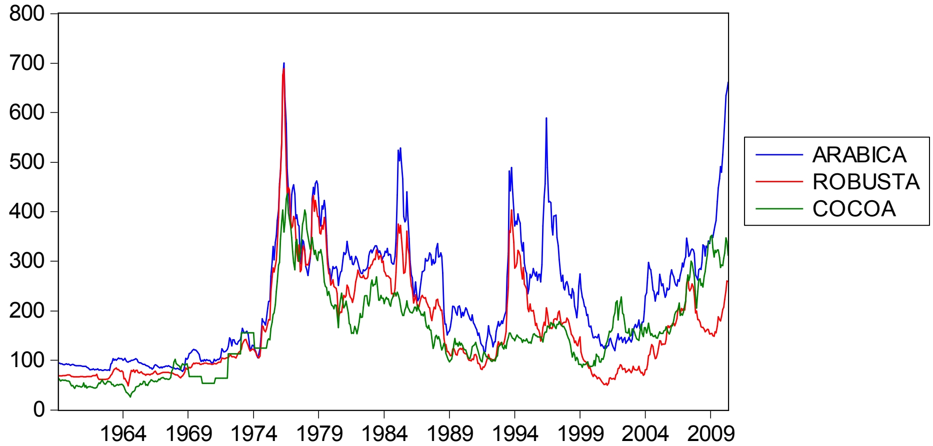
Involving over fifty producing countries, of which thirty are importers, coffee is one of the most widely traded commodities. Coffee is a perennial crop that is an agricultural commodity produced from the same root structure for two or more years. Coffee production starts three years after planting the tree and keeps on producing for 15 years (Kebede 1992). It is also noteworthy that coffee is a seasonal crop; seasons vary from country to country which makes supply for the most part unpredictable. For many developing country governments, the private and intergovernmental sectors coffee production, trade and consumption is a critical contributor to socio-economic development. The International Coffee Organization (ICO) is the main intergovernmental organization in charge of collecting and sharing information on coffee and of establishing international cooperation in the coffee sector. Created in 1963 with the support of the United Nations, the ICO gathers 97 per cent of the producing countries and 80 per cent of the consuming countries. Its goals are: to make sure that the private sector and governments cooperate at the policy-level, to promote market transparency by providing a wide range of statistics on the world coffee sector and to insure a certain standard of living and working conditions in the coffee producing countries in Africa, Asia and Latin America. In 1882, with its entry into the Coffee Exchange of New York (later part of the Coffee, Sugar and Cocoa Exchange) coffee prices became more volatile. Now, the Intercontinental Exchange (ICO) which is part of the New York Board of Trade (NYBOT) governs the world Arabica price through Futures U.S. Coffee "C" contracts. Robusta coffee has been traded for over twenty years on the London International Financial Futures Exchange (LIFFE).

1.2 Cocoa

Cocoa, although produced and exported in smaller volumes, has quite a few similarities with coffee. Ninety per cent of the cocoa producing countries also produce coffee (Annexes - Doc 1). While primarily consumed in Organization for Economic Cooperation and Development (OECD) countries, cocoa is exclusively produced in developing countries; which makes cocoa price volatility an important issue for CDDCs. Unlike coffee, cocoa becomes productive only four to five years after planting and can remain productive for decades. Cocoa harvests and thus productivity levels are highly dependent on prevalent weather conditions. The International Cocoa Organization (ICCO) mandates focuses on enhancing the economic, social and environmental sustainability of the world cocoa economy. Its members account for 80 per cent of the world cocoa producing countries and 60 per cent of the consuming countries. Since 1925, cocoa has been traded since 1925 on the New York Cocoa Exchange before joining the Coffee, Cocoa and Sugar Exchange and later the ICE, as part of NYBOT. But cocoa is also and most importantly traded by the United Kingdom, cocoa futures contracts are denominated in UK pounds.

Graph 1.2 shows the short-term evolution in arabica, robusta and cocoa prices. It highlights short-run volatility in commodity prices with more accuracy than long-run variations (Graph 1.1). We notice several peaks especially for arabica prices which have reached historical records of about 700 US cents per kilogram in 2010. The three commodities prices have been increasing since 2000 when deregulation on futures markets started. What is more, cocoa prices seem more stable over the long-run than coffees prices. Despite its relatively low variability, cocoa prices still provides significant opportunities for traders. One of the reasons is that, cocoa trade takes place on two major exchanges in London and in New York, and thus provides important arbitrage opportunities.

Graph 1.2 Monthly current prices evolution 1960-2011 (cents/kg)



Source: *ICO, ICCO*

This study will first provide an overview of the global food markets and the causes of major food commodity prices surges in chapter 2. Then, Chapter 3 presents the data employed for use in the empirical analyses. Chapter 4 deploys various GARCH models to estimate historical price volatilities expressed as conditional variances of three specific commodities: arabica, robusta and cocoa. In chapter 5 we consider the price-effects of both energy and financial products, through oil and futures prices, on coffee and cocoa. A causality analysis is conducted using Granger-causality and cointegration methods making use of oil and futures prices in order to explore potential long-term trend similarities. Chapter 6 considers the results of the empirical sections of the study, and outlines a few policy recommendations aimed at reducing risks associated with price volatility in CDDCs.

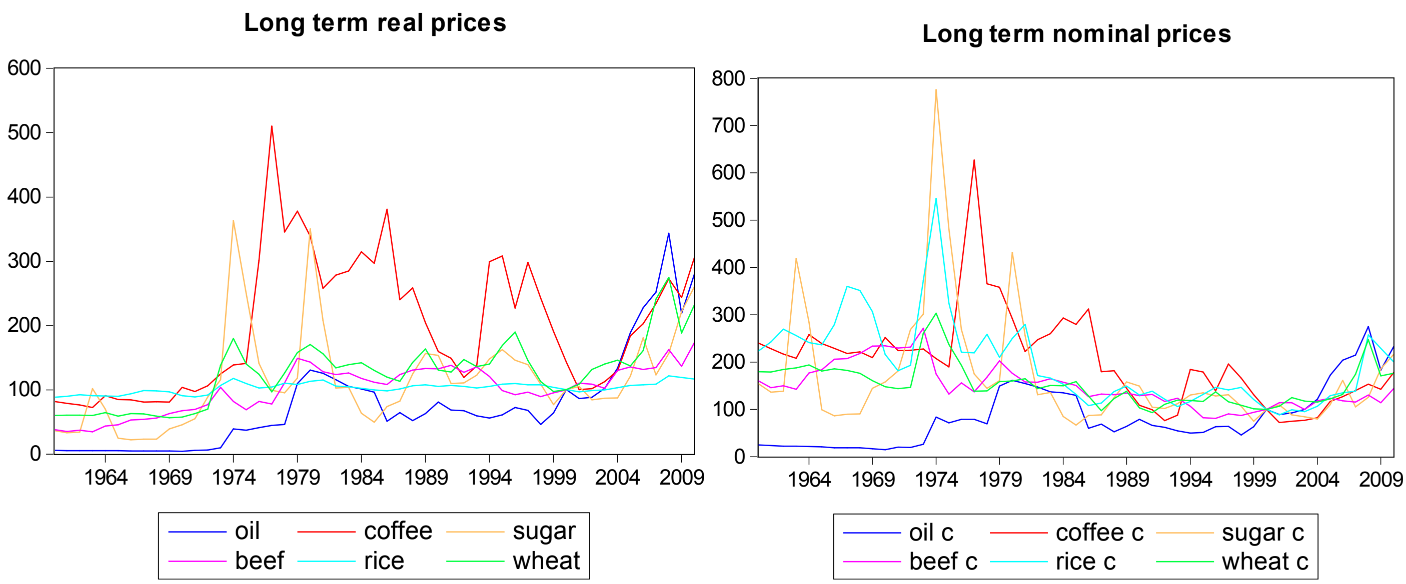
The aim of this study is to understand price behavior and volatility in the coffee and cocoa markets. The extent of oil price spillover effects on coffee and cocoa markets is crucial as persistently high crude oil prices may mean that food price surges will last longer than in previous booms (Baffes 2007). Comparisons with the financial sector on the other hand aims to help CDDCs better manage and hedge price volatilities independently of the futures volumes traded.

2. Overview of the global food markets and recent prices developments

2.1 Global trends

The 2008 world food crises had a negative impact on the stability of the world economy due to the collapse of most primary commodity prices. The direct consequences of this crisis were significant increases in world poverty and hunger. The World Bank estimates that the number of people in extreme poverty increased by 20 million (World Bank 2009). Meanwhile, the FAO estimates that more than 75 million people were driven into hunger between 2006 and 2010 (FAO 2011). In fact, over the last five decades the nominal prices of agricultural commodities exhibit a declining trend while the real prices (constant 2000) rose significantly (see Graph 2.1 below). Although a few commodities are still below their historic peaks (sugar, coffee etc), the recent overall increase marks an end to the secular decline in real commodity prices observed during the last 30 years. On the other hand, the nominal prices do not exhibit a price explosion but rather stay stable or even slightly decreasing since the 1979 financial crisis. One notable exception is oil prices, which are historically high in both real and nominal terms.

Graph 2.1 Price trends for oil and 5 major food commodities 1960-2010 (base 2000=100)



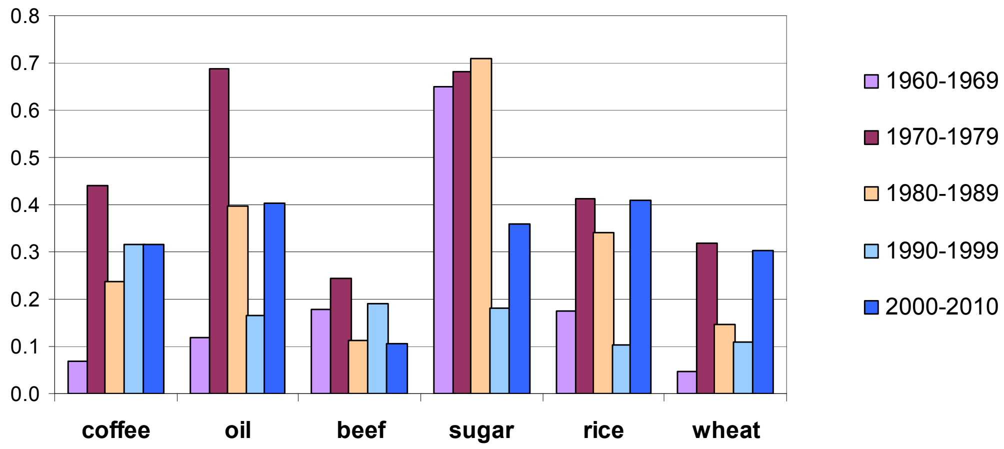
Source: *Unctadstat (2011)*

Examining the short-term constant prices provides a better insight with regard to recent food price developments. The Graph 2.2 below presents the coefficients of variation (*CV*) for various food commodities and oil.

$$CV = \frac{\sigma}{|\mu|} \qquad (1)$$

The coefficient of variation (1) connects the standard deviation (σ) to the mean (μ) so that the context of the mean of the data is considered allowing for cross-commodity comparisons. *CV* is a basic measure of price dispersion; it serves to compare the degree of variability from one data series to another.

Graph 2.2 Decadal Coefficients of variation for 6 major commodities 1960-2010



Source: *Unctadstat (2011)*

Comparisons over the last 4 decades show that recent price volatility is not unprecedented for individual commodities (Calvo-Gonzales, Shankar and Trezzi, 2010); however, this situation is not the same universally for all products. The *CV* is extremely sensitive to outliers hence; for example, the large amplitude of price swings that occurred during the 1979 financial crisis[3] for a broad range of commodities biases the indicator. Although the *CV* does not reach its 1980 historical record, most of the commodities' volatility has significantly risen over the last decade, which justifies the present economic and political turmoil about food price volatility. Indeed, the actual debate about food price volatility has become a high profile issue only over the last

[3] The financial crisis of 1979-1981 had many similarities to the recent global financial crisis of 2009-2010. For example, the US dollar was falling, inflation in the USA was approaching 13% and a high level of unemployment at 13% was exacerbated by a concomitant energy crisis in 1979 which let to rapidly escalating energy food prices. On commodity markets, precious metals again became a safe haven for investors with gold reaching $850 and silver $50 an ounce.

decade. Peter Wahl (2008) argued that this result is a consequence of the financialization of commodities that began in 2000, following the dot-com boom and bust of 1995-2000. In order to address the upturn in food prices, the G20 has asked ten international organizations to collaborate in elaborating research for a policy report to "*mitigate the risk associated with the price volatility of food and other agricultural commodities*" (FAO, IFAD, IMF 2011). Although food prices and volatility on food markets are major and global issues, some countries (e.g. net food import dependent LDCs) are much more exposed to the resulting food insecurity.

2.2 Price transmission in LDCs & net importing countries

2.2.1 Commodity price transmission

In developed countries, large increases in commodity prices do not necessarily have the same impact on final product prices because most of the food consumed has been processed. In fact, only 20 to 25 per cent of the retail food prices rely on commodities prices, the rest covers costs related to labor, processing, marketing and advertising, transportation, distribution and taxes (Schaffnit-Chatterjee 2011). Food prices are said to be "vertically integrated and concentrated" meaning that the commodity price transmission is rather weak in developed countries. However, in the LDCs most consumed food is not processed or at least, less than in the developed countries. Therefore, following the 2007-2008 prices surges in agricultural commodities, the affordability of food products was more worrying in developing countries than in the developed ones. Rapsomanikis (2011) shows that; although world price swings reflect in domestic prices in developing countries, the price adjustment from world level to the domestic level is slow. In fact, for the net food importing countries, the full adjustment period to world price levels is estimated to nine to ten months (Rapsomanikis 2011). Besides, crisis events such as the food commodity peaks in 2008 are transmitted much faster at the global scale.

2.2.2 Food prices: drivers of inflation

Another reason why the LDCs were particularly affected by the food crisis is because they spend a larger share of their income on food. Some low income countries spend up to 70-80 per cent of their income on food (UNCTAD 2009).

Consequently, a larger share of their Consumer Price Indices (CPI) corresponds to food prices. In the U.S.A. for instance, food expenditures account for only 8 per cent of the CPI, while they represent more than 50 per cent for Tanzania and Malawi (Schaffnit-Chatterjee 2011). Hence, food prices are important inflation drivers in LDCs. Inflation lowers the purchasing power of households who most likely reconsider their spending decisions. In developing countries or LDCs, food-related cost rises may mean more child labor and reduces a household's capacity to meet educational and health care needs. The global recession following the 2008 financial crisis played an important role in enhancing the initial impact of the food crisis but other various factors (e.g. climate change and / or short-term disruptions to food supply) also seem to affect food prices and volatility.

2.3 Identifiable causes

2.3.1 Energy prices and biofuels production

Both production and distribution require a large amount of energy such as: crude oil, petroleum products, coal and natural gas. Agricultural production activities involve chemical fertilization, tractor fuel, irrigation, and the heating or cooling of storage plants. Thus, an increase in oil prices will raise the production costs and drive food prices higher. Increases in oil prices have also promoted the emergence of the biofuel[4] industry (Penaranda and Micola 2009). In fact, the use of biofuels may have contributed to the growing demand for agricultural commodities (OECD 2006); notably because it is made of sugar crops and vegetable oils (e.g. oil seeds). Therefore, additional demand for foodstuff causes food prices to rise.

2.3.2 Macroeconomic factors

Inflation, USD exchange rates and sometimes interest rates prove partly responsible for high food prices. Besides, real prices are in general more sensitive to changing macroeconomic conditions than those for manufactures or services. The World Bank estimates that weakness of the dollar accounted for 15% of the food price increases between 2002 and 2008 (Mitchell 2008). Indeed, US $ started depreciating

[4] Biofuels are defined as "transportation fuels derived from biological sources". International Energy Agency 2004a.

in 2002 against OECD currencies, and then later against developing countries currencies. Thus, import costs decreased and import demand for US commodity started to rise. The major agricultural commodities (wheat, rice, maize, coffee, etc) are quoted in dollar therefore; exports to the US have become more expensive while imports from the US have become cheaper.

2.3.3 Trade policies

Exports restrictions, quotas, tariffs and bans on food products are widely instituted to insure domestic food security. Unfortunately, they have often triggered instability and worldwide increases in prices. They also have a market clearance function and therefore, discourage incentives from the farmers. Despite the World Trade Organization (WTO) Doha negotiations and other bilateral agreements to regulate trade-distorting domestic policies, importers remain deeply concerned about supply unreliability (WTO 2004).

2.3.4 Global warming and weather events

Climate change strongly impacts whether the harvest will be good or bad for it increases the frequency of extreme weather events. Over the last decade, weather events such as drought in Russia, freezes in Brazil and, heavy rains in Canada and in Australia caused major disruptions in the agricultural commodities production i.e. grains, and tropical foodstuff. Global warming also proves partly responsible for livestock and crops' diseases thereby, threatening food security and exacerbating food supply problems.

2.3.5 Speculation's impact on price increases and volatility

Although supply and demand fundamentals played a significant role in the food crisis outbreak, it is an insufficient explanation for such increases and volatility hikes in food prices. Various studies suggest that the observed price swings and volatility is due to speculative behavior that has been escalating over the last ten years. Unlike traditional commercial speculators who only hedge the price risk[5], non-

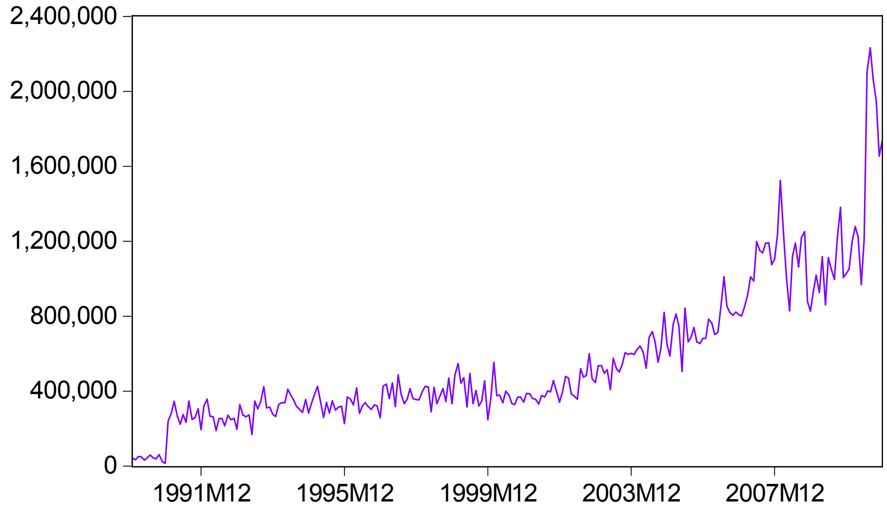
[5] Risk that the value of a security/ commodity will drop over time.

commercial speculators who have no interest in the traded commodities try to benefit from anticipated increases or falls in prices. On the one side, commercial participants buy or sell commodities to protect themselves against short term price volatility, on the other side; the experienced speculative traders who, for the most part, trade commodities they have no interest in.

The growth in commodity market participants increases market liquidity, therefore accommodating the hedging needs of producers and consumers. However on the other hand, diversity and complexity of financial instruments and players in the commodity markets call for closer monitoring of their impact on market stability, risk management of financial institutions and the development of commodity markets. Also, the increased correlation of commodity derivatives markets and other financial markets suggests a potentially higher risk of spillover.

Following the 2000 U.S. Commodity Futures Modernization Act, no position limits, disclosure or regulatory oversight was required. This Act allowed for the first time purely speculative Over the Counter (OTC) derivatives contracts to be hedged on exchanges. Consequently, the number of derivatives traded on commodity exchanges increased by more than five times between 2002 and 2008 (Schutter 2010). By 2008 the price volatility had become so high that commercial speculators were unable to continue hedging price risks (IATP 2008).

Graph 2.3 Futures volume of food-commodities traded on LIFFE (1990-2010)



Source: *NYSE - LIFFE monthly and annual statistics*

LIFFE futures contracts, as opposed to ICE's (NYBOT), do not differentiate futures volume from the two types of traders: commercial (hedgers) and non-commercial (speculators)[6]. Accordingly, the futures volume evolution presented in Graph 2.3 includes both kinds of trades. One sees that the commodity futures volume traded on LIFFE was approximately constant until 2001 when it started increasing at a constant pace. The year 2008 was marked with a downturn in the total futures volume traded. Since mid-2010 the commodity-futures trade went up with a renewed vigor. As this trade -data is not the only results of speculative moves; it is not entirely conclusive regarding price formation. Indeed, up until 2007 futures prices were unbiased estimators of spot prices on both exchanges NYBOT and LIFFE, due to the immediate reaction of speculators to new market information release (Nardella 2007). Nevertheless, financial speculation cannot be analyzed in isolation as, the relationship between speculative positions and futures prices may not be constant over time but subject to unaccounted-for structural shifts. For example a shift that can take place is a change in the trade policy of e.g. grain exporters. i.e. export bans etc.

3. Data

In order to study coffee price volatility, two main types of coffees will be considered; Arabica and Robusta. The World Bank historical data on commodity markets (Pink Sheet) gathers a wide set of data from different databases. Table 1 (Annexes) lists the commodities prices series, sources and units of measurement. This study only considers producing-exporting countries that are members of the ICO and ICCO. The deflator that is used to compute constant prices from current price ($Cons\tan t = Current / MUV * 100$) is the UN Unit Value Index of Manufactured goods exports by developed market-economy countries (MUV). Shares and indexes are computed according to the World Bank Commodity Price Index (Annexes - doc1).

For the first section of this study on volatility of GARCH-type models, the sample size is 249 observations. We use logarithmic transformations of monthly constant prices of arabica, robusta from January 1990 to September 2010 (12

[6] "Commercial traders are market participants who try to avoid or reduce a possible loss in the cash market by making counterbalancing transactions in the futures market. On the other hand, non-commercial traders do not produce or use a commodity, but risk their own capital by trading futures in that commodity and in the hope of making a profit on price change" ICCO (2011).

months*20 years+9 months= 249 months)[7]. For the second part of the study, we use the logarithms of monthly current prices for arabica, robusta, cocoa and oil, also gathered in the World Bank pink sheet. Daily futures prices of Arabica, Robusta and cocoa were collected from Bloomberg. Monthly prices were then computed in order to conduct a causality analysis. Cocoa and robusta futures prices are extracted from LIFFE and therefore are converted from sterling pound to US dollars using monthly average of the spot exchange rate of the Bank of England statistics.

4. GARCH-type volatility for coffee and cocoa prices

Before elaborating on factors involved in the price determination process, we need to assess the trends in price levels and in price volatility for different coffee varieties and cocoa. For many years, coffee and cocoa prices seemed to have similar trends (see above Graph 1.2). Comparing Arabica and Robusta prices, it is evident that their trends were more close together before the end of the 1980s until their constant and current prices started to show distinctive trends. The correlation coefficient for cocoa and Robusta for the period 1970-1990 was more than twice that of 1990-2010. Arabica's correlation with the other two commodities was also significantly higher during the 1970-1990 periods (Annexes- Table 2). In a 2005 study; ICO (2005) identify three main types of volatility; historical volatility, conditional volatility of the generalized autoregressive conditional heteroskedasticity (GARCH) type, and implied volatility[8]. We will now explore the two formers in more depth.

4.1 Historical volatility

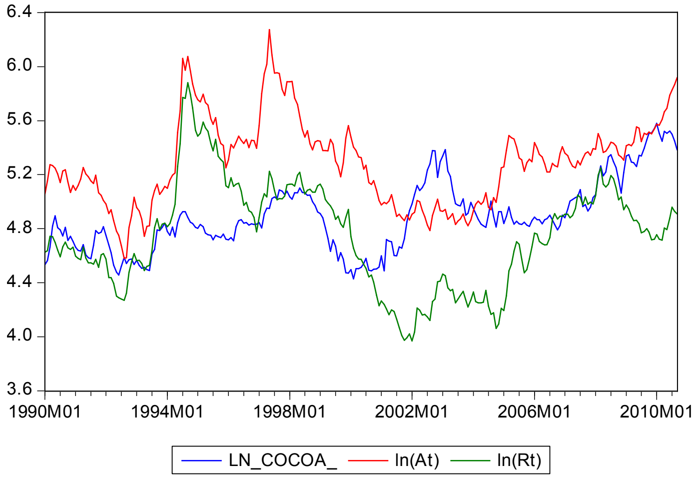
Historical volatility is computed on the basis of past price information. Transforming the constant prices in logarithms allows the computation of returns that is per cent variation. Evolution of returns over time provides a first insight in price volatility of a security.

$$\mathrm{Return} = \ln(p_t / p_{t-1}) \approx (p_t - p_{t-1}) / p_{t-1} = \%\ \text{price variation} \qquad (4.1)$$

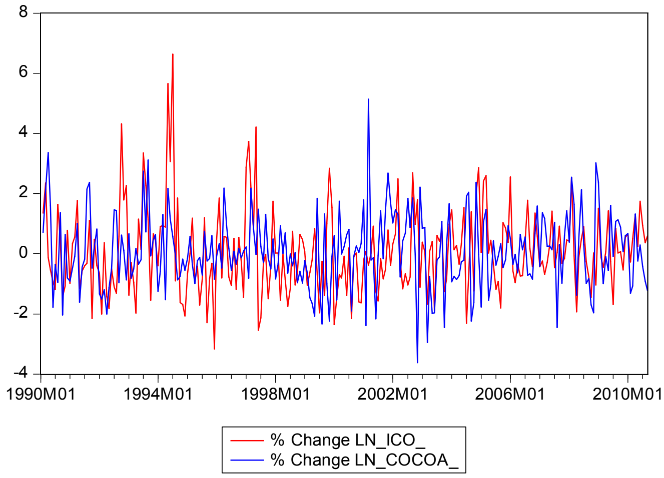
[7] The 1990-2010 period corresponds to the free market period on commodity markets.
[8] Implied volatility is based on predicted options prices and needs greater focus on other time series. Also, the implied volatility should incorporate all market information and investor expectations.

Graph 4.1 Coffee and cocoa prices (in logarithms) and returns 1990-2010

***ln* (price)**



Returns of coffee and cocoa price



Source: *ICO, ICCO*

$\ln(A_t, R_t, Cocoa_t)$:Napierian logarithm of Arabica, Robusta, Cocoa constant price at time t

The Graph 4.1 above present time series for coffee and cocoa prices and price-variations from January 1990 to September 2010. In the second graph Arabica and Robusta are put together to form the ICO composite price namely coffee price. At first sight, it seems as though the price variability was relatively higher for coffee during the first decade (Annexes- Graph 1). As for cocoa, its volatility is relatively higher since 2000. Standard deviation and coefficient of variation are other historical volatility measures that make it easier to compare various commodities while considering their average price risk level. In this case, CV is more accurate than the standard deviation for although one could expect the mean to be comparable for Arabica and Robusta, it is not as clear for coffee and cocoa. The descriptive statistics (Annexes-Table 3) reveal that the "price-riskier" commodity is Robusta, followed by Arabica and then, Cocoa shows the least variability in its prices. In other words, Robusta prices have experienced more extreme shocks than the two others during the last twenty years. Nevertheless, both CV and SD are weak measures of volatility as they are strongly influenced by outliers and thus tend to overestimate volatility in non-trending series (Swaray 2002). Other indicators of volatility in a given distribution can be measured with the kurtosis and skewness coefficients. The Kurtosis describes the distribution of a data series toward the mean. The kurtosis of a standard and normal distribution is 3; if it is less than 3, as in the case this study's coffee and cocoa commodities, the distributions are platykurtic therefore, the distributions have small tails; the data is less concentrated around the mean. In other terms, the degree of variance of the data is relatively larger. This indicates that the variance may vary over time. Skewness on the other hand measures the asymmetric tendency of the deviations. The magnitude of the variation may not be the same for positive and negative deviations. Indeed a positive skewness indicates that positive deviations dominate negative deviations and vice versa. According to this indicator, the volatility of arabica, robusta and particularly cocoa are all positively asymmetric. Nonetheless, these should also be considered with caution as they assume that the standard deviation of the price series, which is constant, is a valid measure of volatility. We will see later in the paper that this assumption does not hold because volatility varies over time and therefore the results of descriptive (static) statistics are neither sufficiently accurate nor reliable to discuss the volatility patterns of arabica, robusta and cocoa. In order to be more precise about price volatility, one needs to assess price behaviors with more powerful analytical tools.

4.2 Unit root tests

Time series processes optimally use past information and give the possibilities of objective judgments and accurate forecasting. Unit root tests, for instance, allow us to elaborate on the stationarity of the time series. In this study, Augmented Dickey Fuller (ADF) unit root test is preferred to Dickey Fuller test for it allows serial correlation problems that are likely to happen with agricultural commodities prices. In fact, ADF tests determine the minimum order *p* necessary to get rid of the serial correlation in the error term. ADF tests for unit root in levels are run with three different specification; the first model **(1)** includes a constant term, the second model **(2)** includes a constant term and a trend and the third specification **(3)** has neither constant nor trend. If models do not have the same test-results, one selects the preferred model leaning on the significance of the coefficients and the adjusted R-squared that provides an absolute measure of the goodness of fit. For all the models, the maximum lag length is set to 15 and Schwarz Information Criterion (SIC) is the model selection criterion. The significance level is set to 95%. The sum of the autoregressive parameters is equal to one indicates the presence of at least one unit root which implies that the series do not follow a random walk.

(1) $$y_t = c + \beta y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta y_{t-j} + \varepsilon_t \qquad (4.2)$$

(2) $$y_t = c + \rho t + \beta y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta y_{t-j} + \varepsilon_t \qquad (4.3)$$

(3) $$y_t = \beta y_{t-1} + \sum_{j=1}^{p} \alpha_j \Delta y_{t-j} + \varepsilon_t \qquad (4.4)$$

Null- and alternative hypotheses are the following:

$H_0 : \sum_{i=1}^{p} \alpha_i = 1$, unit root; the t-statistic has a non-standard distribution.

$H_1 : \sum_{i=1}^{p} \alpha_i < 1$, no unit root

Results of this test prove that the three time series: Arabica, Robusta and Cocoa have a unit root regardless of the model specification (see Table 4.1 below). Indeed, the t-statistics of the tests are for each specification of each model superior to the critical values. Therefore the time series are not stationary; prices of coffee and cocoa do not follow a random walk. This result was expected given the net upward trends in the graphs showing the evolution of the logarithms of real prices over time (Annexes- Graph1). Also, note that for all these regressions, R-squared and adjusted R-squared are very low which indicates the low estimation and predictive power of the independent variables on the dependent variables.

Table 4.1 Unit roots in levels

		Arabica		***Cocoa***		***Robusta***	
Lag length		1		0		1	
		t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic		0.377	0.7923	0.801	0.8847	0.022	0.6889
Critical values:	1%	-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942	
	10%	-1.616		-1.616		-1.616	

First-differencing is a very useful tool especially for autoregressive (AR) modeling which requires trend stationarity in the series. Thus, once the presence of unit roots in price levels is established, first difference unit roots tests are run to remove trending and thus evaluate the persistence in price volatilities. Table 4.2 presents the results of unit root tests on first differences indicates the absence of unit roots in the firstly-differenced series. Indeed, in each model and for every specification, the ADF t-statistic is largely inferior to the critical values. Stationarity in the first differences is also noticeable in the Graph 1 (Annexes) showing the percentage variation in price; the linear adjustment trend is nearly constant.

Table 4.2 Unit root in first differences

		Arabica		***Cocoa***		***Robusta***	
Lag length		1		0		1	
		t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic		-12.7869	0.00	-14.7013	0.00	-11.9869	0.00
Critical values:	1%	-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942	
	10%	-1.616		-1.616		-1.616	

Although price levels prove non-stationary for the last two decades, price-first-differences are stationary which indicates the presence of at least one unit root in the series. In other terms, despite one observes increasing coffee and cocoa prices, the returns of those commodities is rather constant. Non-stationarity in both coffees and cocoa prices suggests the existence of long-run equilibrium relationships that will be analyzed with cointegration models later in the study.

4.3 Conditional volatility of GARCH type

Food price variations are greatly concerning agricultural economists for they are often large and unpredictable. Uncertainty of price developments leads to higher price risks borne by the producers, exporters, importers and stock holders who are then very likely to review their investment decisions. In order to prevent disruptions in both coffee and cocoa markets one needs to model an accurate measure of volatility that takes into account specifications relative to each commodity and allows predicting future price developments. ARCH and GARCH processes defined as "mean zero, serially uncorrelated processes with non-constant variances that are conditioned on past information" (Aradhyula and Ho 1988) are useful economic analysis tools with strong forecasting accuracy. The GARCH models use past prices to model and forecast conditional variances. GARCH models are convenient for they consider a wide range of possible specifications to model volatility and allow empirical and realistic examination of the persistence and asymmetry in coffee price volatility. Any GARCH model assumes that the prices have a time-varying (non-constant) variance which means that in some periods, markets are more volatile than in others. The objective of this subsection is to characterize the conditional variance of price series of arabica, robusta and cocoa. Let us assume that the Arabica prices series P_t^A [9] are generated by the autoregressive process:

$$P_t^A = c + \sum_{i=1}^{p} \phi_i P_{t-1}^A + \varepsilon_t \qquad (4.5)$$

While the conditional variance is elaborated on a GARCH (1, 1) model with a constant, past information about volatility (ε_{t-1}^2) and past forecast variance (h_{t-1}^2):

$$\varepsilon_t \left| \Omega_{t-1} \sim N(0, h_t) \right.$$
$$h_t^2 = \delta + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \qquad (4.6)$$

The conditional variance h_t^2 of the information set available at time t-1 Ω_{t-1} considers varying confidence intervals of volatility. Table 4 (Annexes) contains univariate GARCH (1, 1) parameters for the mean and the variance equations of coffees and cocoa. The preferred regression has the AR order *p* and the moving average (MA) order *q* that minimize the Schwarz information criterion (SIC). Also, regressions are run using a range of $\{1; 5\}$ for *p* and $\{0; 5\}$ for *q* and the combination of *p* and *q* with the lowest SIC is the preferred model. R-squared is the absolute measure of fit whereas the SIC measures the relative goodness of the fit among different specifications. The Arabica results show that AR(1) is the specification that maximizes the quality of the fit . In this case MA parameters are insignificant thus removed. Robusta on the other hand is best approximated with the model ARMA(1,1) and, both the AR and the MA coefficients are significantly different from 0. Finally cocoa is better approximated by an AR(1) model. For cocoa, adding a MA parameter lowers the goodness of the fit since it adds an insignificant variable to the model. All the coefficients in table 4 of the Annexes are significant and the regressions show a

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[9] P_t^R stands for robusta price and P_t^C for cocoa price

high adjusted R-squared, meaning that the estimated parameters of the conditional mean have a strong explanatory power of the historical movements. Prices are thus best modeled as follow:

$$Cocoa: P_t^C = 4.94 + 0.98P_{t-1}^C + \varepsilon_t^C \tag{4.7}$$

$$Arabica: P_t^A = 5.26 + 0.97P_{t-1}^A + \varepsilon_t^A \tag{4.8}$$

$$Robusta: P_t^R = 4.61 + 0.97P_{t-1}^R + 0.24\varepsilon_{t-1}^R + \varepsilon_t^R \tag{4.9}$$

Given the high adjusted R-squared, it would seem that GARCH models perform well at modeling conditional variance. Nonetheless, it is no guarantee that the GARCH process is a statistically valid improvement over the AR(MA) process (Aradhyula and Holt 1988). Also, it is relevant to run a test of the GARCH hypothesis that the conditional variances are indeed not constant.

$$H_0: \alpha = 0, \beta = 0$$

$$H_1: \alpha \neq 0 or \beta \neq 0$$

A Wald test of the joint significance of α and β is provided for the three commodities in Table 5 (Annexes). The statistics used in a Wald test is the Chi-squared; if the *p-value* of the chi-squared exceeds the significance level (0.05) the null hypothesis of stationarity in the volatility cannot be rejected. Results indicate that *p-values* of the Chi-squared distributions of Arabica, Robusta and Cocoa are all equal to 0, thus, we reject the null hypothesis of stationarity in the conditional forecast variances; GARCH is an improvement over the AR process for the three tropical commodities. In a GARCH model ($\alpha + \beta$) is the measure of the persistence in volatility, if this measure equals to one it means there is an Integrated-GARCH (IGARCH) process. IGARCH signifies that the volatility is not mean-reverting; any shock to volatility is permanent. The conditional variance graphs (Annexes - Graph 4) seem to suggest that among the three commodities cocoa is the one with the slowest mean-reversion; shocks in its price have lasting effects on volatility. To verify this observation, a Wald Test is run with the following hypotheses:

$$H_0: \alpha + \beta = 1$$

$$H_1 : \alpha + \beta \neq 1$$

Results in table 6 (Annexes) prove that at the 5 per cent significance level, Cocoa and Robusta have a persistent measure approximately equal to one. However, Arabica 's persistence patterns are not as strong as for the two other commodities (p=0.0495 ~0.05) nonetheless, non-stationarity of volatility is weakly rejected at a five per cent significance level and strongly rejected at a ten per cent significance level. In sum, considering specific price models for each commodity and a GARCH(1,1) variance process, price shocks have permanent effect on volatility levels and these effects show more persistence for Cocoa and Robusta.

4.4 Asymmetric volatilities with EGARCH models

From GARCH analysis, one infers that shocks in prices are reflected in volatility, but one might also consider how variability changes evolve when shocks are positive or negative. Such a distinction can be modeled with econometric tools and by adding precision to the model it provides a better forecasting tool. Economically speaking, understanding volatility in response to positive or negative shocks is crucial for the producers. For that purpose, it is possible to implement symmetry or leverage effect in the variance to GARCH models. The most widely used, EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) process models the logarithm of conditional variance in order to determine whether or not the observed volatility reacts asymmetrically to *good* and *bad* news. Unlike GARCH models, EGARCH model have a positive conditional variance by construction due to the use of logarithm in the variance definition and also, it does not impose non-negativity constraints on parameters. Thus for example, *good news* in the case of a commodity might be favorable weather forecasts for coffee and cocoa crops or policies that promote agricultural development and growth; whilst *bad news* such as a natural disaster or calamitous weather event (hurricane, tornado, flooding etc) but also sharp rises in oil prices for instance. Economists such as Daniel Nelson (1991) and William Schwert (1989) have noticed that for some financial assets, price decreases tend to trigger higher volatility levels than price increases of the same magnitude. In his research, Schwert finds evidence that 'the stock volatility is higher during recessions and financial crisis' (Nelson 1991).In order to assess this feature on Cocoa, Arabica and EGARCH this study models EGARCH as follow:

$$\log(h_t^2) = \delta + \pi_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}^2}} \right| + \pi_2 \frac{\varepsilon_{t-1}}{\left| h_{t-1}^2 \right|} + \beta \log(h_{t-1}^2) \qquad (4.11)$$

In this model the effect of residual is exponential and not quadratic. The asymmetry is measured in the coefficient π_2; if it is negative and significant, as for many financial assets, there is positive asymmetry and negative price shocks have a stronger impact on price volatility than positive shocks. The impact of positive shocks (good news) is measured by $(\pi_1 + \pi_2)\big/\sqrt{h_{t-1}^2}$ whereas the impact of negative shocks is captured by $(\pi_1 - \pi_2)\big/\sqrt{h_{t-1}^2}$. The hypothesis tested by the EGARCH model is the following:

$$H_0 : \pi_2 = 0$$

$$H_0 : \pi_2 \neq 0$$

Results in table 7 (Annexes) show the EGARCH preferred regressions for Cocoa, Arabica and Robusta with regard to the SIC. Only Robusta has the same ARMA orders *p* and *q* in EGARCH and in the GARCH (1, 1) models. Results also show that none of the asymmetric π_2 coefficients is negative hence; the volatility behavior in response to shocks differs from that of the financial assets. The coefficient π_2 for cocoa is small (π_2 =0.035) and approximately equal to zero (*p*-value = 0.69>0.05) meaning that positive and negative shocks have approximately the same impact on volatility. Also, *SIC* = -2.742 in GARCH (1, 1) model while *SIC* = -2.721 in EGARCH model. As the preferred model is the one that minimizes SIC, GARCH (1, 1) is a better approximation of the cocoa series than EGARCH. Because the asymmetry term is insignificant, keeping π_2 in the model does not add any prediction power and reduces the goodness of fit. On the other hand, the asymmetry coefficients for Arabica and Robusta are large and significant: for Arabica, $\pi_2 = 0.422$, and for Robusta $\pi_2 = 0.351$ and, both p-values are equal to zero. SIC indicates that the EGARCH describes the volatility in world coffee prices better than the GARCH(1, 1).

The significant and positive π_2 suggests that positive shocks have a more prominent effect on the observed volatility than negative shocks. This may be observed from Graph 5 (Annexes) where the 1994 upward peak in Arabica and Robusta variance series is not directly followed by high variance periods. On the contrary, the conditional variances of both coffees seemed higher in the periods before the peak (1992-1994) than after the peak (1994-1997). The 1994 price increases triggered a peak in the conditional variance then followed by low variability in the variance. However the price falls in 2000 triggered lower levels of variability in the variance until the end of 2001. For cocoa, there is no obvious sign that the variability of the conditional variance differs in the period after a positive shock in 2001 and in the period following a negative shock in 2003.

Empirical examination of the varying volatility of coffees and cocoa allows us to estimate the best fit for the models one of these three commodities. For cocoa, prices follow an autoregressive process of order one AR(1) and its conditional variance is a GARCH (1,1) process.

$$P_t^C = 4.940 + 0.976\mathrm{P}_{\mathrm{t\text{-}1}}^{\mathrm{C}} + \varepsilon_t$$

$$h_t^2 = 0.001 + 0.247\varepsilon_{t-1}^2 + 0.622 h_{t-1}^2$$

Arabica and Robusta prices follow an ARMA model of order *p*=4 *q*=2 for Arabica and *p*=1 *q*=1 for Robusta. Both coffees conditional variances are better estimated with the EGARCH model. Resulting equations for Arabica are as follows:

$$P_t^A A_t = 5.410 + 1.248\mathrm{P}_{\mathrm{t\text{-}1}}^{\mathrm{A}} + \text{-}1.048\mathrm{P}_{\mathrm{t\text{-}2}}^{\mathrm{A}} + 1.037\mathrm{P}_{\mathrm{t\text{-}3}}^{\mathrm{A}} + \text{-}0.269\mathrm{P}_{\mathrm{t\text{-}4}}^{\mathrm{A}} + \text{-}0.088\varepsilon_{t-1} + 0.931\varepsilon_{t-2} + \varepsilon_t$$

$$\log(h_t^2) = \text{-}3.178 + \text{-}0.036\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}^2}}\right| + 0.422\frac{\varepsilon_{t-1}}{\left|h_{t-1}^2\right|} + 0.402\log(h_{t-1}^2)$$

Equations for Robusta can be written as bellow.

$$P_t^R = 4.747 + 0.980 P_{t-1}^R + 0.223\varepsilon_{t-1} + \varepsilon_t$$

$$\log(h_t^2) = -2.308 + 0.015\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}^2}}\right| + 0.351\frac{\varepsilon_{t-1}}{\left|h_{t-1}^2\right|} + 0.579\log(h_{t-1}^2)$$

In this chapter we first interpreted historical volatilities with descriptive statistics and static indicators such as *CV*. These measures provide a rough estimate of the price trends and volatility patterns for arabica, robusta and cocoa however, their lack of accuracy and compliance with commodity prices behavior is very likely to induce misleading conclusions. For this reasons, we utilize the more robust GARCH models to assess and estimate volatility in world coffee and cocoa prices. Although the price-correlations between the three studied commodities is very high; to 0.8 in the long-run (Annexes- Table 2), specificities in terms of their price volatility are less obvious and requires more complex models. Volatility, expressed by the conditional variance of price of series, is modeled with different features for Arabica, Robusta and cocoa. Looking at the price series for these three commodities demonstrates volatility clustering that is conditional variance is high in some periods and low in others. Such a pattern usually suggests that there might be persistence in volatilities and series are best estimated with a varying variance. The results of the empirical study show different results for each of the three tropical commodities. The price model AR(1) used for cocoa price series means its price at period *t* depends on a constant and on the price at period *t-1.* Robusta's price model uses a constant past price and volatility information at an order of one ARMA(1,1). The model ARMA(4,2) used for Arabica price series indicates that price formation uses past price information on the preceding four periods and past news about volatility on the last two periods. The conditional variance definition follows a EGARCH process with similar coefficients and a positive and significant π_2 for both coffees which shows that for their volatility is more affected by positive shocks in prices than by negative price shocks. Concretely; a large increase in oil (listed as a negative shock) prices will have less impact on coffee price variability than a large decrease in oil price (positive shock) of the same magnitude. Cocoa, on the other hand does not show any asymmetric pattern in its varying volatility.

5. FUELS AND SPECULATION: CAUSALITY ANALYSIS

This section emphasizes the role of some external factors on coffee and cocoa prices. Logically, changes in commodities prices result from changes in their fundamentals namely, supply and demand. However for non-essential goods such as cocoa and coffee, demand and supply are not strongly involved in the price determination process. Graph 6 (Annexes) shows that in those sectors, variation in fundamentals do not reflect the extent of the price surges that occurred during the past 20 years. The percentage changes in demand have been relatively low for coffee and cocoa since 1990. Despite changes in supply for both products having been larger and more frequent, this still provides an inadequate explanation of the observed high variability levels in coffee and cocoa prices. One of the reasons for the detachment between production and price in commodity markets can be explained by the *Separation theorem* according to which "when a future market exists, the optimum production of the firm does not depend upon the (subjective) distribution of the random price nor upon the firm's attitude toward risk" (Broll and Zilcha 1992). That is whenever a futures market is available, the price and the production of the commodity grow independently. Therefore, we do not dwell upon empirical analysis of the fundamentals for coffee and cocoa, but rather focus on other drivers of commodity prices. This section will focus on two external factors affecting both coffees and cocoa prices namely, the energy sector represented by crude oil prices and the financial sector seen through futures prices. In this section all the commodities prices will be denominated in current dollar prices. Indeed only current prices are traded in the financial markets whereas, constant dollar prices provide a better fit for estimating historical volatility (as seen in the previous section). Table 1 (Annexes) lists the data specifications, sources and units of measurement for the empirical study.

Barnard (1983) highlighted the potential for fuels to be disruptive to agricultural commodity prices. Such activities as: planting, fertilization, harvesting, storage and transportation require an important amount of diverse fuels; the most usual being crude oil, coal, gas, and more recently biofuels. Also, it has been argued that the prices of coffees and cocoa are influenced by oil prices (Baffes J. 2007). Not only is the fuels sector known to be a large contributor to commodity prices formation but also, the recent development in financial markets are said to be partly responsible for price surges in major commodities prices. Both coffees and cocoa current prices have had relatively high volatilities over the years hence providing traders with significant "*trend-following opportunities"* (ICE 2011). The Granger tests will assess the long- and short-term causality links (with various lags included) between oil and commodities prices and also, between cash and futures prices of cocoa and coffee. Balcombe and Rapsomanikis (2008) expressed the difficulty of distinguishing long-run impacts from short-run impacts regarding the impacts of oil on sugar. Therefore, cointegration methods should determine whether a linear long-run relationship exists between these prices.

5.1 Cross commodity causality: Oil vs. Coffee and Cocoa

Cocoa is grown in farms by smallholders or family subsistence farming; many farms in Africa possess less than one hectare under cocoa (ITC 2001). Larger plantations exist in Brazil, Ecuador and Malaysia but since cocoa production is hardly mechanized, large plantation does not improve profitability - benefit/cost ratio. Although cocoa is particularly sensitive to weather conditions and diseases that may seriously restrict production; relatively little fertilizer are utilized (FAO 2006). On the other hand, coffee production is fully mechanized and uses various chemical fertilizers made of minerals such as nitrogen (N), potassium (K) and in a lesser measure phosphate (P). As the world population continues to grow, so does the demand for agricultural products. Fertilizers play an increasing role in insuring soil fertility in order to respond to the global demand for food. The FAO defines fertilizers as the "inorganic manufactured products that supply plant nutrients" (FAO 2006). Nitrogen fertilizers are necessary to healthy growth of coffee trees. Potassium fertilizers, referred to as Potash (K), enable the seeds formation. Although it is not indispensable to coffee growth, phosphate fertilizers (P) help coffee trees to develop their roots, flowering and fructification. All the chemical fertilizers above mentioned were developed by the chemical industry for petroleum; hence the high correlation between fertilizers and oil prices. This study will only consider the indirect effect of fertilizers on coffee and cocoa price through oil. Fuels are also required for storage and transportation thus directly enhancing transmission effect of oil price on coffee and cocoa prices. It is hypothesized that the oil spill on coffee would be more obvious than the one from oil to cocoa due to a more important use of machines and fertilizers. A graphic analysis of annual current price- variations in the long term (Annexes - Graph 8), suggests that coffee and cocoa prices changes were often preceded by variations in the oil price of the same magnitude over the last fifty years. The graph 7 (Annexes) with the annual current prices proves similar developments in the oil prices and in the beverages prices, especially between oil and cocoa. The aim of this subsection is to determine whether causality between oil prices and coffee and cocoa prices holds in the long-run considering the time-horizon: 1990-2010 and also, whether the similar trend between oil and, cocoa and coffee is empirically confirmed.

We first conduct Granger causality tests for oil and arabica, robusta, and cocoa using large lag lengths in order to account a long adjustment period of the commodities prices to variation in oil price. A definition of Granger-causality can be formulated as follows; 'x is a Granger cause of y if present y can be predicted with better accuracy by using past values of x rather than by not doing so, other information being identical' (Charemza and Deadman 1992). We obtain the following results:

Table 5.1 Granger-causality tests results

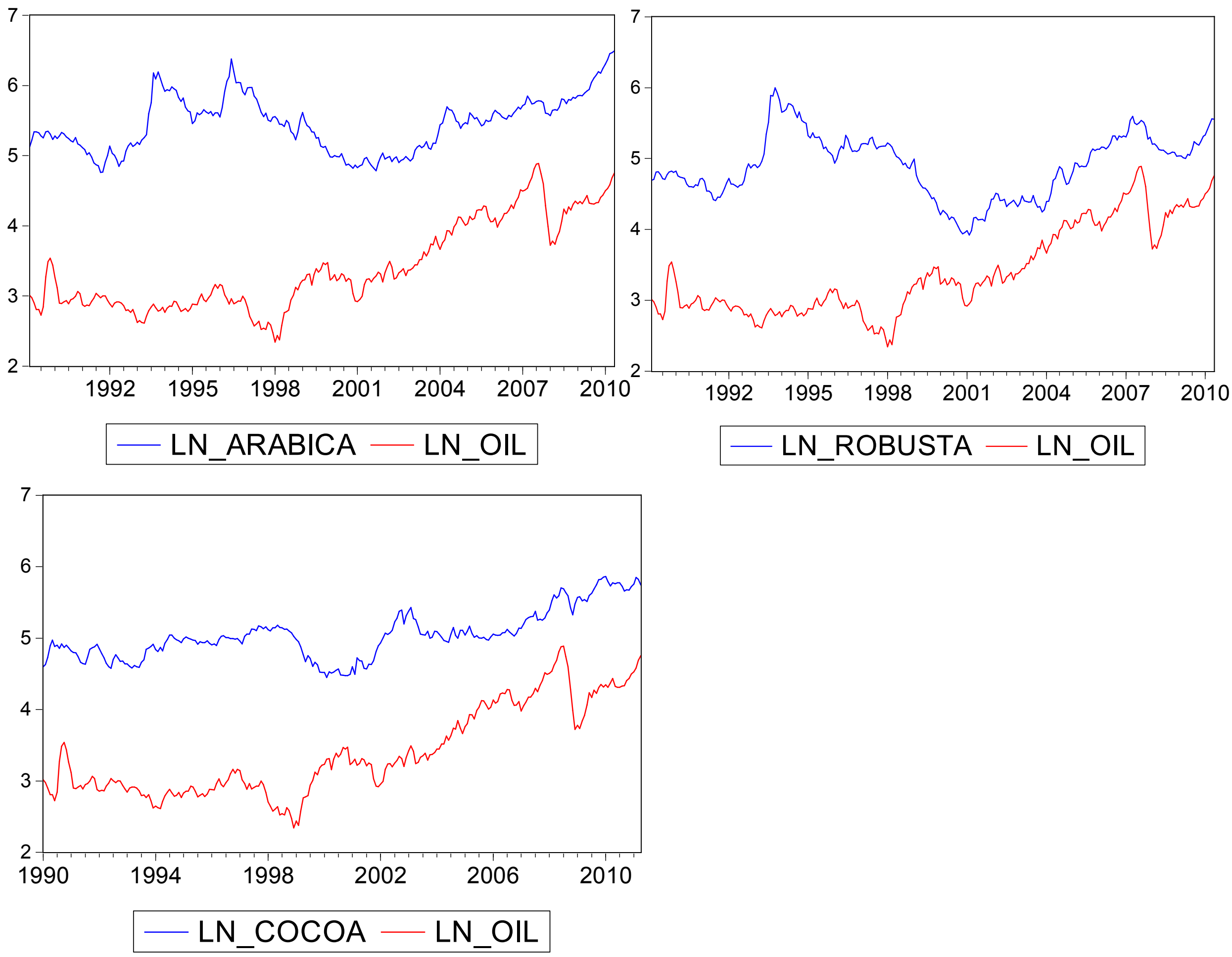
Null Hypothesis	*Lags included*	*Observations*	*F-statistic*	*Prob.*
LN_OIL does not → LN_ARABICA	48	208	1.901	0.003
LN_ARABICA does not → LN_OIL			1.152	0.270
LN_OIL does not → LN_COCOA	36	220	1.736	0.012
LN_COCOA does not → LN_OIL			1.025	0.441
LN_OIL does not → LN_ROBUSTA	51	205	1.694	0.012
LN_ROBUSTA does not → LN_OIL			1.091	0.349

Source: *Annexes - Table 1*

The p-values indicate the probabilities to reject the null hypotheses while they are true. We cannot reject that oil price Granger-causes arabica, robusta and cocoa prices at a 5 percent level (p-values: *Prob.* > 0.05). However, independently of the number of the lags included, none of the tests conclude that cocoa, arabica and robusta prices Granger-cause oil price at a 5% level. Also, this first approach tells us that past oil prices at present 'Granger-cause' coffee and cocoa prices for different lag lengths but, reversal is not valid. It is important to highlight that the oil-commodity causality conclusions are dependent on the number of lags included. Results tell us that oil price spillover effects on arabica and robusta takes approximately 4 years while it takes only 3 years for cocoa; which seems consistent with observations outlined in Graph 8 (Annexes).

The concept of cointegration enables us to further in determine the possible relationship between the variables. Now that a long-run causality link is established between oil and beverages, we use cointegration tests to ascertain the long-run relationship between oil and beverages. In other words, we test whether the long-run causality validated above, conveys similar long-term trends for oil, cocoa and coffee. Empirically, two *I(*1*)* cointegrated series are defined so if a linear combination of both is stationary (*I*(0)) meaning that; an adjustment between those two variables prevent errors to become larger in the long term. Also, before testing cointegration one needs to make sure that current coffees-, cocoa-, and oil prices follow an *I*(1) process.

Graph 5.1 Cash prices of arabica, robusta, and cocoa vs. oil prices (in log) 1990-2011



Source: *ICO, ICCO, World Bank*

It seems obvious from the graph 5.1 that none of the prices series are stationary. In conformity with the graphs, results from ADL tests reveals the unit root presence in levels (p-values > 0.05) but not in first differences (p-values < 0.05) hence, prices of the studied commodities are $I(1)$ (Annexes- Table 8). Now that the series are proven non-stationary one can test whether they are cointegrated or not. There are several tests for cointegration; this study applies the Granger cointegration test. The method consists in; first, estimating the equation (5.1), generating the residuals series $\hat{u}_t$ and then, running an ADL unit root test on those residuals by means of the equation (5.2). Cointegration of the series implies that ADL unit root test of the Ordinary Least Squares (OLS) residuals $\hat{u}_t$ concludes stationarity.

$$C_{t,a} = c + \eta.Oil_t + u_{t,a} \qquad (5.1)$$

$C_{t,a}$: Current price at time t of a : $\{ A_t \ , R_t , Cocoa_t \}$

$$\Delta\hat{u}_{t,a} = \beta\hat{u}_{t-1,a} + \sum_{j=1}^{p} \alpha_{j,a} \Delta\hat{u}_{t-j,a} + \varepsilon_{t,a} \qquad (5.2)$$

Results of equation (5.1) are presented in Table 9 of the Annexes. Both the oil variable and the constant are significant. The reported adjusted R-squared provide a first hint regarding the cointegration of the variables. In the first regression it indicates that variations in cocoa prices explain 45% of the variations in oil prices. Arabica prices-variations explain 10% of oil variations. The last regression exhibits an adjusted R-square of only 0.02 meaning that robusta prices variations account for 2% of oil price variations. Table 10 in the Annexes shows the results of the ADL performed on the residuals series as formulated in the equation (5.2). Test results indicate that only cocoa prices are cointegrated with oil prices at a 5% level since the ADL statistic (-2.2436) is comprised between the 1% critical value (-2.574) and the 5% critical value (-1.942). Cointegration between oil prices and coffees prices (arabica and robusta) is weakly rejected at a 10% level. Such conclusions tell us that although coffee production uses more mechanics and petro-chemical fertilizers than cocoa, there is no linear relationship between coffee and oil whereas, such a relationship is acceptable for cocoa and oil. In fact, cocoa and oil series move together in the long-run.

Short-run price movements are analyzed in order to complete the picture of the linkage between beverage commodities and oil. Short-impact of oil price shocks on coffee and cocoa prices are tested with Granger causality methods including lag length up to 12 months. Tests results (Annexes- Table 11) suggest that short term causality is only noticeable between cocoa and oil series. Causality from oil price to cocoa price is found for: 1 lag included (with 10% significance), 12 lags included (with 5% significance) and, 24 lags included (with 5% significance). Note that when lag 12 the spill of cocoa on oil is positively accepted. Nonetheless, in the short-run shocks in oil price do not reflect on both coffees current prices.

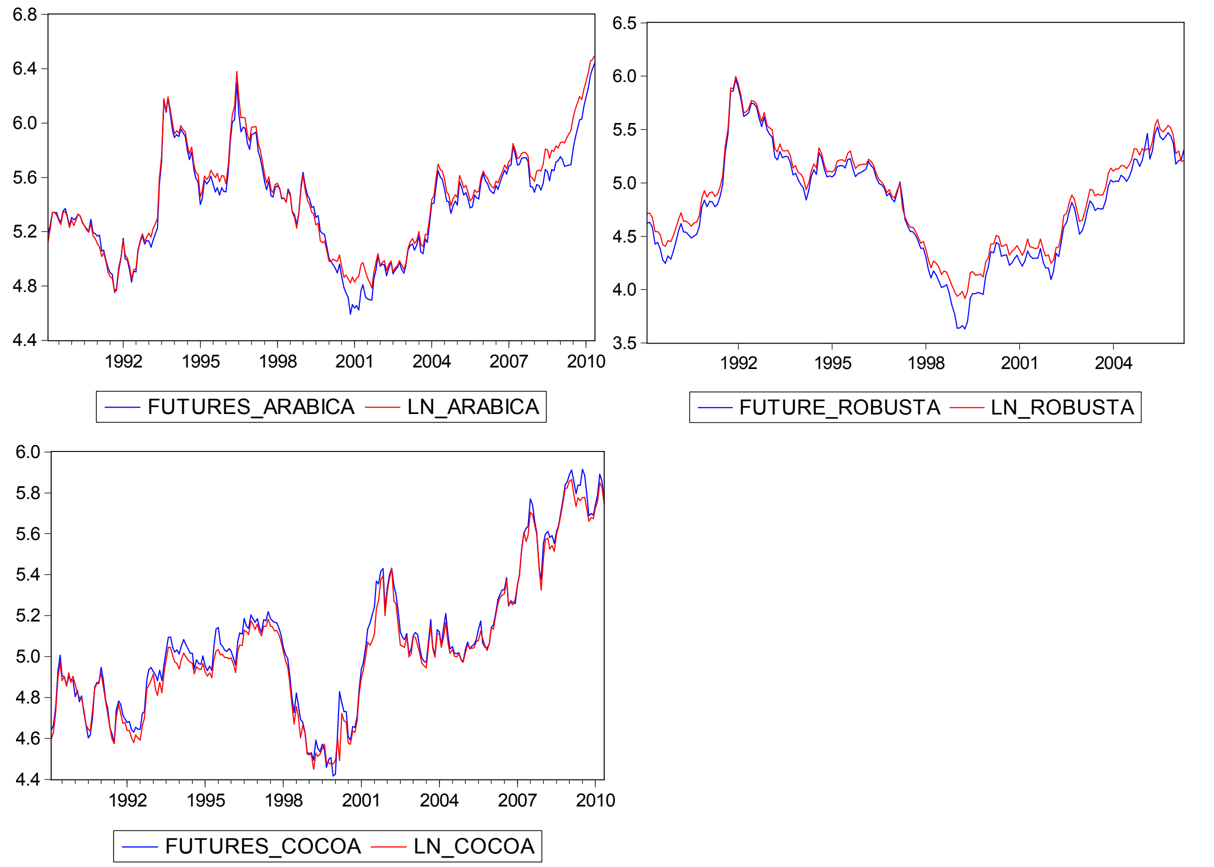
Graphs of long-horizon annual data show that oil price movements seem to spillover into cocoa and coffee prices. This section shows that although long-run causality from the oil sector to the beverage commodity sector is a valid assumption, only cocoa shares the same long-term trend as oil. Besides, a short-run analysis confirms the consistency of the long-run equilibrium relationship between cocoa and oil prices. As oil prices are a given for LDCs and most CDDCs, not much can be done policy-wise in order to reduce vulnerability to oil price fluctuations of coffee and cocoa exporting countries.

5.2 Speculation: Coffee- Cocoa futures

The futures market was invented to transfer price risk in the cash markets. The global coffee industry is traded on two main exchanges, ICE trades Arabica futures called Coffee "C" contracts denominated in US dollars while, LIFFE trades Robusta futures known as Robusta contracts in British pound (GBP). Although there are more futures markets in Brazil, France, India and Japan, this study will focus only on the two above mentioned. Cocoa is traded in ICE and LIFFE thereby, cocoa futures contracts are denominated both in US dollar and in GBP. This study uses LIFFE cocoa futures prices as the currency correlation is higher with the GBP than with the US dollar. Both coffee and cocoa futures contracts require an agreement on delivery period and price. The delivery period is pre-determined by a set of trading position and the market forces assess the price. A few conditions must be met in order to support any future markets; cash market prices must exhibit some volatility, a continuous price risk exposure, enough participants with competing price goals, and a quantifiable underlying basic commodity with standardize-able characteristics (ITC 2002).

Our concern arises from drastic events that occurred during the last decade and that may have altered the nature of the relationship between futures and cash prices of agricultural commodities. Many economists argue that the 2000 deregulation of financial instruments (futures) and physical instruments (OTC) encouraged speculators to massively trade commodities they had no interest in; and therefore, aggravating the extent of price surges in food and energy sectors and, destabilizing businesses and farmers budgets (Ash and al 2010, Gilbert and Morgan 2010). In fact, since 1990 years cash coffees and cocoa prices and futures prices have moved quite similarly, irrespective of the growing speculative moves. Also, futures markets seem efficient as, futures prices and cash prices are convergent. It is notable from the Graph 6 below it seems hard to detect which price leads the other because it seems like both futures and cash prices are moving simultaneously.

Graph 5.2 Cash and futures prices for coffees and cocoa (in log) January 1990- April 2011



Source: *Bloomberg, ICO, ICCO*

Cash and futures price series have very similar trends over the long term. Also, it seems very likely that both variables are cointegrated. However, we verify first that futures prices are *I*(1) before analyzing any causality relation. The test results confirm that futures prices series are *I*(1), for there is a unit root in level series (Prob.>0.05) but none in first-differenced series (Annexes- Table 12). If the two price series are *I*(1) and the linear combination of them is I(0) variables are cointegrated and thus bivariate models can be specified to take into account the linear relationship between the two series in the short-run. Therefore, we realize Granger cointegration tests and obtain results (Annexes - Table 12, 13) for the equations (3) and (4):

$$C_{t,a} = \varphi + \chi . F_{t,a} + u_{t,a} \tag{5.3}$$

$C_{t,a}$: Cash price at time *t* for commodity a : $\{ A_t \ , R_t , Cocoa_t \}$

$F_{t,a}$: Future price at time *t* for commodity a : $\{ A_t \ , R_t , Cocoa_t \}$

$$\Delta \hat{u}_{t,a} = \gamma \hat{u}_{t-1,a} + \sum_{j=1}^{p} \pi_{j,a} \Delta \hat{u}_{t-j,a} + \varepsilon_{,at} \tag{5.4}$$

OLS equation shows very high adjusted R-squared for every linear regression of futures prices on cash prices meaning that variations in futures prices of arabica, cocoa and robusta explain about 98% of their variations in current prices and vice versa (Annexes- Table 13). ADL tests results in table 5.2 attests the rejection of the null hypothesis of unit root in the residuals at a 1% level (Prob. <0.05), thereby futures series and their corresponding cash prices series are cointegrated

Table 5.2 ADL unit root test on residuals

	Arabica futures		*Cocoa futures*		*Robusta futures*	
	t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic γ	-2.789	0.0054	-9.139	0.000	-2.803	0.0052

Source: *Annexes table 14*

The cointegration order (1, 1) and the cointegrating vector [1, - $\hat{\chi}$] corresponding to [1, 0.98] for arabica, [1, 1.02] for robusta and [1, 0.925] for cocoa can be positively accepted. Engle and Granger (1987) have demonstrated that all cointegration series have an error correction representation. Positively accepted cointegration suggests that an error correction model (ECM) can be realized to assess short-term prices adjustments. As two series cannot be estimated nor predicted simultaneously like in equation (5.3), we estimate the error correction mechanism with unrestricted OLS in equation (5.5):

$$\Delta C_{t,a} = \alpha_0 + \alpha_1 \Delta F_{t,a} + \alpha_2 (C_{t-1,a} - \chi . F_{t-1,a}) + \varepsilon_{t,a} \qquad (5.5)$$

Nevertheless, equation (5.5) cannot be directly estimated for the two reasons: first, χ coefficient is not proven cointegrating coefficient for $C_{t,a}$ and $F_{t,a}$ but also, the orders of integrations are different for the variables; $\Delta C_{t,a}, \Delta F_{t,a} \sim I(0)$ while, $C_{t-1,a}, F_{t-1,a} \sim I(1)\ \forall a$. The integration orders must be the same for all variables to maintain the cointegration condition $\varepsilon_{t,a} \sim I(0)$. Therefore we replace χ by its previously computed OLS estimate $\hat{\chi}$ so that $\Delta C_{t,a}$, $\Delta F_{t,a}$ and $(C_{t-1,a} - \hat{\chi}.F_{t-1,a})$ are all $I(0)$ (Charemza and Deadman 1991). After this operation the model is correctly specified and the errors $\varepsilon_{t,a}$ are $I(0)$. In order to see whether $\hat{\chi} = 1$ we conduct Wald tests in the three OLS equations and obtain the following test results:

Table 5.3 Wald Test for ECM: $\hat{\chi} = 1$

Chi-square	*Value*	*df*	*Probability*
Arabica	4.50	1	0.034
Robusta	9.31	1	0.002
Cocoa	169.97	1	0.000

Source: *Annexes Table 15*

According the statistic Chi-square, arabica and cocoa equations allow $\hat{\chi} = 1$ at a 5% level and, robusta equation considers $\hat{\chi} = 1$ at a 1% level. Hence, the Engle Granger (5) equation can be simplified as follow:

$$\Delta C_{t,a} = \alpha_0 + \alpha_1 \Delta F_{t,a} + \alpha_2 (C_{t-1,a} - F_{t-1,a}) + \varepsilon_{t,a} \qquad (5.6)$$

Table 16 (Annexes) shows the results of this equation. The variables of the short-run ECM present difference specificities among commodities. In the three models, the constant term α_0 is insignificant at a 10% level. The arabica model suggests that variations in all the variables together are responsible for 95% of the variation in arabica cash price. About 90% of the variations of robusta current price is explained by the model. As for cocoa, its adjusted R^2 suggests that the model has a prediction power of about 70%.

Despite the low frequency of monthly data, it is possible to estimate the speed of adjustment between futures and cash prices. ECM gives a satisfying representation of short-run adjustments between cash and futures markets for arabica, robusta and cocoa. Short-run adjustments are consistent with the long-run relationship equilibrium existing between cash and futures series suggesting that the speed of adjustment is very fast, and futures cocoa and coffee markets are efficient.

6. Policy recommendations and Conclusions

The concerns about volatility in food prices have become a greater issue over the last few years and this, even after the relapse of the 2008 food crisis. Indeed, recent weather catastrophes, oil price surges, inflation, and declining value of the U.S. dollar, growing financialization on futures exchange markets have greatly led to the unpredictability and suddenness of food price developments. Several international organizations have investigated policy responses in order to mitigate the risks associated with high prices and volatilities in the global food market. A policy recommendation put forward at the G20 meeting in April 2011 [10] suggests strengthening the long term productivity, sustainability and resilience of the CDDCs agricultural sector, through enhanced public investment and national food security programs. Increasing transparency in food and futures markets and, eliminating domestic trade policies are other ground rules that would reduce trade distortions and markets instabilities (Staatz and Weber, 2011 and, Limao and Panagariya, 2003). At a macro level volatility repercussions varies from long- to short- term but also, from importing to exporting countries.

This study examines volatility and, oil and futures spillover effects on 3 major tropical commodities: arabica, robusta and cocoa. Volatility developments and

[10] Policy reports elaborated by FAO, IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, IFPRI, and the UN HLTF (2011).

implications are analyzed from the supply-side that is, exporting LDCs and CDDCs. In this case, large prices decreases are simultaneously reflected on the trade balance and in the longer term have a detrimental effect on growth. On the other hand, sudden peaks in prices incite producers to increase production and adjust their investment decisions, which may trigger even more instability in the markets. The results of the presented GARCH models provide an accurate and meaningful assessment of commodity price volatility. Arabica, robusta and cocoa price series are stochastic processes with time-dependent means that is; shocks affecting the prices are permanent. The conditional variances are also found variant over time due to volatility clustering, which justifies the use of GARCH specifications. Further analysis reveals uneven effects in arabica and robusta prices: volatilities are more affected by positive shocks than by negative shocks. However, cocoa volatility reacts quite symmetrically to the markets shocks whether positive or negative.

This paper estimates causality links between oil price and, both coffees and cocoa prices in the long-run. It appears that variations in coffee and cocoa prices follow oil price variations with, respectively 4 and 3 years interval. Nevertheless, the hypothesis of long-run equilibrium relationship only holds between oil and cocoa prices. Baffes (2007) detected that the oil-elasticity on cocoa was high and significant while the oil-coffee elasticity was particularly low; despite the heavier use of petro-chemical fertilizers in coffee production. In summary, oil price developments have no significant effect on coffee price variability in the short-run. On the other hand, for policy-makers more attention needs to be paid to oil price surges in the cocoa farming sector, as oil prices strongly influence cocoa prices and volatilities in the short- and long-run.

Lastly, we examined the relationship between arabica, robusta and cocoa cash prices and their corresponding future prices. Deregulation of financial and physical instruments in 2000, along with the introduction of new electronic trading opportunities in 2007 has raised concerns about efficiency in the coffees and cocoa futures markets. However, in this study, the observed cointegration between cash and futures series between 1990 and 2010 suggests that both ICE and LIFFE futures markets are unbiased and therefore, serve as price discovery channels for coffee and cocoa sector participants (see Chapter 5). The very short adjustment period noticeable between futures and cash prices suggest that, hedging strategies mitigate price risk only if they are an immediate reaction to market activity. Nonetheless, the unbiasedness of futures markets does not necessarily imply full-hedging of price risk (Broll and Zilcha 1992). In fact, the *Separation theorem* states that unbiased futures estimators of the spot prices do not imply that price risk is entirely avoided. Recent studies have shown that; over the last few years, large speculative activity increased price risk for cash market participants that are commercial traders (Schaffnit-Chatterjee, 2011 and, Schutter, 2010). As a consequence of increasing speculative activity, small farmers growing cocoa and coffee in LDCs and developing countries become even more exposed to price risk. Few alternatives to manage price risk are available to local farmers. Some have suggested the creation of local commodity exchanges which are more accessible to commercial hedgers (Gabre-Madhin 2010 and, Fortenbery and Zapata 2004), for instance; the Ethiopia Commodity Exchange that reduces the incentives of speculators by imposing mandatory delivery and higher margins. Such initiatives may largely reduce price risk and thus, promote economic stability in many CDDCs.

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Terms & Acronyms

ADL	Augmented Dickey Fuller
CDDCs	Commodity-dependent developing countries
CFA	Communaute Financiere Africaine
FAO	Food and Agriculture Organization of the United Nations
IATP	Institute for Agricultural Trade Policy
ICA	International Coffee Agreements
ICCO	International Cocoa Organization
ICO	International Coffee Organization
IFAD	International Fund for Agricultural Development
IFPRI	International Food Policy Research Institute
IMF	International Monetary Fund
ICE	Intercontinental Exchange
ITC	International Trade Centre
LDCs	Least Developed Countries (*)
LIFFE	London International Financial Futures and Options Exchange
MDG	Millennium Development Goals
NYBOT	New York Board of Trade
ODA	Official Development Assistance
OECD	Organization of Economic Cooperation and Development
SIC	Schwarz Information Criterion
UN-CTAD	United Nations Conference on Trade and Development
UN-HLTF	United National High-Level Task Force on the Global Food Security Crisis
WFP	United Nations World Food Programme
WTO	United Nations World Trade Organization

* LDCs: forty-eight countries designated by the UN using three criteria: "low-income", "human assets weakness", "economic vulnerability": Afghanistan, Angola, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Cambodia, the Central African Republic, Chad, the Comoros, the Democratic Republic of Congo, Djibouti, Equatorial Guinea, Eritrea, Ethiopia, the Gambia, Guinea, Guinea-Bissau, Haiti, Kiribati, the Lao People's Democratic Republic, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Myanmar, Nepal, Niger, Rwanda, Samoa, Sao Tome and Principe, Senegal, Sierra Leone, the Solomon Islands, Somalia, Sudan, Timor-Leste, Togo, Tuvalu, Uganda, the United Republic of Tanzania, Vanuatu, Yemen and Zambia

Annexes

Table of Content

Doc 1 Beverage exporting countries

Cacao exporting countries	Coffee exporting countries	Tea exporting countries
Brazil	Angola	China
Cameroon	Brazil	India
Côte d'Ivoire	Burundi	Indonesia
Dominican Republic	Central African Republic	Vietnam
Ecuador	Colombia	Turkey
Gabon	Costa Rica	Sri lanka
Ghana	Cote d'Yvoire	Kenya
Malaysia	Cuba	Japan
Nicaragua	Ecuador	Argentina
Nigeria	El Salvador	Iran
Papua New Guinea	Ethiopia	Bangladesh
Sierra Leone	Gabon	Malawi
Togo	Ghana	Uganda
Trinidad and Tobago	Guatemala	
Venezuela	Honduras	
	India	
	Indonesia	
	Kenya	
	Liberia	
	Mexico	
	Nicaragua	
	Panama	
	Papua New Guinea	
	Philippines	
	Sierra Leone	
	Tanzania	
	Thailand	
	Timor-Leste	
	Togo	
	Uganda	
	Vietnam	
	Yemen	

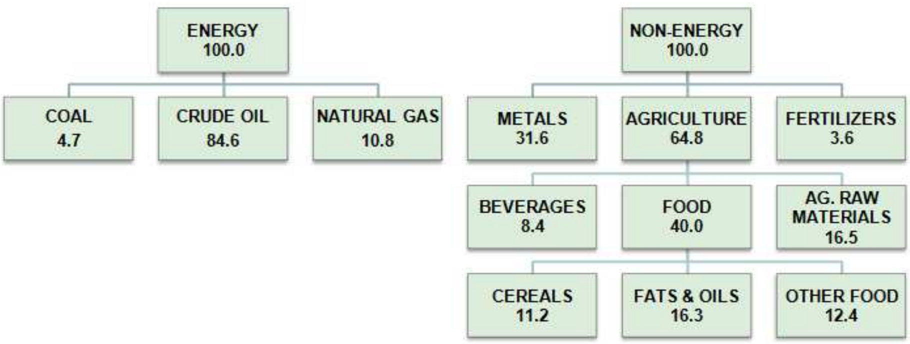
Source: *FAO (2011)*

Table 1 **Specifications for commodity prices**

Section	Commodities	Period (mm/yyyy)	Price Specifications	Source	Unit
4	Arabica	01/1990 - 09/2010	Monthly average constant prices	ICO	USc/kg
4	Robusta	01/1990 - 09/2010	Monthly average constant prices	ICO	USc/kg
4	Cocoa	01/1990 - 09/2010	Monthly average constant prices	ICCO	USc/kg
5	Arabica	01/1990 - 04/2011	Monthly average current prices	ICO	USc/kg
5	Robusta	01/1990 - 04/2011	Monthly average current prices	ICO	USc/kg
5	Cocoa	01/1990 - 04/2011	Monthly average current prices	ICCO	USc/kg
5	Petroleum Crude	01/1990 - 04/2011	Monthly average of three spot current prices Brent, Dubai, and West Texas Intermediate	Bloomberg World Bank	$/bbl
5	Arabica futures prices	01/1990 - 04/2011	Daily current prices	Bloomberg	US$/lb
5	Robusta futures prices	11/1991 - 01/2009	Daily current prices	Bloomberg	US$/MT
5	Cocoa futures prices	01/1990 - 04/2011	Daily current prices	Bloomberg	GBP/MT

Doc 2

World Bank Commodity Price Index: Groups and weights



Sum of components may not equal group total due to rounding.
Source: World Bank Development Prospects Group

Table 2 Correlations in current & constant prices

SHORT RUN

Current

1968-1990		Cocoa	Arabica	Robusta
256 obs.	**Cocoa**	-		
	Arabica	0.84	-	
	Robusta	0.90	0.96	-

1990-2011		Cocoa	Arabica	Robusta
256 obs.	**Cocoa**	-		
	Arabica	0.60	-	
	Robusta	0.36	0.77	-

Constant

1990-2010		Cocoa	Arabica	Robusta
249 obs.	**Cocoa**	-		
	Arabica	0.29	-	
	Robusta	0.09	0.76	-

LONG RUN

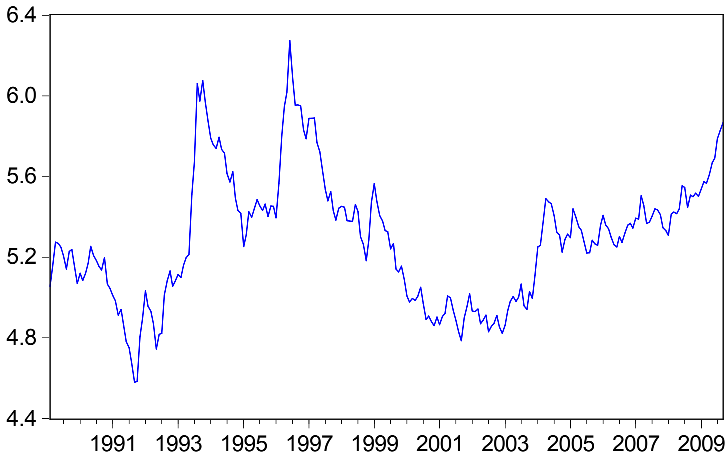
1960-2010		Cocoa	Arabica	Robusta
	Cocoa	-		
	Arabica	0.908	-	
	Robusta	0.418	0.921	-

Table 3 Descriptive Statistics of Arabica, Robusta and Cocoa (in log)

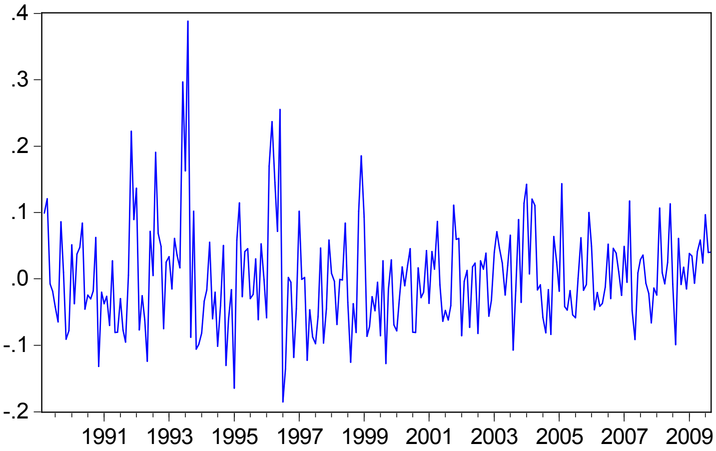
	ln(Rt)	ln(At)	ln(Ct)
Mean	4.746	5.293	4.891
Median	4.755	5.299	4.847
Maximum	5.881	6.274	5.580
Minimum	3.969	4.579	4.427
Std. Dev.	0.391	0.321	0.264
Skewness	0.226	0.383	0.575
Kurtosis	2.768	2.828	2.841
Standard deviation	**0.082**	**0.061**	**0.054**
Sum	1181.668	1317.876	1217.934
Sum Sq. Dev.	37.918	25.523	17.332
Observations	249	249	249

Graph 1 Coffees and Cocoa: monthly prices & volatility (short term)

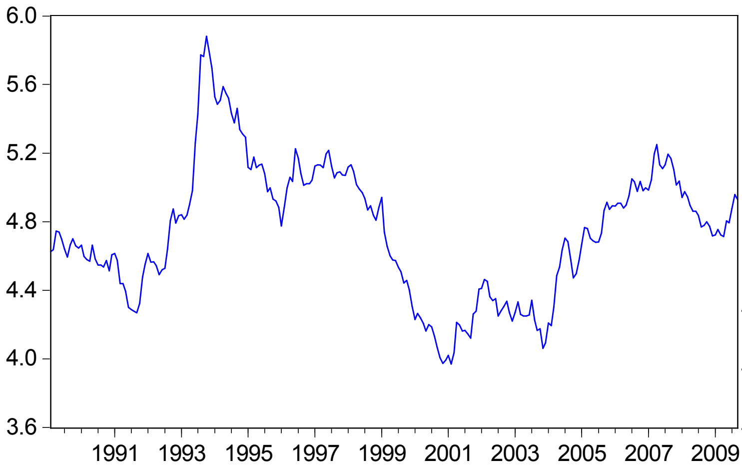
LN_ARABICA



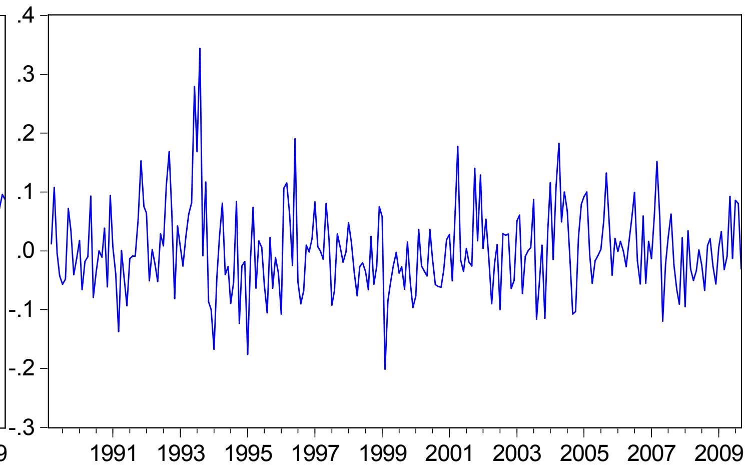
Differenced LN_ARABICA



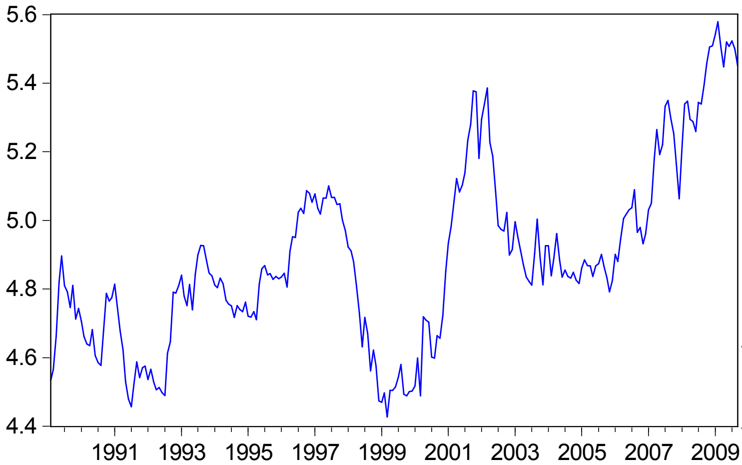
LN_ROBUSTA



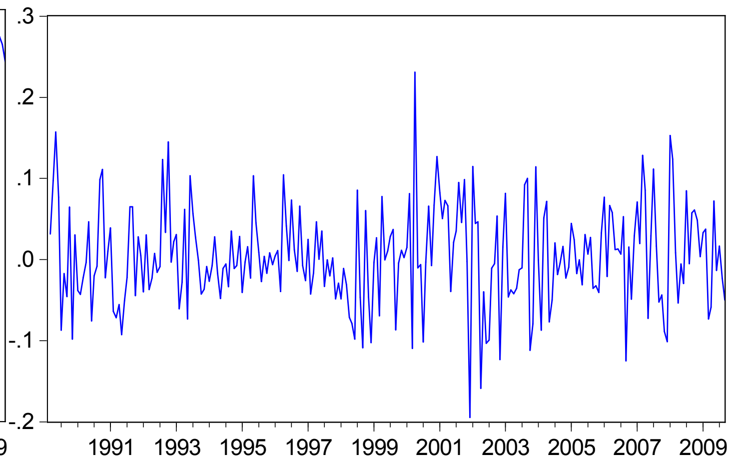
Differenced LN_ROBUSTA



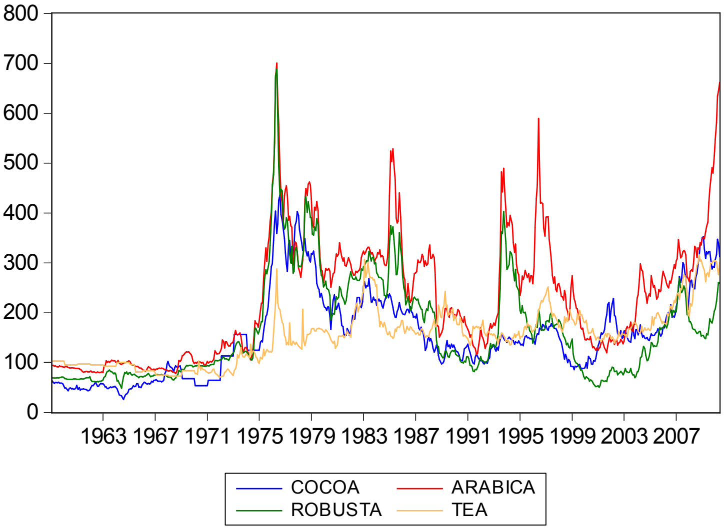
LN_COCOA



Differenced LN_COCOA



Graph 2 Monthly Price volatilities of beverage commodities in the long run (1960-1990)



Graph 3 % Change in Beverage annual prices

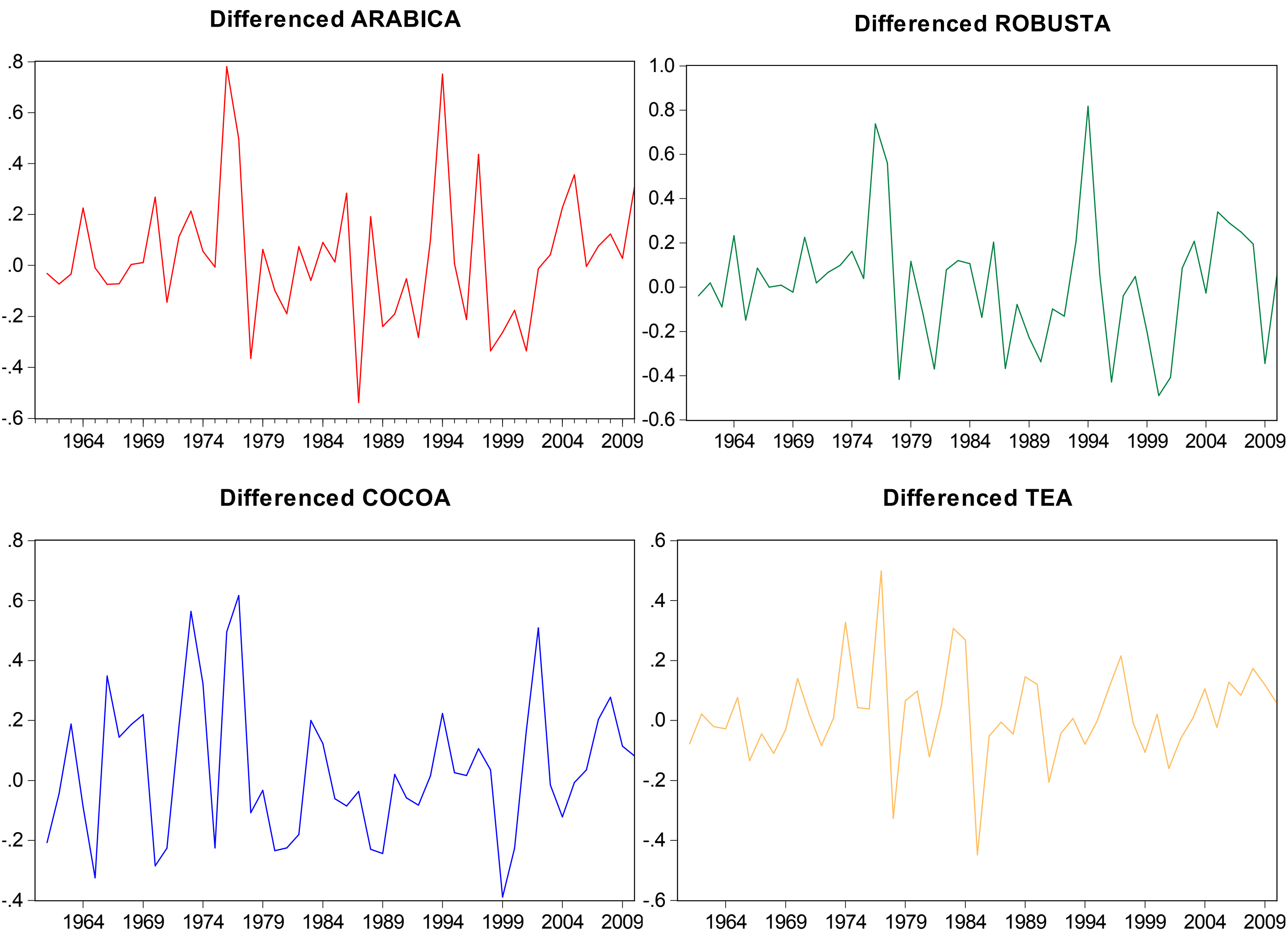


Table 4 GARCH (1, 1) tests results

Cocoa: AR (1) $Cocoa_t = c + \phi_1 p_{t-1} + \varepsilon_t$

Arabica: AR (1) $A_t = c + \phi_1 p_{t-1} + \varepsilon_t$

Robusta: ARMA (1,1) $R_t = c + \phi_1 p_{t-1} + \gamma_1 \varepsilon_{t-1} + \varepsilon_t$

Conditional variance $h_t^2 = \delta + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2$

		Cocoa	Arabica	Robusta
ARMA	c	4.940	5.260	4.610
		(0.158)	(0.132)	(0.206)
	φ	0.976	0.969	0.972
		(0.011)	(0.015)	(0.014)
	γ			0.241
				(0.075)
GARCH	δ	0.001	0.002	0.002
		(0.000)	(0.001)	(0.001)
	α	0.247	0.178	0.144
		(0.080)	(0.067)	(0.067)
	β	0.622	0.505	0.525
		(0.121)	(0.210)	(0.244)
	α+β	0.870	0.682	0.669
	Schwarz	-2.742	-2.264	-2.418
	Adjusted R^2	0.947	0.940	0.968

Table 5 Wald Test: Test of the GARCH hypothesis

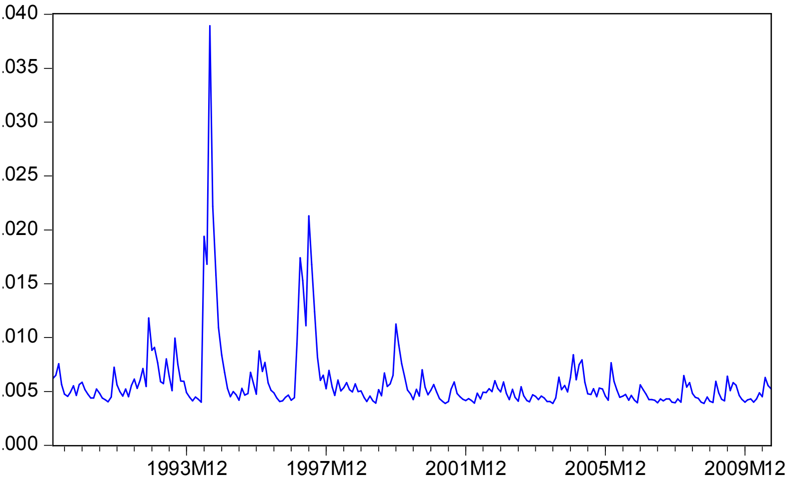
Wald Test: $H_0 : \alpha = 0, \beta = 0$					
	Test Statistic	*Value*	*df*	*Probability*	
	F-statistic	53.76003	(2, 243)	0.000	
Equation: COCOA_GARCH	*Chi-square*	107.5201	2	0.000	REJECT
	F-statistic	31.58837	(2, 243)	0.000	
Equation: ARABICA_GARCH	*Chi-square*	63.17674	2	0.000	REJECT
	F-statistic	15.88593	(2, 242)	0.000	
Equation: ROBUSTA_GARCH	*Chi-square*	31.77186	2	0.000	REJECT

Table 6 Wald test: Test of the persistence in volatility

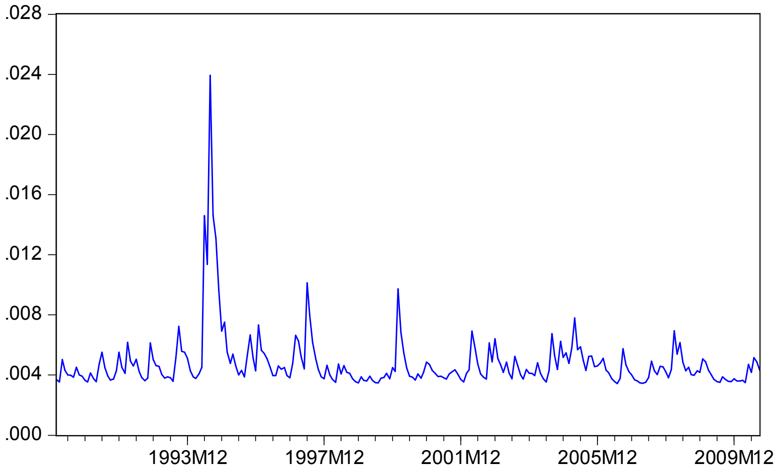
Wald Test: $H_0 : \alpha + \beta = 1$	*Test Statistic*	*Value*	*df*	*Probability*
	t-statistic	1.472505	243	0.1422
Equation: COCOA_GARCH	*F-statistic*	2.16827	(1, 243)	0.1422
	Chi-square	2.16827	1	0.1409
	t-statistic	1.963981	243	0.0507
Equation: ARABICA_GARCH	*F-statistic*	3.85722	(1, 243)	0.0507
	Chi-square	3.85722	1	0.0495
	t-statistic	1.637205	242	0.1029
Equation: ROBUSTA_GARCH	*F-statistic*	2.680439	(1, 242)	0.1029
	Chi-square	2.680439	1	0.1016

Graph 4 Conditional variances GARCH (1, 1)

Arabica



Robusta



Cocoa

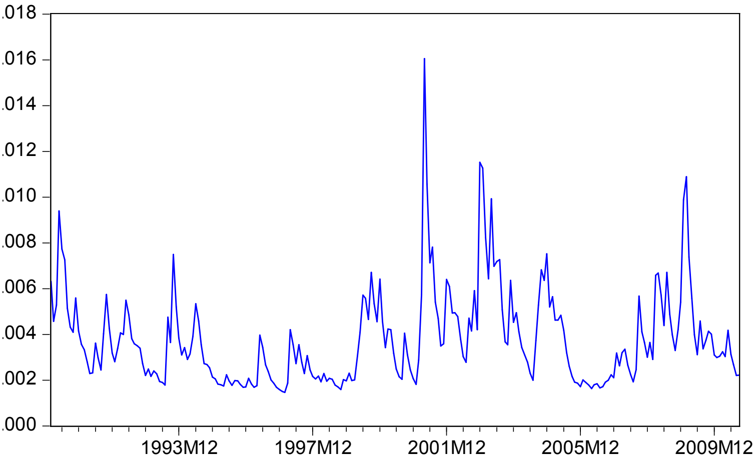


Table 7 EGARCH: tests results for Cocoa, Arabica and Robusta

Cocoa: AR (1) $Cocoa_t = c + \phi_1 p_{t-1} + \varepsilon_t$

Arabica: ARMA (4, 2) $A_t = c + \phi_1 p_{t-1} + \phi_2 p_{t-2} + \phi_3 p_{t-3} + \phi_4 p_{t-4} + \gamma_1 \varepsilon_{t-1} + \gamma_2 \varepsilon_{t-2} + \varepsilon_t$

Robusta; ARMA (1, 1) $R_t = c + \phi_1 p_{t-1} + \gamma_1 \varepsilon_{t-1} + \varepsilon_t$

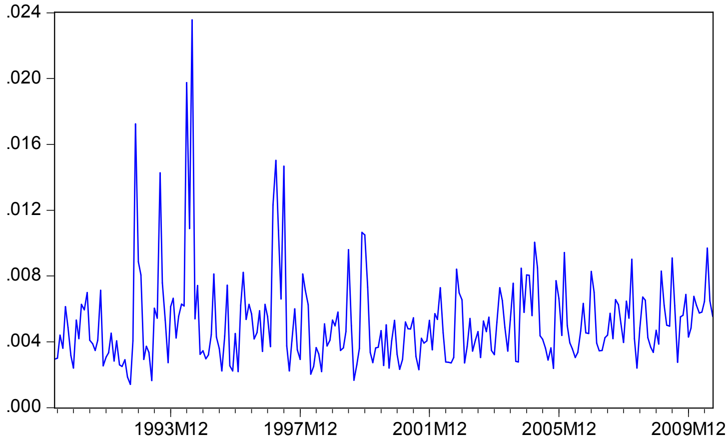
EGARCH: $$\log(h_t^2) = \delta + \pi_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}^2}} \right| + \pi_2 \frac{\varepsilon_{t-1}}{\left| h_{t-1}^2 \right|} + \beta \log(h_{t-1}^2)$$

		Coefficient	**Cocoa**	**Arabica**	**Robusta**
ARMA		*c*	4.911	5.410	4.747
			0.139	0.285	0.258
	AR	ϕ_1	0.974	1.248	0.980
			0.010	0.075	0.010
		ϕ_2	-	-1.048	-
			-	0.096	-
		ϕ_3	-	1.037	-
			-	0.080	-
		ϕ_4	-	-0.269	-
			-	0.069	-
	MA	γ_1	-	-0.088	0.223
			-	0.029	0.067
		γ_2	-	0.931	-
			-	0.032	-
EGARCH		δ	-2.073	-3.178	-2.308
			0.710	0.574	0.777
		π_1	0.542	-0.036	0.015
			0.135	0.141	0.146
		π_2	**0.035***	**0.422**	**0.351**
			0.090	**0.104**	**0.086**
		β	0.712	0.402	0.579
			0.117	0.110	0.138
		SIC	-2.721	-2.280	-2.466

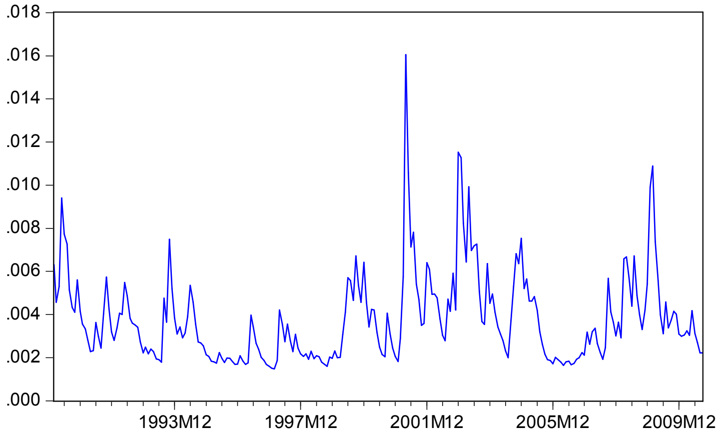
* Only Cocoa π_2 coefficient is significantly equal to 0

Graph 5 Conditional variances EGARCH

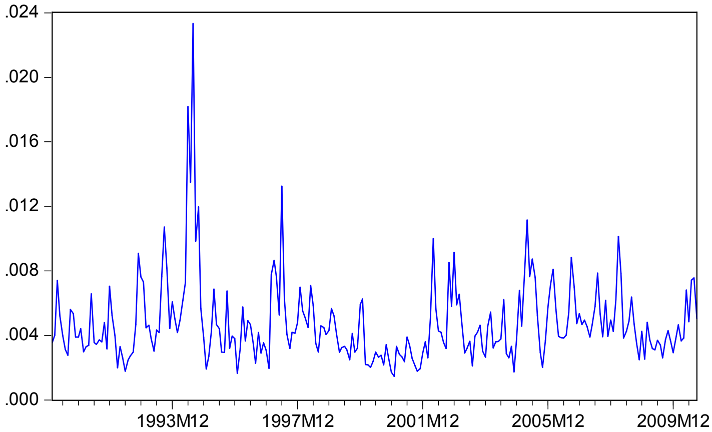
Arabica



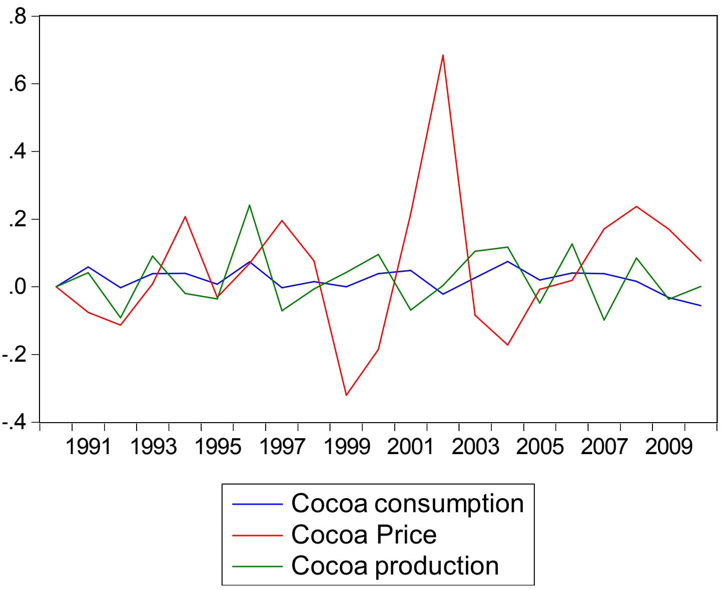
Cocoa

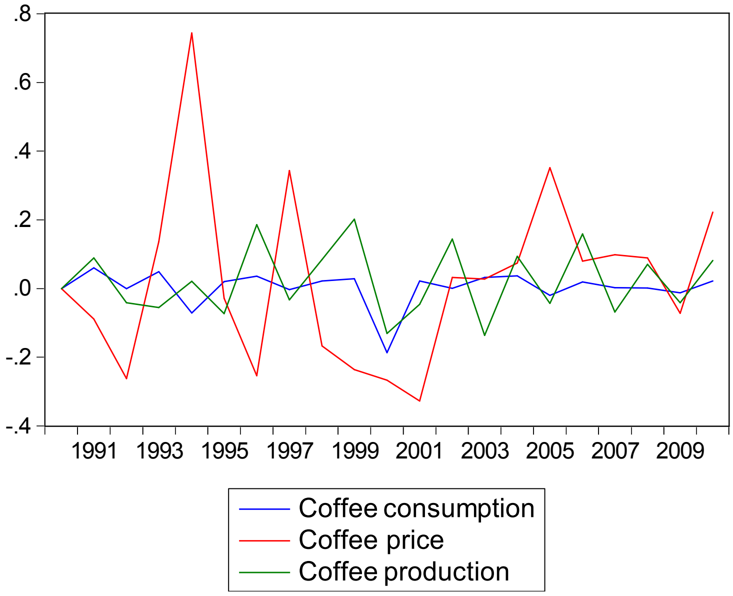


Robusta



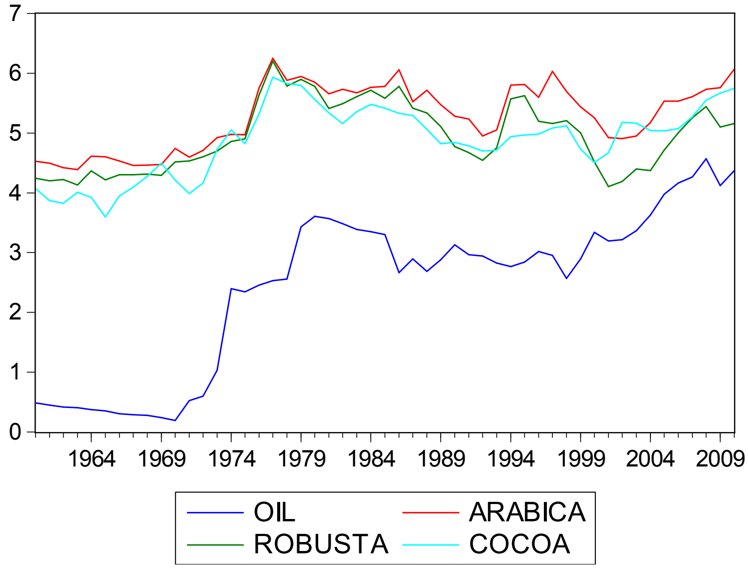
Graph 6 % Changes in Prices, consumption and production of coffee (ICO) and cocoa



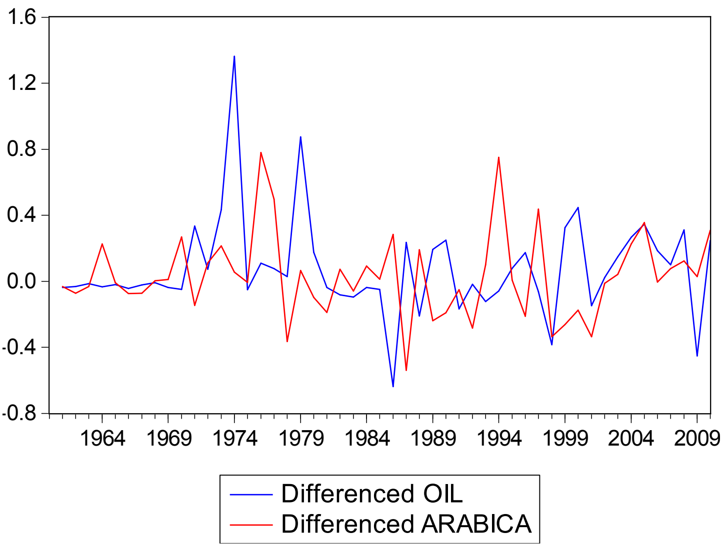


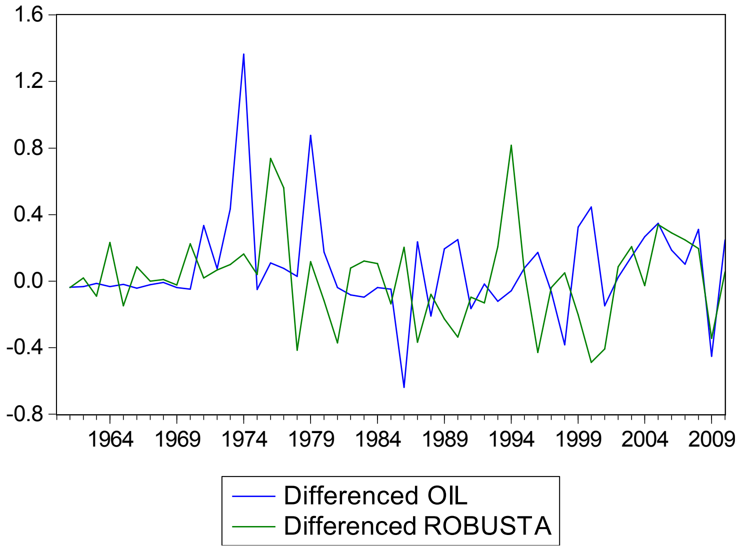
Source: *ICO, ICCO*

Graph 7 Evolution of Arabica, Robusta, Cocoa, and Oil current prices



Graph 8 Percent Variation in Cocoa- Arabica- Robusta prices vs. Oil prices





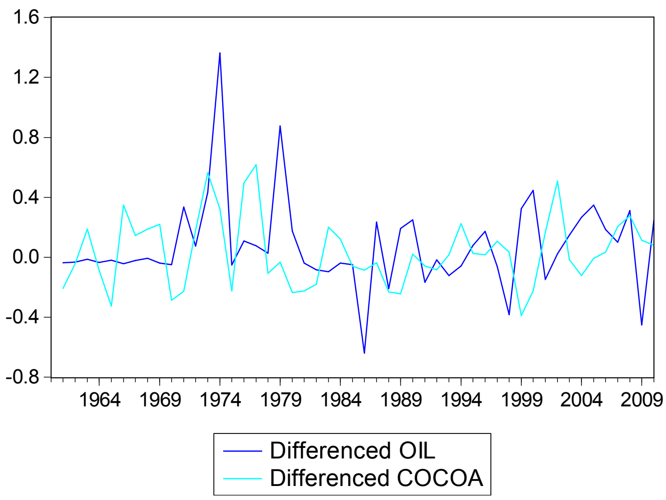


Table 8 Unit root in level and first-difference for Arabica Robusta Cocoa and Oil

Unit root in levels

		Arabica		Cocoa		Robusta		Oil	
Lag length		1		0		1			
		t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic		0.746	0.875	1.1	0.929	0.408	0.801	0.784	0.882
	1%	-2.574		-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942		-1.942	
Critical values:	10%	-1.616		-1.616		-1.616		-1.616	

Unit root in first-differences

		Arabica		Cocoa		Robusta		Oil	
Lag length		1		0		1			
		t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic		-12.800	0.000	-14.094	0.000	-11.790	0.000	-11.486	0.000
Critical values:	1%	-2.574		-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942		-1.942	
	10%	-1.616		-1.616		-1.616		-1.616	

Table 9 Ordinary Least Squares equation

Method: Least Squares

Dependent Variable:		LN_COCOA		LN_ARABICA		LN_ROBUSTA	
Variable		*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
	η (LN_OIL)	0.368	0.025	0.211	0.037	0.105	0.044
	C	3.796	0.087	4.735	0.129	4.539	0.153
Adjusted R-squared		0.453		0.112		0.018	

Table 10 Cointegration: ADL test on residuals

		Arabica		Cocoa		Robusta	
Lag length		1		0		1	
		t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic		-1.614	0.1003	-2.2436	0.0242	-1.569	0.1096
	1%	-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942	
Critical values:	10%	-1.616		-1.616		-1.616	

Table 11 **Granger-causality tests results with different lag length**

Null hypothesis		Lag 1	Lag 2	Lag 4	Lag 8	Lag 12	Lag 18	Lag 24
LN_OIL does not LN_ARABICA	*F-statistic*	2.321	1.074	0.843	1.528	1.383	0.924	1.159
	Prob.	0.1289	0.343	0.499	0.148	0.175	0.55	0.285
LN_ARABICA does not → LN_OIL	*F-statistic*	0.262	0.171	0.285	0.676	0.745	0.823	0.675
	Prob.	0.609	0.843	0.887	0.712	0.706	0.672	0.871
LN_OIL does not → LN_COCOA	*F-statistic*	3.299	1.877	1.19	0.93195	1.918	1.421	1.669
	Prob.	0.0705***	0.155	0.31	0.49	0.034**	0.124	0.032**
LN_COCOA does not → LN_OIL	*F-statistic*	0.84	0.935	0.633	1.304	2.097	1.569	1.213
	Prob.	0.36	0.394	0.594	0.242	0.018**	0.071	0.236
LN_OIL does not → LN_ROBUSTA	*F-statistic*	1.497	0.435	0.368	0.648	0.879	0.512	0.693
	Prob.	0.222	0.648	0.831	0.736	0.568	0.95	0.854
LN_ROBUSTA does not → LN_OIL	*F-statistic*	0.033	0.098	0.133	0.189	0.559	0.856	0.939
	Prob.	0.856	0.906	0.97	0.99	0.872	0.633	0.549

Note: *, **, and *** denote significance at 1%, 5%, and 10% level, respectively

Table 12 **Unit root in level and first-difference for Arabica Robusta Cocoa futures prices**

Unit root in levels

		Futures Arabica "C"		***Futures Cocoa***		***Futures Robusta***	
Lag length		1		0		1	
		t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic		0.675	0.861	0.728	0.871	0.24	0.755
	1%	-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942	
Critical values:	10%	-1.616		-1.616		-1.616	

Unit root in first-differences

		Futures Arabica "C"		***Futures Cocoa***		***Futures Robusta***	
Lag length		1		0		1	
		t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic		-13.451	0.000	-12.819	0.000	-11.19	0.000
Critical values:	1%	-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942	
	10%	-1.616		-1.616		-1.616	

Table 13 Ordinary Least Squares equations

Method: Least Squares

Dependent Variable:	LN_COCOA		LN_ARABICA		LN_ROBUSTA	
Variable	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*	*Coefficient*	*Std. Error*
χ	0.981	0.006	1.0213	0.01	0.925	0.0058
φ	0.0647	0.0318	-0.069*	0.055	0.446	0.0278
Adjusted R-squared	0.989		0.976		0.982	

* denotes insignificance at a 5% level

Table 14 Cointegration: ADL test on residuals

		Arabica futures		***Cocoa futures***		***Robusta futures***	
Lag length		0		0		0	
		t-statistic	*Prob.*	*t-statistic*	*Prob.*	*t-statistic*	*Prob.*
ADL statistic		-2.789	0.0054	-9.139	0.000	-2.803	0.0052
	1%	-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942	
Critical values:	10%	-1.616		-1.616		-1.616	

Table 15 Wald Test: $\hat{\chi} = 1$

Wald Test				
	Test Statistic	Value	df	Probability
Arabica	t-statistic	2.12	254	0.035
	F-statistic	4.50	(1, 254)	0.035
	Chi-square	4.50	1	0.034
Cocoa	t-statistic	-3.05	254	0.003
	F-statistic	9.31	(1, 254)	0.003
	Chi-square	9.31	1	0.002
Robusta	t-statistic	-13.04	205	0.000
	F-statistic	169.97	(1, 205)	0.000
	Chi-square	169.97	1	0.000

Table 16 OLS Error Correction Model

$$\Delta C_{t,a} = \alpha_0 + \alpha_1 \Delta F_{t,a} + \alpha_2 (C_{t-1,a} - F_{t-1,a}) + \varepsilon_{t,a}$$

Dependent Variable $\Delta C_{t,a}$ **:**	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	α_0	-0.001	0.002	-0.729	0.466
$a: Arabica$	α_1	0.907	0.013	69.790	0.000
	α_2	-0.030	0.018	-1.724	0.086
	adjusted R^2	0.951			
$a: Cocoa$	α_0	-0.001	0.003	-0.226	0.821
	α_1	0.800	0.032	24.993	0.000
	α_2	0.034	0.033	1.018	0.310
	adjusted R^2	0.716			
	α_0	0.005	0.003	1.445	0.150
$a: Robusta$	α_1	0.843	0.021	40.622	0.000
	α_2	-0.059	0.032	-1.844	0.067
	adjusted R^2	0.892			