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

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**Noemie Eliana Maurice and Junior
Davis**

Discussion paper 1

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

Noemie Eliana Maurice¹ and Junior Davis²

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. Our analysis of coffee and cocoa historical prices shows that, coffee price volatility has uneven or differing reactions depending on the nature of the market shock. Oil price spillover effects on coffee and cocoa markets are also assessed using cointegration and causality models. Long-run causality is found between oil prices, and coffee and cocoa prices but, only cocoa has an equilibrium relationship with oil in the long-term. Given the results, this study proposes some policy recommendations for managing price risk and addressing regulation in cocoa and coffee exporting countries.

Keywords: Commodity price volatility, financialization, error correction modelling, cointegration theory, commodity dependent developing countries, least developed countries.

JEL classification: E30; F24; O11

¹ Erasmus School of Economics, Erasmus University, Rotterdam, The Netherlands. E-mail: noemiee.maurice@gmail.com

² UNCTAD, Special Unit on Commodities United Nations. E-mail: junior.davis@unctad.org. The authors would like to thank Ms. Laurent (SUC) for assistance with statistical data collection.

Contents

1	Introduction	4
2	Overview of the world coffee and cocoa markets	5
2.1	<i>Commodity price volatility</i>	7
3	Modelling coffee and cocoa price volatility	10
4	Impact of oil spillover effects and speculation on coffee and cocoa prices	16
4.1	<i>Cross commodity causality: Oil vs. Coffee and Cocoa</i>	17
4.2	<i>Cointegration models and results: the effect of speculation</i>	19
5	Policy recommendations and conclusions	21
6	Terms & Acronyms	28
7	Annexes	29

Figures

Figure 1	Coefficients of variation for commodities in the short- and long run	9
Figure 2	Percentage variations in Prices, consumption and production of (A) coffee and (B) cocoa	16

Tables

Table 1	Specification for commodity prices	11
Table 2	Granger-causality tests results	18

1 Introduction

Since 2000, 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 volatility³ 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. The World Bank estimates that 119 million more people have been pushed into hunger as a result of the 2008 food crisis. There are now an estimated 1.02 billion malnourished people worldwide (World Bank 2009).

Meanwhile, the FAO estimates that more than 75 million people were driven into hunger between 2006 and 2010 (FAO 2011). LDCs and CDDCs were particularly harmed by this crisis. Indeed, in most of the LDCs, consumed food is not processed or at least, less than in the developed countries. Therefore, following the 2007-2008 food prices crisis, the affordability of food products became more worrying in developing countries than in the developed ones. 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).

Although supply and demand fundamentals played a significant role in the food crisis outbreak, many other factors contributed to the economic turmoil. For example, large increases in oil prices contributed to rising production costs and drove food prices higher. Besides, the World Bank estimates that weakness of the dollar accounted for 15% of the food price increases between 2002 and 2008 (Mitchell 2008). Additionally, over the last decade, weather events such as drought in Russia, freezes in Brazil and, heavy rains in Canada and in Australia caused major

³ 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.

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. Price fluctuations are inherent in agricultural markets – partly due to the supply-demand dynamics and the unpredictability of weather patterns and harvest yields.

There are debates as to the extent to which activity in futures trades and over the counter markets (OTC) for agricultural commodities impact on this volatility. Whatever the cause, extreme volatility in food prices deters producers from making the necessary investments for increasing productivity and production: this is one of the underlying causes of continued worldwide food insecurity.

This study intends to explore the gravity of the commodity trade and development problematique vis-à-vis high food, 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. This study will first provide an overview of the world coffee and cocoa markets. Next, we introduce the data employed for use in the empirical analyses. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models for Arabica, Robusta and cocoa are then estimated and interpreted. We then empirically consider the price-effects of both energy and financial products using Granger-causality and cointegration methods to explore potential long-term trend similarities. Last, we consider the empirical results to formulate a few policy recommendations aimed at reducing risks associated with price volatility in CDDCs.

2 Overview of the world coffee and cocoa markets

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. In fact, 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 different varieties of coffee and traded on separate exchange markets. Coffee and cocoa have similar long-run price trends (Graph 2- Annexes). Moreover, to the production of both commodities is mostly located in LDCs and developing countries

in Africa, South America and South Asia (Annexes- Doc1). Thus, coffee and cocoa price volatility is of acute economic importance for CDDCs whereas the tea trade for instance has no major impact on its main producers' (China and India) trade balances. As coffee and cocoa are the two major export crops of the Sub-Saharan African region (SSA), they represent a major source of income for many LDCs or developing countries that have strong commodity-export dependence. For instance, cocoa crop exports provide a livelihood for 25 per cent of the Cote d'Ivoire's population (FAO 2006) while, the share of coffee in total exports represents 79 per cent in Burundi and 64 per cent in Ethiopia (FAO 2006). For coffee and cocoa exporting CDDCs, price volatility is a major cause of 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 as extreme volatility in prices deters producers from making the necessary investments for increasing productivity and production. For most importing countries, changes in coffee or cocoa prices would probably only result in relatively minor changes in consumption habits.

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. 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, and the private sector 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. 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. The Intercontinental Exchange (ICE) which is part of the New York Board of Trade (NYBOT) governs the world Arabica price through Futures U.S. Coffee "C" contracts while Robusta coffee has been traded for over twenty years on the London International Financial Futures Exchange (LIFFE).

Cocoa, although produced and exported in smaller volumes, has many 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. Cocoa harvests and thus productivity levels are highly dependent on prevalent weather conditions. The mandates of the International Cocoa Organization (ICCO) focus on enhancing the economic, social and environmental sustainability of the world cocoa economy. Since 1925, cocoa has been traded on the New York Cocoa Exchange before joining the Coffee, Cocoa and Sugar Exchange and later the ICE, as part of NYBOT. Cocoa futures contracts is primarily traded and denominated in UK pounds.

2.1 Commodity price volatility

Commodity prices have shown considerable volatility over the past decade.⁴ The price boom between 2002 and 2008 was the most pronounced in several decades – in magnitude, duration and breadth. Moreover, the price decline following the onset of the recent global crisis in mid-2008 stands out both for its sharpness and for the number of commodities affected. Since mid-2009, and especially since the summer of 2010, global commodity prices have been rising again rapidly (excepting some temporary setbacks in the second quarter of 2011).

There are many explanations for the apparent volatility in commodity markets, including the so-called financialization of commodities as an asset class. The high prices across a broad range of commodities -- and the potential diversification benefits of a wide array of investment opportunities -- has attracted speculative investors (e.g. hedge funds, commodity index and exchange-traded-funds) into commodity markets. Between 2003 and 2008, speculative investment in commodity indexes was estimated to have increased from \$15 billion to around \$200 billion.

⁴ Price volatility is a measure of price variation from one period to the next.

The issue of commodity price development and the financialization of commodity trading is discussed further in Annex 1.

Long-term comparisons show that recent price volatility is not unprecedented for individual commodities.⁵ For example, oil price volatility in 2008, while remarkable, remained well below its spike of the early 1970s. Examining the short-term constant prices provides a better insight with regard to recent food price developments. The chart below presents the coefficients of variation (CV) for various food commodities and oil.

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

The CV (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.

Figure 1 shows the long-term volatility of commodities prices using monthly nominal prices for 6 commodities over the period 1960-2011 and indicates that the recent price fluctuations are not extraordinary for specific commodities (Calvo-Gonzales, Shankar and Trezzi, 2010). The volatility of coffee prices was similar to that of most agricultural products in the past. Petroleum and sugar prices were the most volatile during the period 1960-1989. Indeed, price volatility in 2000-2011 fell with respect to its long-term average for 85% of the commodities, and rose for 15% of the commodities.

However, it should be noted that the volatility estimates in this paper do not take into account trends which could be important in the context of a commodity super cycle,⁶ as for example in the case of real metals prices. Moreover, the high speed and

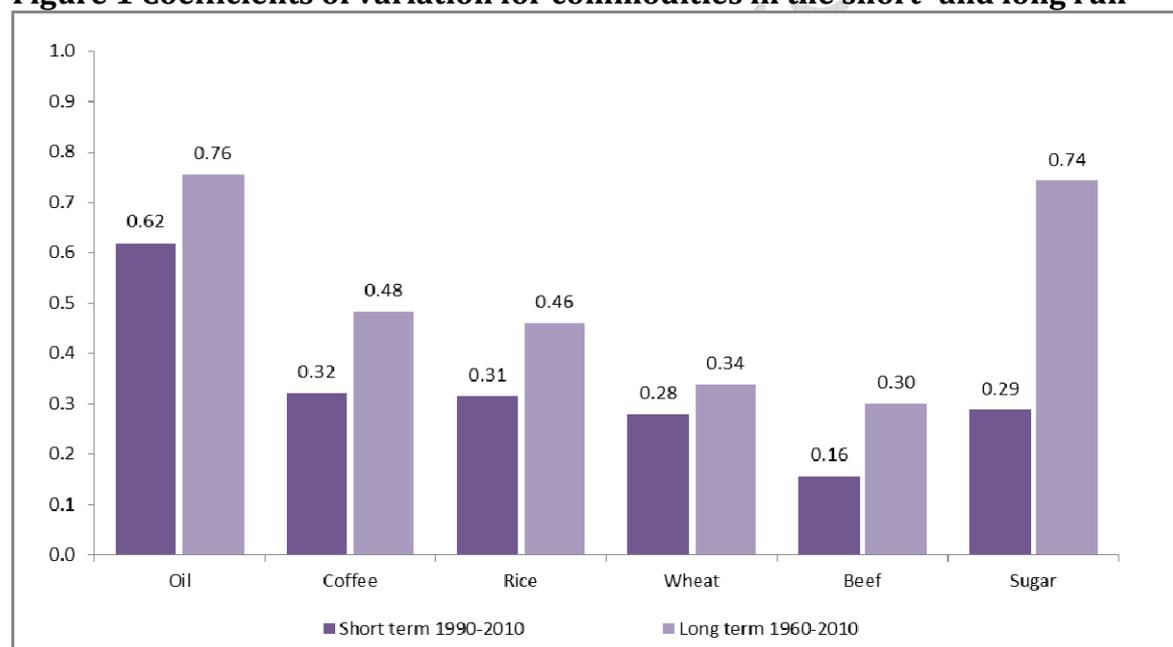
⁵ Jacks DS, O'Rourke KH and Williamson JG (2011). Commodity Price Volatility and World Market Integration since 1700. Review of Economics and Statistics, (forthcoming) and Calvo-Gonzales O, Shankar R and Trezzi R (2010). Are Commodity Prices More Volatile Now? A Long-Run Perspective. Policy Research Working Paper No. 5460, World Bank, Washington, DC, October.

⁶ John T. Cuddington and Daniel Jerrett (2008). Super Cycles in Real Metals Prices? IMF Staff Papers, Vol. 55, No. 4. International Monetary Fund.

amplitude of recent price swings for a broad range of commodities clearly distinguishes them from earlier ones (Baffes and Haniotis, 2010).⁷ More specifically, the magnitude of the most recent upswing of food and metals prices was above the historical average, while the magnitude of the price rebound for oil was similar to historical averages, but occurred at a higher speed.

The volatility of coffee prices was similar to that of most agricultural products over the past 50 years. Petroleum and sugar prices were the most volatile during the period 1960-2010. However, it should be noted that the volatility estimates below do not take into account trends which could be important in the context of a commodity super cycle, as for example in the case of real metals prices (Cuddington and Jerret, 2008).

Figure 1 Coefficients of variation for commodities in the short- and long run



Source: Unctadstat (2011).

The coefficient of variation is very sensitive to outliers hence; for example, the large amplitude of price swings that occurred during the 1979 financial crisis⁸ for a broad

⁷ Baffes J and Haniotis T (2010). Placing the 2006/08 commodity price boom into perspective. Policy Research Working Paper No. 5371, World Bank, Washington, DC, July.

⁸ 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 led to

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. We explore these issues empirically in sections 3 and 4 of the paper.

3 Modelling coffee and cocoa price volatility

In this paper on coffee and cocoa price volatility and GARCH-type models, the sample size consists of 249 observations. We use logarithmic transformations of monthly constant prices of Arabica and Robusta from January 1990 to September 2010 (12 months*20 years+9 months= 249 months)⁹. For the second part of the study, we use the logarithms of monthly current prices for Arabica, Robusta, cocoa and oil. Daily futures prices of Arabica, Robusta and cocoa were collected from Bloomberg. Monthly averages were computed in order to conduct a causality analysis. Cocoa futures prices are extracted from the London International Financial Futures and Options Exchange (LIFFE) and therefore are converted from UK (£) pounds sterling to US dollars using the monthly average of the Bank of England's spot exchange rate statistics.

Table 1 lists the commodity price series, sources and units of measurement utilized in this paper. The deflator that is used to compute constant prices from current price ($Constant = Current / MUV * 100$) is the UN Unit Value Index of Manufactured (MUV) goods exports.

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.

⁹ The 1990-2010 period corresponds to the free market period on commodity markets.

Table 1 Specification for commodity prices

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

Source: ICO, ICCO Bloomberg, the World Bank

Food price variations are often large and unpredictable. Greater price unpredictability and uncertainty about future developments, often leads to higher price risks being borne by producers, exporters, importers and stock holders who are then very likely to review their investment decisions. To reduce disruptions in both coffee and cocoa markets will require an empirically accurate measure of volatility that takes into account specifications relative to each commodity and allows the prediction of 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.

GARCH models use past prices to model and forecast conditional variances. They also allow a wide range of possible specifications to both model volatility and examine volatility persistence and asymmetry in coffee prices over time. Any GARCH model assumes that 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 section of the paper 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 ¹⁰ are generated by the autoregressive process:

$$P_t^A = c + \sum_{i=1}^p \phi_i P_{t-i}^A + \varepsilon_t \quad (4.1)$$

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

$$h_t^2 = \delta + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \quad (4.2)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$$

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 both 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). In addition, regressions are estimated 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. The Arabica results show that AR(1) is the specification that maximizes the quality of the fit. 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. All the coefficients in table 4 of the Annexes are significant and the regressions show a high adjusted R-squared, meaning that the estimated parameters of the conditional mean have a strong explanatory power of historical price movements. Given the high adjusted R-squared, it would seem that GARCH models perform well at modelling conditional variance. Nonetheless, this is no guarantee that the GARCH process is a statistically valid improvement over the AR(MA) process (Aradhyula and Holt, 1988). It is thus

¹⁰ P_t^R stands for Robusta price and P_t^C for cocoa price

relevant to test the GARCH hypothesis that the conditional variances are in fact, not constant using the following hypothesis:

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

$$H_1 : \alpha \neq 0 \text{ or } \beta \neq 0$$

A Wald test of the joint significance of α and β is conducted 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.

From our GARCH analysis, it is possible to infer that shocks in prices are reflected in volatility, but one might also consider how changes in variability evolve when shocks are positive or negative. Such a distinction may be modelled with econometric tools and, by adding precision to the model, provide a better forecasting tool. Understanding volatility in response to positive or negative shocks is crucial for CDDC producers so they can predict future volatility in commodity prices with more accuracy and thus, improve the estimation of future revenue streams. We do this by introducing symmetry or leverage effects in the variance to GARCH models. The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) is the most widely used of these models to estimate the logarithm of conditional variance in order to determine whether or not the observed volatility reacts asymmetrically to *good* and *bad* news. *Good news* in the case of a commodity might be favourable weather forecasts for coffee and cocoa crops or policies that promote agricultural development and growth; whilst *bad news* may for example be a natural disaster or calamitous weather event (hurricane, tornado, flooding etc) or sharp rises in oil prices for instance. Nelson (1991) and Schwert (1989) maintain that stock volatility is higher during recessions and financial crisis. In order to assess this for cocoa and coffee we estimate the following EGARCH:

$$\log(h_t^2) = \delta + \pi_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}^2}} \right| + \pi_2 \frac{\varepsilon_{t-1}}{|h_{t-1}^2|} + \beta \log(h_{t-1}^2) \quad (4.3)$$

In this model the effects of residuals is exponential and not quadratic. The asymmetry is measured by 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 $(\pi_1 + \pi_2)/\sqrt{h_{t-1}^2}$ whereas the impact of negative shocks is captured by $(\pi_1 - \pi_2)/\sqrt{h_{t-1}^2}$. The hypothesis tested by the EGARCH model is the following:

$$H_0 : \pi_2 = 0$$

$$H_0 : \pi_2 \neq 0$$

The results in Table 7 (see Annex) show the EGARCH preferred regressions for cocoa, Arabica and Robusta with regard to the SIC. Results show that none of the asymmetric π_2 coefficients is negative and, only π_2 for cocoa is approximately equal to zero ($\pi_2 = 0.035$) meaning that, positive and negative shocks have approximately the same impact on its volatility. In addition, the GARCH (1, 1) model has a smaller SIC than the EGARCH model and thus, cocoa volatility is better approximated with the asymmetry specification. 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. The SIC indicates that the EGARCH describes the volatility in world coffee prices better than the GARCH (1, 1). Positive shocks have a more prominent effect on the observed volatility than negative shocks.

An empirical examination of the varying volatility of coffees and cocoa allows us to estimate the best fit for the modelling 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. 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.

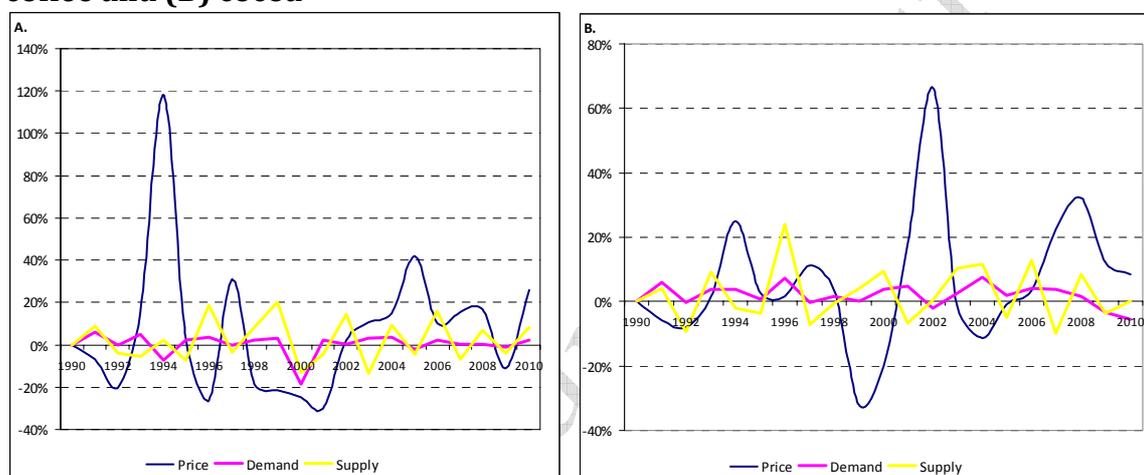
Although the price correlations between the three commodities is very high (0.8 in the long-run) (see Annexes- Table 2), specificities in terms of their price volatility are less obvious and requires more complex models.

Volatility, expressed by the conditional variance of the price series, is modelled with different features for arabica, robusta and cocoa, and suggests that there may be persistence in volatilities and that price series are best estimated with a varying variance. We find different results for each of the three tropical commodities. The price model AR(1) is used for the cocoa price series, robusta's prices are modelled with ARMA(1,1) process and, Arabica prices follow a ARMA(4,2) process. The conditional variance definition follows an EGARCH process with similar coefficients and a positive and significant π_2 for both coffees, which suggests that, their volatility is more affected by positive shocks in prices than by negative price shocks. Moreover, a large increase in oil prices (listed as a negative shock) will have a lower impact on coffee price variability than a steep decline in oil prices (positive shock) of a similar magnitude. Cocoa, on the other hand does not show any asymmetric pattern in its varying volatility. Thus, in a world of high oil prices, coffee price volatility is not as excessive as in a context of low oil prices; whilst cocoa price volatility is largely unchanged.

4 Impact of oil spillover effects and speculation on coffee and cocoa prices

This section addresses two of the main underlying causes of coffee and cocoa price volatilities. Logically, changes in commodity prices result from changes in their fundamentals namely, supply and demand. Graph 6 (see Annexes) shows that for non-essential goods, variation in fundamentals do not necessarily reflect the extent of the price surges that have occurred over the past 20 years (see Figure 2).

Figure 2 Percentage variations in Prices, consumption and production of (A) coffee and (B) cocoa



Source: ICO, ICCO accessed July 2011.

One of the reasons for the detachment between production and price in commodity markets may 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). Thus whenever a futures market is available, the price and production of the commodity may grow independently. Therefore, we do not dwell upon an empirical analysis of the fundamentals for coffee and cocoa, but rather focus on two external drivers of these commodity prices namely, the energy sector represented by crude oil prices and the financial sector which is reflected by futures prices. In this section, all the commodity prices are denominated in current dollar prices as only current prices are traded in the financial markets. However, constant dollar prices provide a better fit for estimating historical volatility.

Barnard (1983) highlighted the potential for fuels to be disruptive to agricultural commodity prices. Activities such as: planting, the application of fertilizer, 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 both coffees and cocoa are influenced by oil prices (Baffes J. 2007), and that current prices have been volatile in recent years hence providing traders with significant “*trend-following opportunities*” (ICE 2011). We utilize Granger-causality tests to assess the long-term causality links between oil and commodities prices while cointegration methods are used to assess the long-run relationship between cash and futures prices of cocoa and coffee.

4.1 Cross commodity causality: Oil vs. Coffee and Cocoa

In sub-Saharan Africa, cocoa is mainly grown by smallholder farmers (≤ 1 hectare) and often on a subsistence basis (ITC, 2001). Larger cocoa plantations exist in Brazil, Ecuador and Malaysia. Although cocoa is particularly sensitive to weather conditions and diseases that may negatively affect production, relatively little fertilizer is utilized (FAO 2006). On the other hand, coffee production is increasingly mechanized and uses various chemical fertilizers (e.g. nitrogen, potassium etc.) which are by-products of the petroleum industry. Here, we only consider the indirect effect of fertilizers prices on coffee and cocoa prices through the oil price. Fuels are also required for storage and transportation thus directly enhancing the potential transmission effect of oil prices on coffee and cocoa prices. Graph 8 (Annexes), shows that coffee and cocoa price changes were often preceded by variations in the oil price of a similar magnitude over the past fifty years. Therefore, we aim to determine whether causality between oil prices and, coffee and cocoa prices holds in the long-run considering the time-horizon: 1990-2010 and then, whether a similar trend between oil and, cocoa and coffee is empirically observed. First, we conduct Granger causality tests¹¹ for crude oil, Arabica, Robusta, and cocoa using large lag lengths in order to account for a long adjustment period of the commodities prices to variations in the oil price, the results of which are presented in Table 2.

¹¹ '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).

Table 2 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

Table 5.1 shows that we cannot reject the hypothesis that the oil price Granger-causes Arabica, Robusta and cocoa price variability at the 5 percent level (p-values: *Prob.* > 0.05). However, the oil price is never Granger-caused by Arabica, Robusta or cocoa prices at the 5 percent level. It is important to highlight that the oil-commodity causality conclusions are dependent on the number of lags included. The results show that oil price spillover effects on Arabica and Robusta take 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 determine the possible relationship between the variables. Now that a long-run causality link has been established between oil and beverages, we use cointegration tests to ascertain the long-run relationship between these variables. Empirically, two $I(1)$ cointegrated series are defined, therefore if a linear combination of both is stationary $I(0)$; an adjustment between these two variables prevents errors becoming larger in the long-term. Also, it is important to ensure current coffee-, cocoa-, and oil prices follow an $I(1)$ process. The results of our ADL tests reveals the presence of unit roots 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). Granger cointegration tests are run by; first, estimating the equation (5.1), generating the residuals series \hat{u}_t and then, estimating an ADL unit root test on those residuals by means of equation (5.2). Cointegration of the series implies that the ADL unit root test of the residuals \hat{u}_t is stationary.

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

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

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

The results of equation (5.1) are presented in Table 9 of the Annexes. The reported adjusted R-squared provides a first hint regarding the cointegration of the variables. In the first regression, it indicates that variations in cocoa, Arabica and Robusta prices respectively explain 45%, 10% and 2% of the variations in oil prices. Test results indicate that, only cocoa prices are cointegrated with oil prices at the 5% level. Cointegration between oil prices and coffees prices (Arabica and Robusta) is weakly rejected at the 10% level. This suggests that although coffee production uses more technological and petro-chemical fertilizer inputs than cocoa, there is no linear relationship between coffee and oil whereas, such a relationship is observed for cocoa and oil. In fact, cocoa and oil price series may trend together in the long-run. In summary, 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 most coffee and cocoa exporting countries are oil importing price-takers, there is limited policy space for them to reduce their vulnerability to oil price fluctuations, whatever the implications for their commodity exports.

4.2 Cointegration models and results: the effect of speculation

The global economic crises since 2008-2009 may have altered the nature of the relationship between futures and cash prices of some agricultural commodities. The 2000 deregulation of financial instruments (futures) encouraged speculators to massively trade commodities in which they had no business interest; and therefore, contributed to the price surges in food and energy sectors, destabilizing businesses and producer incomes (Ash et al., 2010, Gilbert and Morgan 2010). In fact, since 1990 cash coffee and cocoa prices and futures prices have tended to move in a similar direction, irrespective of increased speculation. It could therefore be argued

that futures markets are quite efficient; as futures prices and cash prices are convergent and it is also likely that both variables are cointegrated. After verifying that futures prices are $I(1)$ (see Annexes- Table 12), we conducted Granger cointegration tests and obtained the following results (see Annexes - Tables 12 and 13) for the equations (5.3) and (5.4):

$$C_{t,a} = \varphi + \chi \cdot F_{t,a} + u_{t,a} \quad (5.3)$$

$C_{t,a}$: 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 : $\{A_t, R_t, Cocoa_t\}$

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

If the two price series are $I(1)$ and the linear combination of them is $I(0)$, the variables are said to be cointegrated and thus, bivariate models may be specified to take into account the linear relationship between the two series in the short-run. ADL test results in table 5.2 attest to the rejection of the null hypothesis of a unit root in the residuals at the 1% level (Prob. <0.05), thereby futures series and their corresponding cash prices series are cointegrated. 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 may 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) maybe estimated to assess short-term price adjustments. We estimate the error correction mechanism with an unrestricted OLS in equation (5.5):

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

We replace χ by its previously computed OLS estimate $\hat{\chi}$ so that $\Delta C_{t,a}$, $\Delta F_{t,a}$ and $(C_{t-1,a} - \hat{\chi} \cdot F_{t-1,a})$ are all $I(0)$ (Charemza and Deadman, 1991) and the error is corrected ($\varepsilon_{t,a} \sim I(0)$). Given the results (Table 15 – Annexes), we assume that $\hat{\chi} = 1$ hence, the Engle Granger (5) equation is simplified as follow:

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

The Arabica model (Table 16 - Annexes) suggests that the predictive power of the model is very high; especially for Arabica and Robusta. Indeed adjusted R-squared for Arabica, Robusta and cocoa models are respectively 0.95, 0.90 and 0.70.

Despite the low frequency of monthly data, it is possible to estimate the speed of adjustment between futures and cash prices. An ECM provides a good 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.

5 Policy recommendations and conclusions

Price fluctuations are inherent in agricultural markets – partly due to the supply-demand dynamics and the unpredictability of weather patterns and harvest yields. There are debates as to the extent to which activity in futures trades and over the counter markets (OTC) for agricultural commodities impact on this volatility. Whatever the cause, extreme volatility in food prices deters producers from making the necessary investments for increasing productivity and production: this is one of the underlying causes of continued worldwide food insecurity. Indeed, recent weather catastrophes, oil price surges, inflation, declining value of the U.S. dollar and, growing financialization on futures exchange markets have greatly led to the unpredictability of food prices and market developments. Several international organizations have investigated policy responses in order to mitigate the risks associated with high prices and volatility in global food markets. A policy recommendation put forward by the G20¹² suggests strengthening the long term

¹² Policy reports elaborated by FAO, IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, IFPRI, and the UN HLTF (2011).

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 would also reduce trade distortions and markets instabilities (Staatz and Weber, 2011 and, Limao and Panagariya, 2003).

This paper examined volatility, oil, and futures spillover effects on three major tropical commodities: Arabica, Robusta and Cocoa. Volatility developments and implications were analyzed from the supply-side that is, exporting LDCs and CDDCs. In this case, large price decreases are simultaneously reflected in the trade balance and in the longer term has a detrimental effect on growth. On the other hand, sudden price hikes may encourage 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 assessment of commodity price volatility. The conditional variances are found variant over time due to volatility clustering¹³, thus reverting to the mean rather than remaining constant or moving in monotonic fashion over time, which justifies the use of a GARCH model. Further analysis reveals uneven effects in Arabica and Robusta price volatilities, which, are more affected by positive shocks than negative shocks. A good harvest in coffee crops will trigger more volatility in its price than a bad harvest. However, cocoa volatility reacts symmetrically to the market shocks whether positive or negative. Cocoa price volatility is evident, regardless of whether there is a good or poor harvest.

This paper investigates causality links between the crude 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-year intervals. Nevertheless, the hypothesis of a long-run equilibrium relationship only holds between oil and cocoa prices meaning that, structural changes in the oil price will be directly reflected in cocoa prices. Baffes (2007) shows that the average elasticity for cocoa; was high and significant while the average coffee elasticity was particularly low; in

¹³ In contrast to the often-assumed log-normal distribution of asset price returns, it is often observed that periods of high price volatility follow periods of low volatility and vice versa.

short a 100 per cent variation in the oil price causes a 49 per cent shift in cocoa prices, but does not cause a significant variation in coffee prices. In summary, oil price developments have no significant effect on coffee price variability in the short-run. On the other hand, policy-makers should closely monitor oil price surges as they appear to strongly influence cocoa prices and their volatility in both the short and long-run.

We also examined the relationship between Arabica, Robusta and cocoa cash prices and their corresponding futures prices. The 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 coffee 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 (statistically) unbiased and therefore, serve as price discovery channels for coffee and cocoa sector participants. The very short adjustment period noticeable between futures and cash prices suggests that, hedging strategies mitigate price risk only if they are an immediate reaction to market activity. Nonetheless, the lack of statistical bias of futures markets does not necessarily imply a 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 major speculative activity has increased price risk for cash market participants, particularly commercial traders (Schaffnit-Chatterjee, 2011 and, Schutter, 2010). As a consequence of increasing speculative activity, small farmers growing cocoa and coffee in developing countries are even more exposed to price risk, especially as few alternatives to manage price risk are available to them. Gabre-Madhin (2010) and, Fortenbery and Zapata (2004) have proposed the creation of local commodity exchanges which are more accessible to commercial hedgers (for example; the Ethiopia Commodity Exchange which 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.

Commodity producers in developed countries are increasingly relying on hedging to mitigate exposure to price volatility. However, the extent of hedging in developing countries remains limited. A few countries have used market-based instruments to mitigate the income risks.¹⁴

The main reason for the low use of financial instruments is the lack of familiarity on the part of both private sector operators (especially farmers and exporters) and, in a few instances, the lack of interest from government officials. Using financial instruments in hedging requires technical and managerial expertise and an institutional framework that ensures adequate reporting, recording, monitoring and evaluating mechanisms. Furthermore, it is also necessary to establish internal control procedures that avoid and protect against speculative transactions.¹⁵

Market-based instruments can play a fundamental role in building tailor-made facilities to address commodity price instability. However, it is doubtful whether the futures markets are as suitable for addressing problems emanating from price variability as they are for reducing uncertainty in revenue flows. This notwithstanding, futures markets do allow Governments to eliminate uncertainty associated with variability.

Apart from emergency measures designed to assist the most vulnerable and the long-term measures designed to tackle excessive commodity price volatility on the supply side, there is a need to consider how the functioning of commodity derivatives markets could be improved in a way that would enable those trading venues to better fulfill their role of providing reliable price signals to commodity producers and consumers.

In light of the vital role of information flows in commodity price developments, a set of four policy responses to improve market functioning should be considered: First,

¹⁴ For example, Mexico hedged, via options, all of its oil sales for 2009 in 2008 at a strike price of US\$ 70 a barrel when the oil price was US\$ 100 a barrel.¹⁴ The cost of purchasing options at US\$ 1.5 billion enabled the programme to make a savings of more than US\$ 5 billion..

¹⁵ Claasens S (1992). How can developing countries hedge their bets? Finance and Development. September 1992.

greater transparency in physical markets would enable the provision of more timely and accurate information about commodities, such as spare capacity and global stock holdings for oil, and for agricultural commodities, areas under plantation, expected harvests, stocks and short-term demand forecast. This would allow commercial market participants to more easily assess current and future fundamental supply and demand relationships.

Second, a better flow of and access to information in commodity derivatives markets, especially regarding position-taking by different categories of market participants, would further improve market transparency. In particular, measures designed to ensure reporting requirements for trading on European exchanges similar to those enforced in US exchanges would considerably improve transparency of trading and discourage regulatory migration.

Third, tighter regulation of financial market participants, such as through establishing position limits, could contain financial investors' impacts on commodity markets. For example, a rule could be applied to physical traders, prohibiting them from taking financial positions and betting on outcomes that they are able to influence due to their strong economic position in physical markets. This calls for finding the right balance between being adopting overly restrictive regulation, which would impair the price discovery and risk transfer functions of commodity exchanges, and overly lax regulation, which equally impairs the basic functions of the exchanges.

Finally, there appears to be support for the contention that the behaviour of financial investors in following investments that align to their own preferences help explain movements in coffee and cocoa prices that the fundamentals alone are unable to account for. The rises in coffee and cocoa prices attracts more speculation from parties with no interests in owning the actual commodity but are investing solely on the basis of expected price changes on futures markets. As a result, the behaviour of financial investors/speculators continues to push prices above the equilibrium price of the commodity. In the very short-run (e.g. in daily price formation), a declining dollar seems likely to stimulate speculation in commodity markets rise in prices. We also find that growing speculation appears to link

financial variables with coffee and cocoa prices during some periods. Although speculation was particularly high over the past four years, the equilibrium between financial and commodity variables holds (i.e. is linked) in the long-term.

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6 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

Notes: *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.

7 Annexes

Annex contents

List. 1	Beverage exporting countries
Graph 1	Coffees and Cocoa: monthly prices & volatility (short term)
Graph 2	Monthly price-volatilities of beverage commodities in the long run (1960-1990)
Graph 3	Returns of Beverage annual prices
Graph 4	Percent variations in: Coffee and Cocoa prices, consumption and production
Graph 5	Evolution of Arabica, Robusta, Cocoa, and Oil current prices
Graph 6	Percent Variation in Cocoa- Arabica- Robusta prices vs. Oil prices
Table 1	Correlations in current & constant prices
Table 2	Descriptive Statistics of Arabica, Robusta and Cocoa (in log)
Table 3	GARCH (1, 1) tests results
Table 4	Wald Test: Test of the GARCH hypothesis
Table 5	EGARCH: tests results for Cocoa, Arabica and Robusta
Table 6	Unit root in level and first-difference for Arabica Robusta Cocoa and Oil
Table 7	Ordinary Least Squares equations
Table 8	Cointegration: ADL test on residuals
Table 9	Unit root in level and first-difference for Arabica Robusta Cocoa futures prices
Table 10	Ordinary Least Squares equations
Table 11	Cointegration: ADL test on residuals
Table 12	Wald Test
Table 13	OLS Error Correction Model

List 1. Beverage exporting countries

<i>Cocoa exporting countries</i>	<i>Coffee exporting countries</i>	<i>Tea exporting countries</i>
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'Ivoire	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 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	-

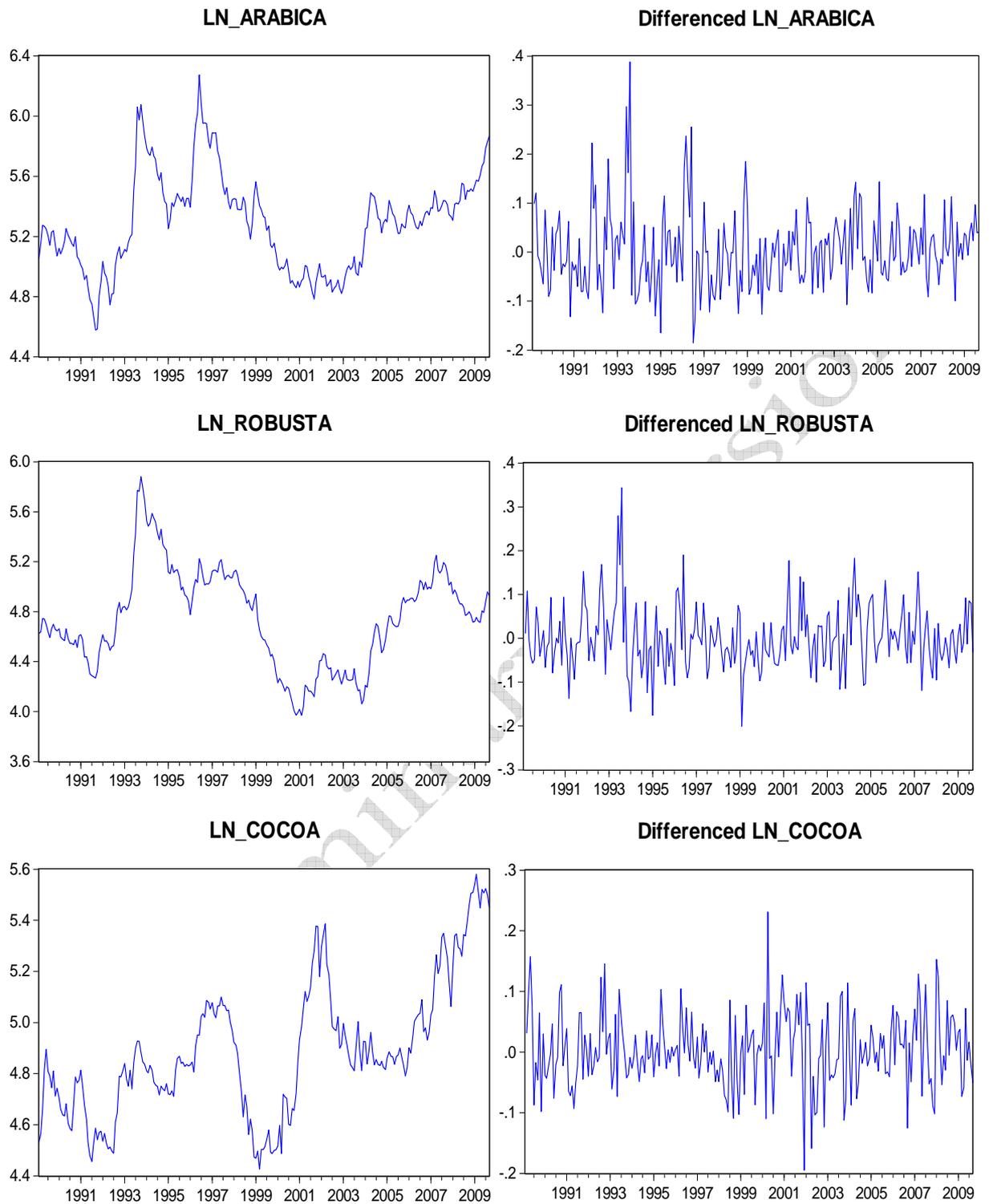
LONG RUN

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

Table 2 Descriptive Statistics of Arabica, Robusta and Cocoa (in log)

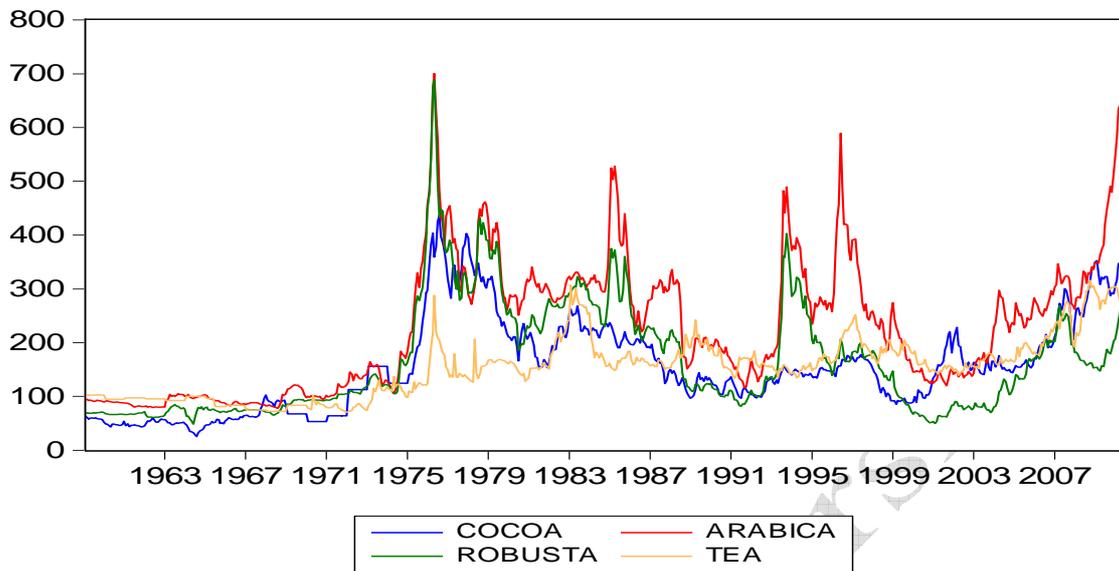
	ln(Rt)	ln(At)	ln(Ct)
Mean	4.746	5.293	4.891
Median	4.755	5.299	4.847
Maximum	5.881	6.274	5.580
Minimum	3.969	4.579	4.427
Std. Dev.	0.391	0.321	0.264
Skewness	0.226	0.383	0.575
Kurtosis	2.768	2.828	2.841
Standard deviation	0.082	0.061	0.054
Sum	1181.668	1317.876	1217.934
Sum Sq. Dev.	37.918	25.523	17.332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

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

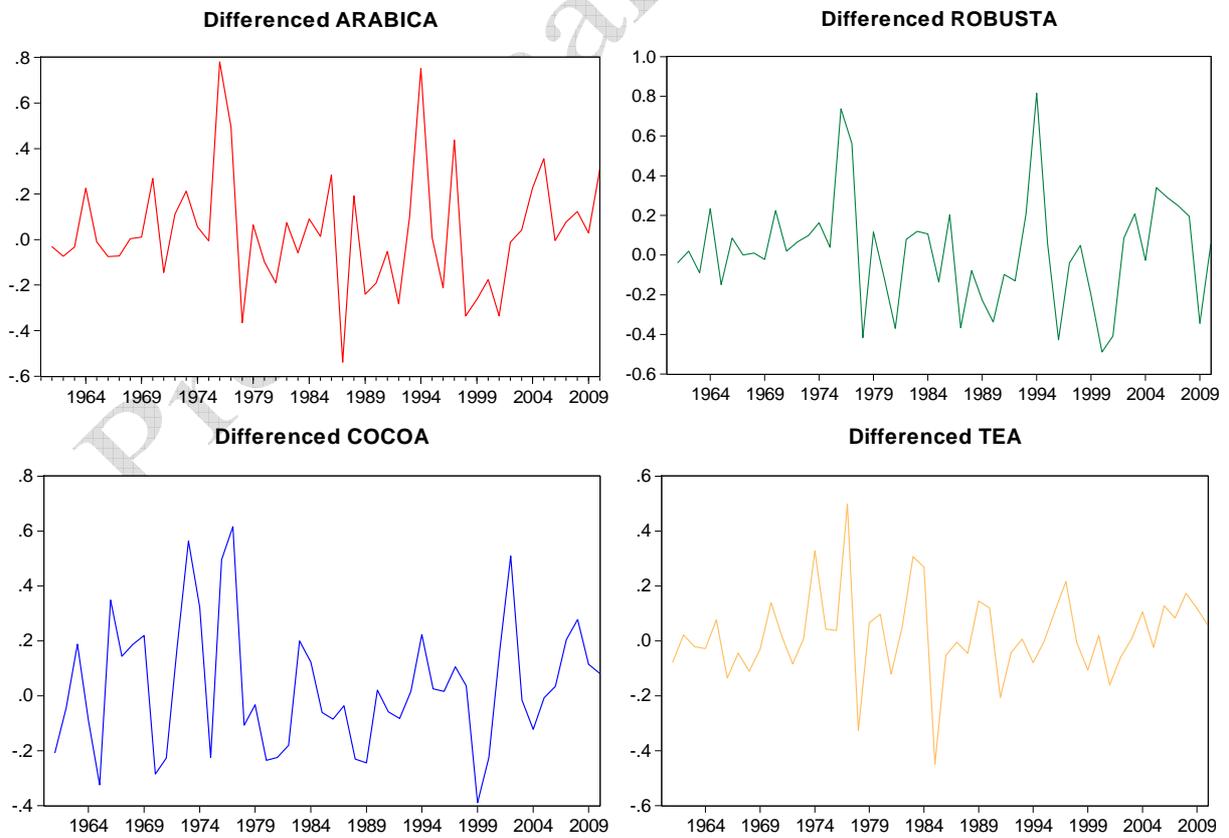


Source: Authors estimates.

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



Graph 3 Returns of Beverage annual prices



Source: Authors estimates.

Table 3 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 (0.158)	5.260 (0.132)	4.610 (0.206)
	ϕ	0.976 (0.011)	0.969 (0.015)	0.972 (0.014)
	γ			0.241 (0.075)
GARCH	δ	0.001 (0.000)	0.002 (0.001)	0.002 (0.001)
	α	0.247 (0.080)	0.178 (0.067)	0.144 (0.067)
	β	0.622 (0.121)	0.505 (0.210)	0.525 (0.244)
	$\alpha + \beta$	0.870	0.682	0.669
	Schwarz	-2.742	-2.264	-2.418
Adjusted R ²		0.947	0.940	0.968

Table 4 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 5 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)

$$R_t = c + \phi_1 p_{t-1} + \gamma_1 \varepsilon_{t-1} + \varepsilon_t$$

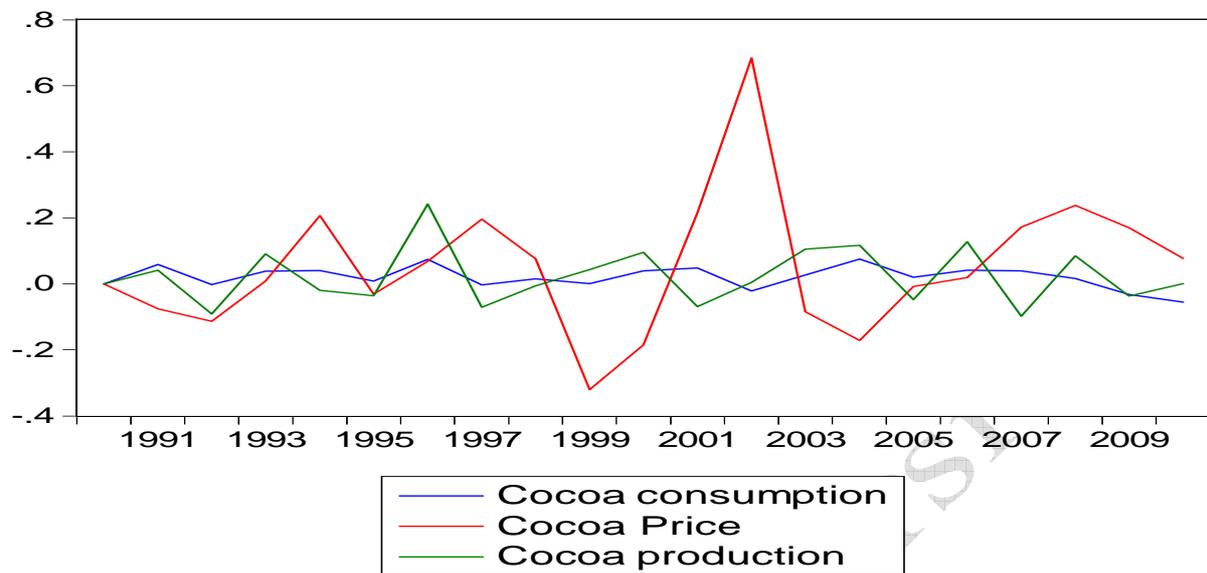
$$EGARCH: \log(h_t^2) = \delta + \pi_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}^2}} \right| + \pi_2 \frac{\varepsilon_{t-1}}{|h_{t-1}^2|} + \beta \log(h_{t-1}^2)$$

	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

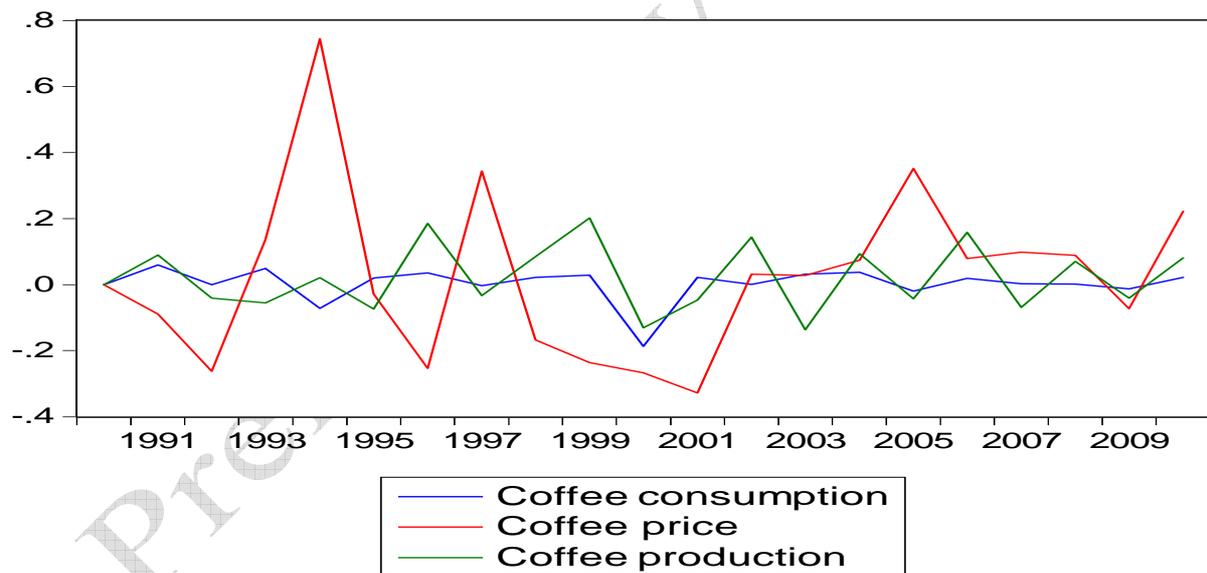
* Note: Only Cocoa π_2 coefficient is significantly equal to 0.

Graph 4 Per cent variations in Prices, consumption and production of coffee and cocoa

Cocoa variations

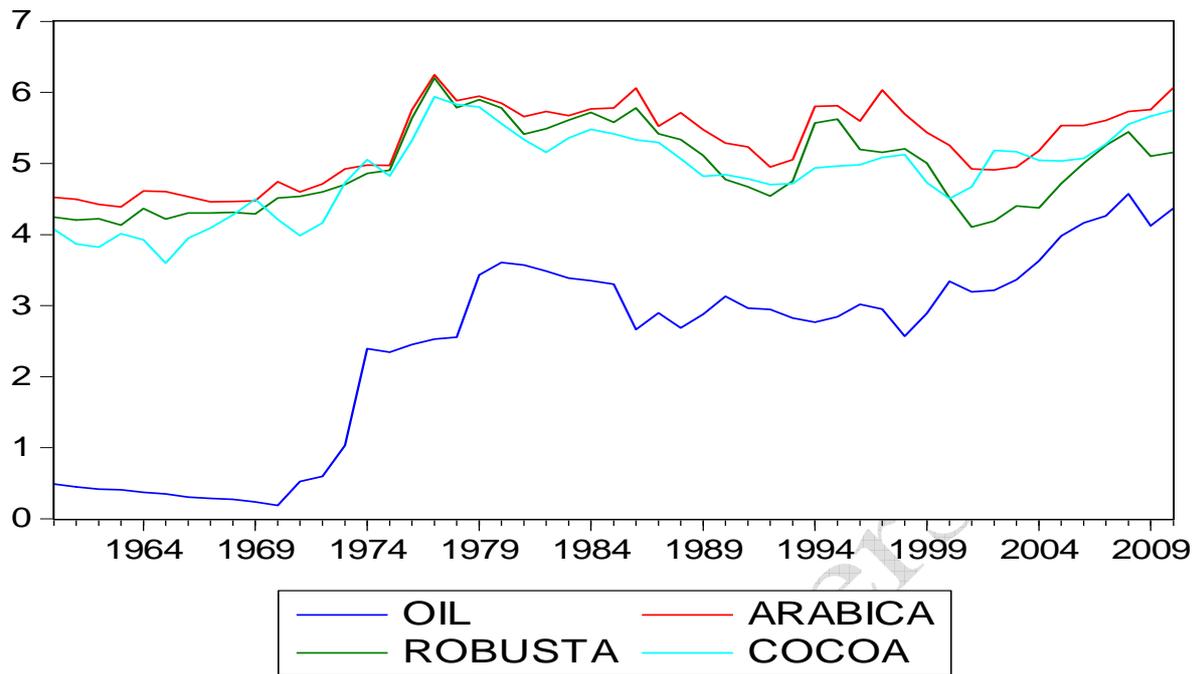


Coffee variations



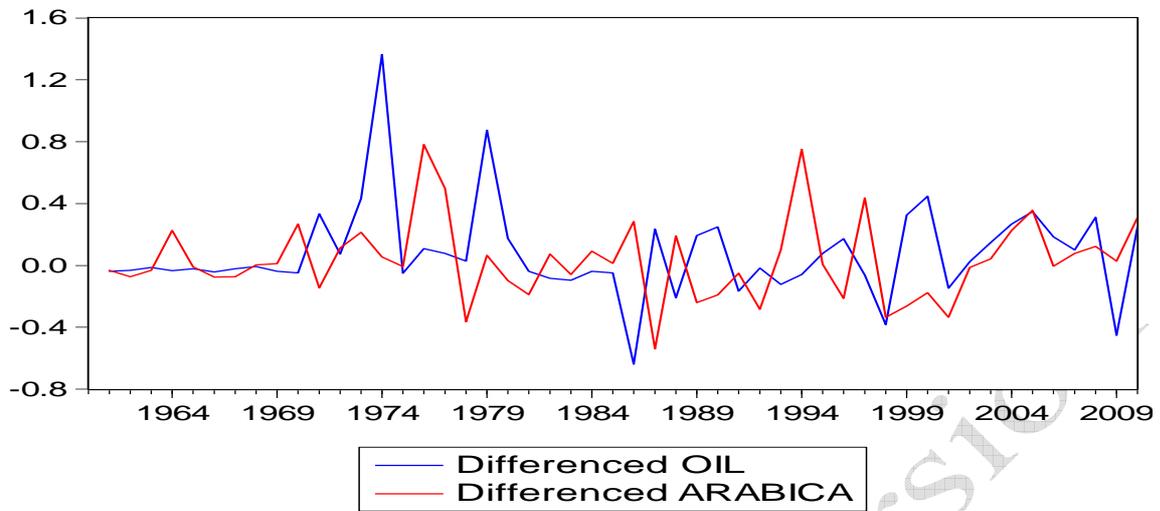
Source: ICO, ICCO

Graph 5 Current prices of: Arabica, Robusta, Cocoa, and Oil

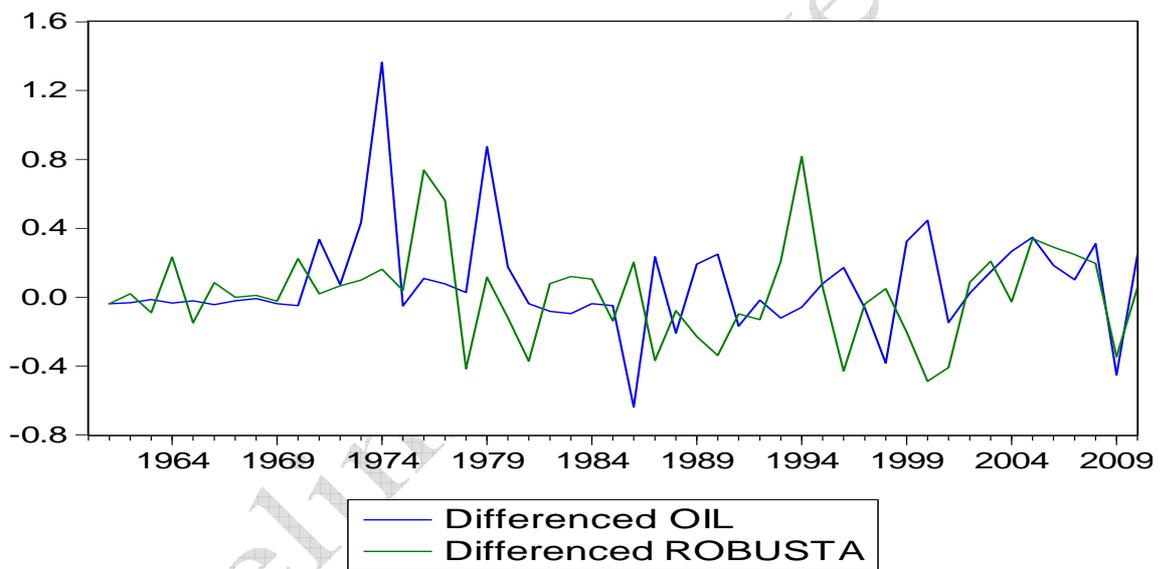


Graph 6 Per cent Variation in Cocoa- Arabica- Robusta prices vs. Oil prices

Arabica vs. oil



Robusta vs. oil



Cocoa vs. oil

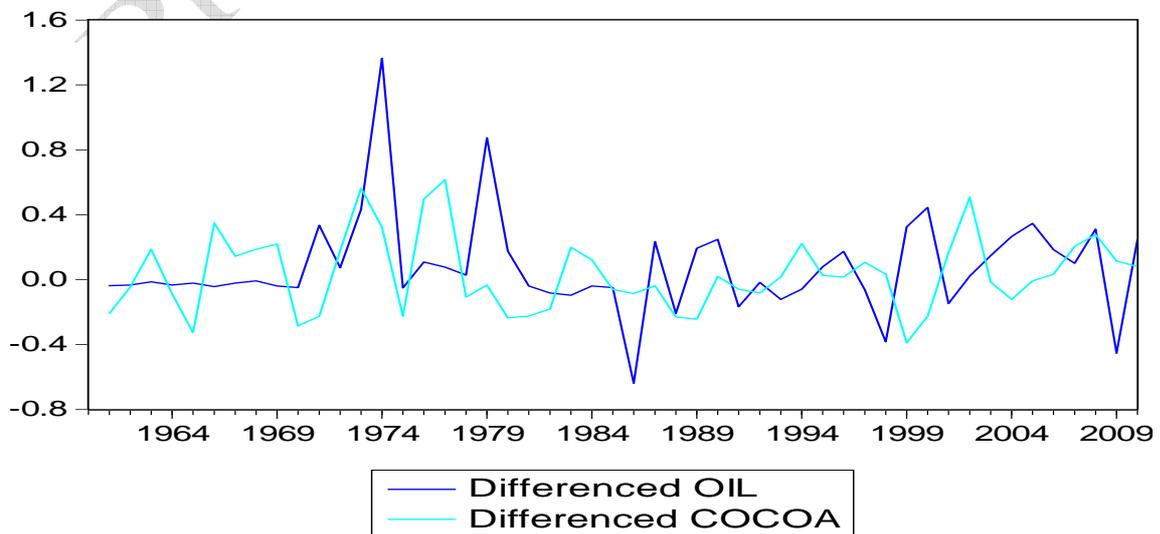


Table 6 Unit root in level and first-difference for Arabica Robusta Cocoa and Oil

	Arabica		Cocoa		Robusta		Oil	
Unit root in first-differences								
Lag length	1		0		1		0	
	t-stat	Prob.	t-stat	Prob.	t-stat	Prob.	t-stat	Prob.
ADL statistic	-12.80	0.00	-14.094	0.000	-11.790	0.000	-11.486	0.000
Unit root in levels								
Lag Length	1		0		1		1	
	t-stat	Prob.	t-stat	Prob.	t-stat	Prob.	t-stat	Prob.
ADL statistic	0.746	0.87	1.1	0.93	0.408	0.801	0.784	0.882
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 7 Ordinary Least Squares equation

Method: Least Squares

Dependent Variable:

	LN_COCOA		LN_ARABICA		LN_ROBUSTA	
Variable	Coef.	Std. Error	Coef.	Std. Error	Coef.	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 8 Cointegration: ADL test on residuals

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

Table 9 Unit root tests for Arabica Robusta Cocoa futures prices

		Futures Arabica "C"		Futures Cocoa		Futures Robusta	
Unit root in first-differences							
	Lag length	1		0		1	
t-							
		t-statistic	Prob.	statistic	Prob.	t-statistic	Prob.
ADL statistic		-13.451	0.000	-12.819	0.000	-11.19	0.000
Unit root in levels							
	Lag length	1		0		1	
t-							
		t-statistic	Prob.	statistic	Prob.	t-statistic	Prob.
ADL statistic		0.675	0.861	0.728	0.871	0.24	0.755
Critical values:	1%	-2.574		-2.574		-2.574	
	5%	-1.942		-1.942		-1.942	
	10%	-1.616		-1.616		-1.616	

Table 10 Ordinary Least Squares equations

Dependent Var.:						
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 11 Cointegration: ADL test on residuals

		<i>Arabica futures</i>		<i>Cocoa futures</i>		<i>Robusta futures</i>	
		<i>t</i> -statistic	<i>Prob.</i>	<i>t</i> -statistic	<i>Prob.</i>	<i>t</i> -statistic	<i>Prob.</i>
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 12 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 13 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.
<i>a : Arabica</i>	α_0	-0.001	0.002	-0.729	0.466
	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			
<i>a : Cocoa</i>	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			
<i>a : Robusta</i>	α_0	0.005	0.003	1.445	0.150
	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			