MPRA
Munich Personal RePEc Archive

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

Maurice, Noemie and Davis, Junior

UNCTAD

2011

Online at https://mpra.ub.uni-muenchen.de/43813/
MPRA Paper No. 43813, posted 15 Jan 2013 20:05 UTC

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

Noemie Eliana Maurice and Junior Davis

November 2012

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

Noemie Eliana Maurice[1] and Junior Davis[2]

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. This paper aims to empirically examine 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 varied impact depending on the nature of the market shock. Oil price spillover effects on coffee and cocoa markets are also assessed using cointegration and error-correction 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

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 volatility[3] 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). The Least Developed Countries (LDCs)[4] and CDDCs were particularly harmed by this crisis. The LDCs were particularly affected by the 2007-2008 food crises because the average household spend around 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 food crisis. For example, large increases in oil prices contributed to rising production costs and drove food prices higher. The World Bank estimated that weakness of the dollar accounted for 15 per cent of the food price increases between 2002 and 2008 (Mitchell 2008). Additionally, over the last decade, major weather events such as drought in Russia, exceptional frosts in Brazil and, excessive rainfall in Canada and Australia caused major disruptions to agricultural production (particularly for cereals). Price fluctuations are inherent in agricultural

[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.
[4] Least developed countries refer to the 48 countries which the United Nations recognises as 'the world's poorest and weakest countries', exhibiting the lowest indicators of social and economic development. They have a population not exceeding 75 million and a per capita gross national income (GNI) of less than US$905). See UN-ORHLSS website: http://www.unohrlls.org/en/ldc/related/59/ (4 January 2010).

markets – partly due to the supply-demand dynamics and the unpredictability of weather patterns and harvest yields.

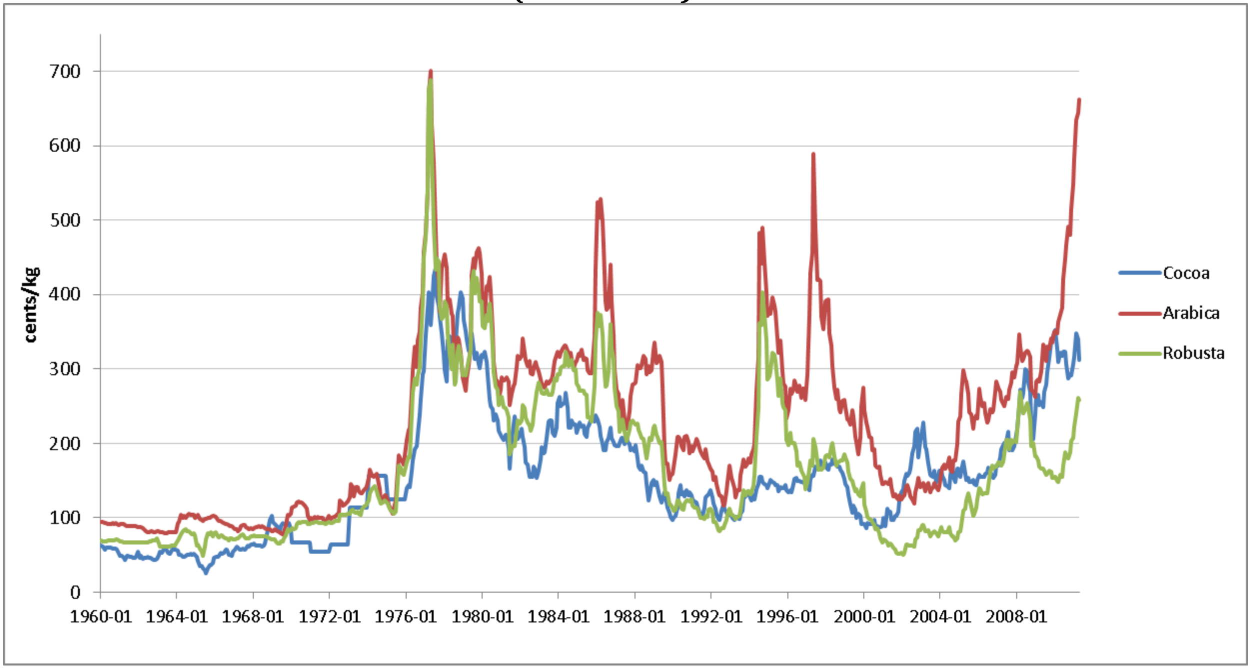
There are also debates as to the extent to which activity in futures trades and over the counter markets (OTC) for agricultural commodities impact on this volatility. Whatever the cause, extreme volatility in food prices deters producers from making the necessary investments for increasing productivity 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 coffee, Robusta coffee 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 commodity 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 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 cereals or meat. In this paper we 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 (see Figure 1).

Figure 1 Monthly current price trends of coffee and cocoa *(1960-2011)*



Source: UNCTADSTAT databse, accessed July 2011.

Most of the production of these commodities is located in LDCs and developing countries in Africa, South America and South Asia (see Table 1 and Figure 2). Thus, coffee and cocoa price volatility is of acute economic importance for CDDCs. As coffee and cocoa are two major Sub-Saharan African (SSA) export crops, they represent a major source of income for many developing countries that have a strong commodity-export dependence. For example, cocoa crop exports in Ghana during 2009-2010 accounted for 55 per cent of total commodity exports. Similarly, cocoa crop exports provide a livelihood for 25 per cent of the Cote d'Ivoire's population and 42 per cent of its commodity exports. During 2009-2010, in Burundi the share of coffee represented 63 per cent of total commodity exports and 30 per cent in Ethiopia (UNCTADSTAT 2012, 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 most likely 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 produced from the same root structure for two or more years. As a seasonal crop; varying from country to country, supply for the most part is often unpredictable. For many developing country governments, and the private sector coffee production, trade and consumption is a critical contributor to socio-economic development.

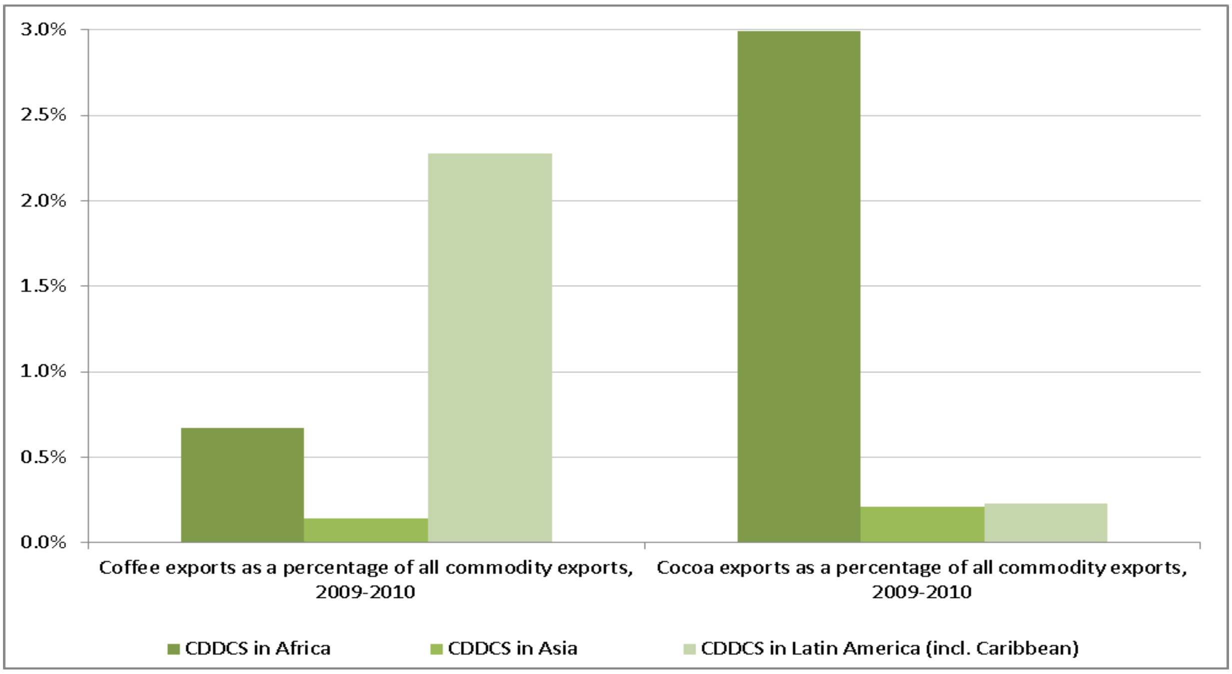
Table 1 Main cocoa and coffee exporting countries

Cocoa exporting countries	*Coffee exporting countries*
Brazil	Angola
Cameroon	Brazil
Côte d'Ivoire	Burundi
Dominican Republic	Central African Republic
Ecuador	Colombia
Gabon	Costa Rica
Ghana	Cote d'Ivoire
Malaysia	Cuba
Nicaragua	Ecuador
Nigeria	El Salvador
Papua New Guinea	Ethiopia
Sierra Leone	Gabon
Togo	Ghana
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 (201*1)

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)[5].

Figure 2 CDDC Coffee and coca exports as a share of all commodity exports (%), 2009-2010



Source: UNCTAD, UNCTADstat (accessed September 2012).
Note(s):
* CDDCs in Asia does not include Oceania
* CDDCs in Latin America (incl. Central America, South America and the Caribbean)
SITC codes: Coffee and coffee substitutes [071]; Cocoa [072]. Primary commodities, precious stones and non-monetary gold (SITC 0 + 1 + 2 + 3 + 4 + 68 + 667+ 971).

Cocoa, although produced and exported in smaller volumes, has many similarities with coffee. Ninety per cent of the cocoa producing countries also produce coffee (see Table 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. Since

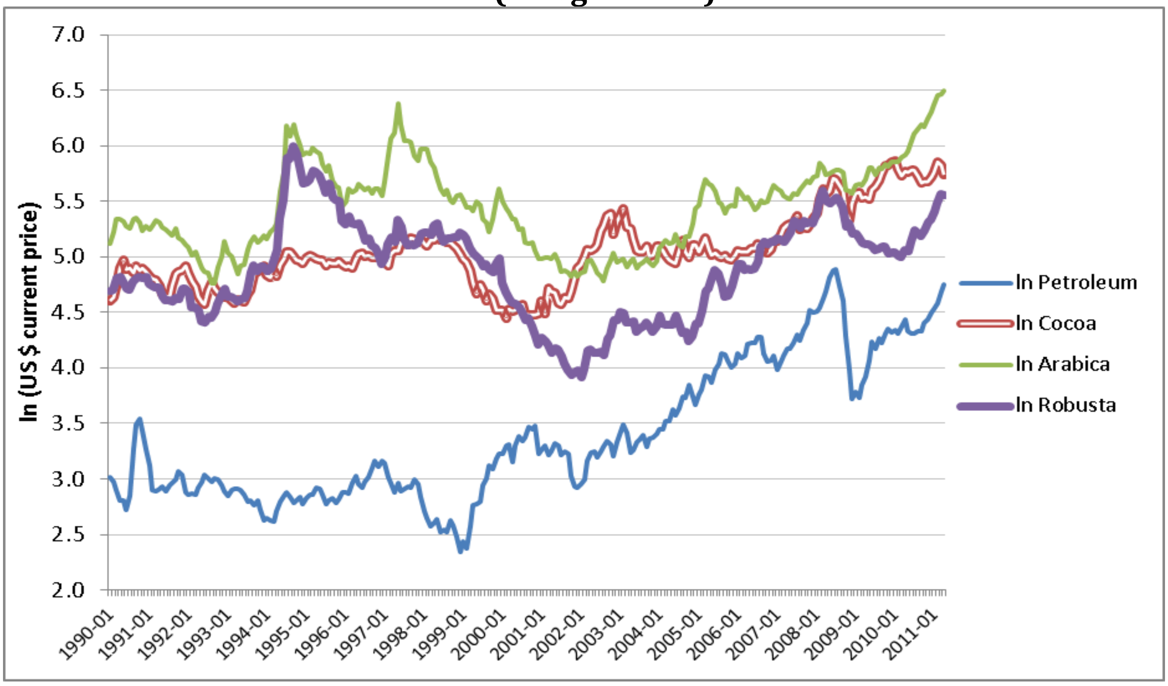
[5] The International Coffee Organization (ICO) is the main intergovernmental organization in charge of collecting and sharing information on coffee and of establishing international cooperation in the coffee sector. In 1882, with its entry into the Coffee Exchange of New York (later part of the Coffee, Sugar and Cocoa Exchange), coffee prices became more volatile. The mandates of the International Cocoa Organization (ICCO) focus on enhancing the economic, social and environmental sustainability of the world cocoa economy.

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[6].

2.1 Commodity price volatility

Commodity prices have shown considerable volatility over the past decade.[7] 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 (UCDR, 2012). Since mid-2009, and especially since the summer of 2010, global commodity prices have again been steadily rising. (see Figure 3).

Figure 3. Current prices of: Arabica, Robusta, Cocoa, and Oil, 1990-2011 (in logarithms)



Source: UNCTADSTAT and World Bank Commodity Price Data (Pink Sheet) (accessed April 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

---

[6] Cocoa futures contracts are primarily traded and denominated in UK pounds.
[7] Price volatility is a measure of price variation from one period to the next.

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 (see UCDR, 2012).

Long-term comparisons show that recent price volatility is not unprecedented for individual commodities.[8] For example, oil price volatility in 2008, while remarkable, remained well below its spike of the early 1970s. Therefore, 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.

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

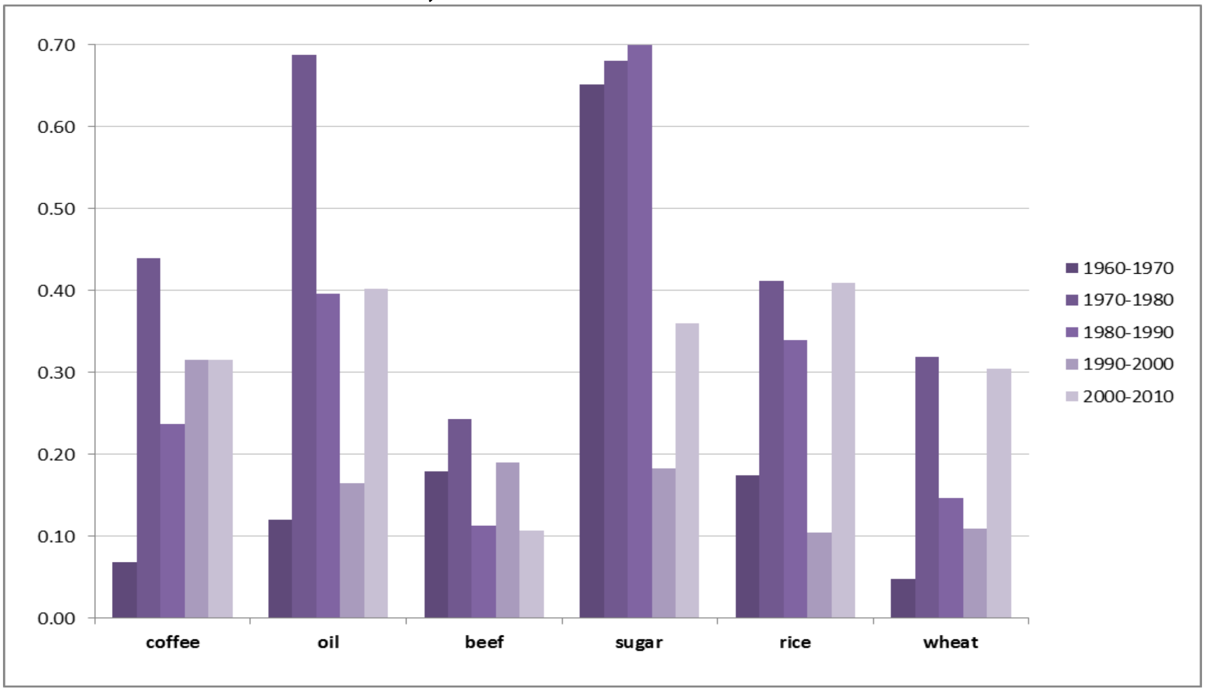
The CV (1) connects the standard deviation (σ) to the mean (μ) so that the mean of the data is considered allowing for cross-commodity comparisons. CV is a basic measure of price dispersion; it serves to compare the degree of variability from one data series to another.

Long-term comparisons show that recent price volatility is not unprecedented for individual commodities (see Jacks, Rourke and Williamson, 2011). Figure 4 presents the coefficients of variation for various food commodities and oil (for comparison purposes).[9] It shows the long-term volatility of commodities prices using annual constant prices for six commodities over the period 1960-2010 and indicates that the more recent price fluctuations during 1990-2010 are unexceptional for some commodities (Calvo-Gonzales, Shankar and Trezzi, 2010). 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

[8] Jacks DS, O'Rourke KH and Williamson JG (2011), and Calvo-Gonzales O, Shankar R and Trezzi R (2010).
9 The coefficient of variation is a basic measure of price dispersion; it serves to compare the degree of variability from one data series to another.

important in the context of a commodity super cycle, as for example in the case of real metals prices (Cuddington and Jerret, 2008). 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 more rapidly (Baffes and Haniotis, 2010).

Figure 4. Coefficients of variation for selected commodities in the short and long run, 1960-1970 to 2000–2010[10]



Note: The coefficient of variation (ratio) is based on annual constant dollar values (2000=100). The time series covers the period 1960–2010. Annual variation in selected real commodity prices, by decade.

The coefficient of variation is very sensitive to outliers hence; for example, the large amplitude of price swings that occurred during the 1979-1981 financial crisis[11] for a broad range of commodities may bias the indicator. Although the CV does not reach its 1970-1980 historical peak, for most of the commodities' volatility has risen significantly over the last decade. We explore some of these issues empirically in sections 3 and 4 of the paper.

[10] The coefficient of variation is based on annual constant dollar values (2000=100). The time series covers the period 1960-2010.

[11] 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 per cent and a high level of unemployment at 13 per cent 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.

3 *Exploring coffee and cocoa price volatility*

In this paper, coffee and cocoa price volatility is empirically investigated using GARCH-type models (comprising a 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)[12]. For section 4 of the paper, 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 are converted from UK (£) pounds sterling to US dollars using the monthly average of the Bank of England's spot exchange rate statistics. Table 2 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.

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 disruption 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.

[12] The 1990-2010 period corresponds to the free market period on commodity markets.

Table 2 Specification for commodity prices

Commodities	Period (mm/yyyy)	Price Specifications	Source	Unit
Arabica (A)	01/1990 - 09/2010	Monthly average constant prices	ICO	US¢/kg
Robusta (R)	01/1990 - 09/2010	Monthly average constant prices	ICO	US¢/kg
Cocoa (C)	01/1990 - 09/2010	Monthly average constant prices	ICCO	US¢/kg
Arabica (A)	01/1990 - 04/2011	Monthly average current prices	ICO	US¢/kg
Robusta (R)	01/1990 - 04/2011	Monthly average current prices	ICO	US¢/kg
Cocoa (C)	01/1990 - 04/2011	Monthly average current prices	ICCO	US¢/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

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 Arabica, Robusta and cocoa price series. Let us assume that the Arabica prices series P_t^A [13] are generated by the autoregressive process:

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

[13] P_t^R stands for Robusta price and P_t^C for cocoa price.

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):

$$\varepsilon_t \left| \Omega_{t-1} \sim N(0, h_t) \right.$$
$$h_t^2 = \delta + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \qquad \textbf{\textit{(4.2)}}$$

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 3 presents 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)[14]. 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.

[14] The Schwarz information criterion (SIC) is a criterion for model selection among a finite set of models. It is based, in part, on the likelihood function, and it is closely related to Akaike information criterion (AIC). Although the original derivation assumes that the observed data is independent, identically distributed, and arising from a probability distribution in the regular exponential family, SIC has traditionally been used in a much larger scope of model selection problems.

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	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

The Arabica results show that AR(1) is the specification that maximizes the best quality of 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 best approximated by an AR(1) model. All the coefficients in Table 3 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). Therefore, we test the GARCH hypothesis that the conditional variances are in fact, not constant using the following hypothesis:

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

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

A Wald test of the joint significance of α and β is conducted for the three commodities in Table 4. 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.

Table 4 Wald Test: Test of the GARCH hypothesis

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

From the 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. 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. Also, Nelson (1991) and Schwert (1989) maintain that stock volatility is higher during recessions and financial crisis. We attempt to model how changes in variability evolve when shocks are positive or negative by introducing symmetry or leverage effects in the variance to GARCH models. The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) is used to estimate the logarithm of conditional variance in order to determine whether or not the observed volatility reacts asymmetrically to "*good*" and, or "*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 for example sharp rises in oil prices. In order to assess this for cocoa and coffee we estimate the following EGARCH:

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

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 $(\pi_1 + \pi_2)\big/\sqrt{h_{t-1}^2}$ whereas the impact of negative shocks is captured by $(\pi_1 - \pi_2)\big/\sqrt{h_{t-1}^2}$. The hypothesis tested with the EGARCH model is the following:

$$H_0 : \pi_2 = 0$$
$$H_0 : \pi_2 \neq 0$$

The results in Table 5 show the EGARCH is preferred for cocoa, Arabica and Robusta regressions with regard to the SIC. Results show that none of the asymmetric π_2 coefficients are negative and, only π_2 for cocoa is approximately equal to zero (π_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 enables the estimation of best fit for the modelling of these three commodities. In the case of 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.

Table 5 EGARCH: test 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
AR		0.139	0.285	0.258
	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.

Although the price correlations between the three commodities is very high (0.8 in the long-run) (see Table 6), specificities in terms of their price volatility are less clear. 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 the 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 (considered 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.

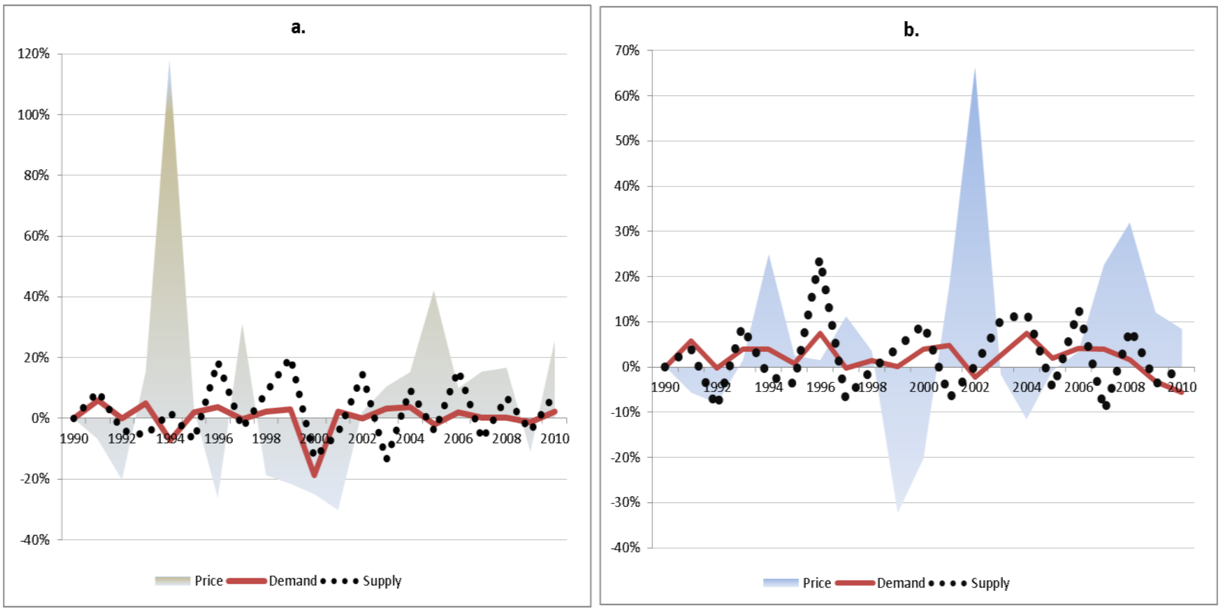
Table 6 Arabica, Robusta and cocoa price correlations in current and constant prices, 1968-2011

SHORT RUN: current prices				
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	0.6	-	
	Robusta	0.36	0.77	-
SHORT RUN: constant prices				
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	

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 volatility. Commodity price variabilty mainly results from changes in their fundamentals namely, supply and demand. Figure 5 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.

Figure 5 Percentage variations in real prices, consumption and production, 1990 to 2010: (a) coffee and (b) cocoa



Source: Authors calulations based on ICO and ICCO data accessed July 2011.

One of the reasons for the disconnection between production and prices in commodity markets may be explained by the *Separation theorem* according to which *"when a futures 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[15].

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

[15] However, constant dollar prices provide a better fit for estimating historical volatility.

and then, whether a similar trend between oil and, cocoa and coffee is empirically observed.

First, we conduct Granger causality tests[16] 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 7.

Table 7 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

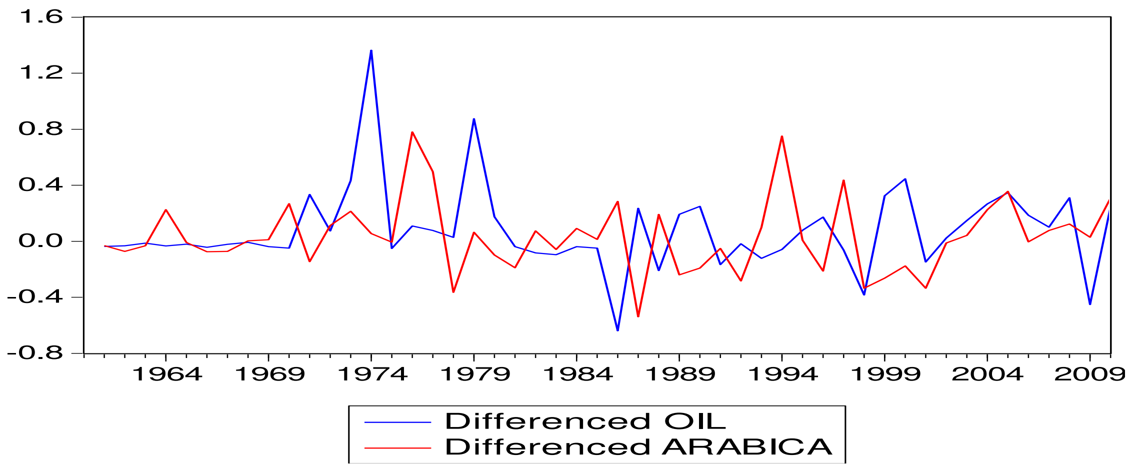
Source: Annex - Table 1.

Table 7 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 not 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 Figure 6.

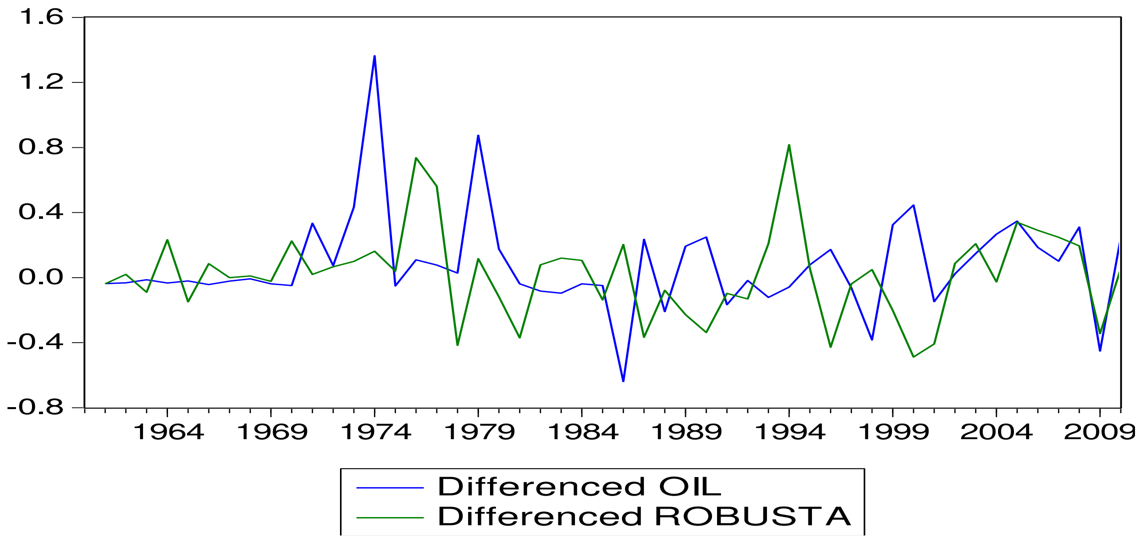
[16] '*x* is a Granger cause of *y* if present *y* can be predicted with better accuracy by using past values of *x* rather than by not doing so, other information being identical' (Charemza and Deadman 1992).

Figure 6 Variation in cocoa, Arabica, Robusta prices vs. oil prices (percent)

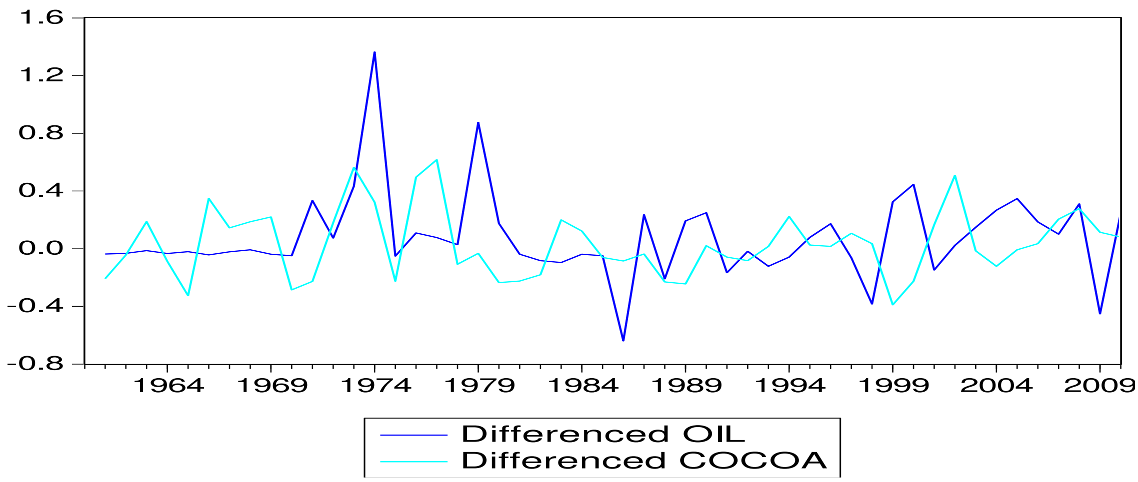
Arabica vs. oil



Robusta vs. oil



Cocoa vs. oil



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 (Balcombe and Davis, 1994). Also, current coffee, cocoa, and oil prices should follow an *I*(1) process. The augmented Dickey-Fuller (ADF) tests reveal 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) (see Table 8).

Table 8 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-statistic	Prob.	t-statistic	Prob.	t-statistic	Prob.
ADF statistic		-13.451	0.000	-12.819	0.000	-11.19	0.000
Unit root in levels							
	Lag length	1		0		1	
		t-statistic	Prob.	t-statistic	Prob.	t-statistic	Prob.
ADF 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	

By means of equation (5.1), Granger cointegration tests are conducted, generating the residuals series $\hat{u}_t$ and then, estimating an ADF unit root test on those residuals by means of equation (5.2). Cointegration of the series implies that the ADF unit root test of the residuals $\hat{u}_t$ is stationary.

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

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

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

The results of equation (5.1) are presented in Table 12. 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.

Table 9 Ordinary Least Squares equations

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	

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 Table 10), we conducted Granger cointegration tests and obtained the following results (see Table 10 and Table 11) for the equations (5.3) and (5.4):

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

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

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

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

Table 10 Unit root tests in levels and first-difference for Arabica, Robusta and cocoa futures prices

		Futures Arabica "C"		Futures Cocoa		Futures Robusta	
Unit root in first-differences							
	Lag length	1		0		1	
		t-statistic	Prob.	t-statistic	Prob.	t-statistic	Prob.
ADF statistic		-13.451	0.000	-12.819	0.000	-11.19	0.000
Unit root in levels							
	Lag length	1		0		1	
		t-statistic	Prob.	t-statistic	Prob.	t-statistic	Prob.
ADF 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	

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. ADF test results in Table 11 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 (see Table 12).

Table 11 Cointegration: ADF test on residuals

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

Table 12 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

Engle and Granger (1987) notes that all cointegration series have an error correction representation. Positively accepted cointegration suggests that an error correction model (ECM) may be estimated to assess short-term price adjustments. We estimate the error correction mechanism with an unrestricted OLS in equation (5.5):

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

We replace χ by its previously computed OLS estimate $\hat{\chi}$ so that $\Delta C_{t,a}$, $\Delta F_{t,a}$ and $(C_{t-1,a} - \hat{\chi}.F_{t-1,a})$ are all $I(0)$ (Charemza and Deadman, 1991) and the error is *corrected* ($\varepsilon_{t,a} \sim I(0)$). Given the Wald test results (see Table 13), we assume that $\hat{\chi} = 1$ hence, the Engle Granger equation is simplified as follow:

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

The Arabica model (see Table 14) 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.

Table 13 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 14 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.
$a: Arabica$	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			
$a: Cocoa$	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			
$a: Robusta$	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			

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 equilibrium relationship existing between cash and futures series suggesting that the speed of adjustment is very fast, and cocoa and coffee futures markets are reasonably 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 G20[17] 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 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

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

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 clustering[18], thus reverting to the mean rather than remaining constant or moving in a monotonic pattern 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 considered potential causality and linkages 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 price elasticity for cocoa; was high and significant while the average coffee elasticity was particularly low; in 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

[18] 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.

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.[19]

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

[19] 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.[19] The cost of purchasing options at US$ 1.5 billion enabled the programme to make a savings of more than US$ 5 billion..

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.[20]

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, 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

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

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.

6 References

Aradhyula and Ho (1988). *GARCH time-series models*: *an application to retail livestock prices.*

Ash, M. et al. (2010). Regulation of commodities futures markets in the reconciliation of the financial reform bill. Letter to the Reconciliation Committee of the US Congress.

Baffes J. (2007). *Oil spills on other commodities*. World Bank.

Charemza Wojciech W. and Deadman Derek F. (1992). Econometrics Practice, General to Specific Modelling, Cointegration and Vector Autoregression.

Combes, Jean-Louis and Guillaumont, Patrick, (2002). Commodity Price Volatility, Vulnerability and Development. *Development Policy Review*, Vol. 20, pp. 25-39, 2002. Available at SSRN: http://ssrn.com/abstract=308971

FAO, IFAD, IMF, OECD, UNCTAD, WFP, the World Bank, the WTO, IFPRI and the UN HLTF (2011). *Price Volatility in Food and Agricultural Markets: Policy Responses*. Draft of Policy report

FAO (2011). *Hunger Statistics*. FAOSTAT.

FAO (2011). Why has Africa become a net food importer? Explaining African agricultural and food trade deficits. Rome: FAO, 2011, 85p.

FAO (2011). Who's Feeling the Effects of Rising Food Prices?

FAO (2008). Number of Hungry People Rises to 963 Million.

FAO (2006). *Fertilizer use by crop*. Fertilizer and Plant Nutrition Bulletin

Fortenbery and Zapata (2004). Developed Speculation and Under Developed Markets-The Role of Futures Trading on Export Prices in Less Developed Countries.

Gabre-Madhin (2010). Structured Commodity trade and Price Volatility: Are Commodity Exchanges the Solution, or the Problem? Presentation to FAO.

Gilbert C.L. and Morgan C. W. (2010). *Commodities Market Speculation: The Risk to Food Security and Agriculture.* Review. Institute for Agriculture and Trade Policy.

IATP (2008). Commodities Market Speculation: The Risk to Food Security and Agriculture. Trade and Global Governance Program.

International Coffee Organization (ICO 2005). *Coffee price volatility*. Working paper.

ICE Futures U.S. (ICE 2011). Cocoa, Coffee "C".

International Trade Centre (ITC 2001). *Cocoa, A guide to trade practices*. Product and market development.

International Trade Centre (ITC 2002). *Coffee, An exporter's guide*. Product and market development.

Kaufman Frederick (2010). THE FOOD BUBBLE, How Wall Street starved millions and got away with it. Report.

Kebede, Yohannes (1992). *Causality and Efficiency in the Coffee Futures Market.* Published in: Journal of International Food & Agribusiness Marketing , Vol. 5, No. 1 (1993): pp. 55-71.

Limao and Panagariya (2003). Why is there an Anti-trade Bias in Trade Policy?

Mitchell Donald (2008). *A note on rising food prices*. Policy Research Working Paper Series from the World Bank.

Nardella M. (2007). Price efficiency and speculative trading in cocoa futures markets.

Nelson Daniel B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, Vol. 59, No. 2, 347-370.

OECD (2006). *Agricultural market impacts of future growth in the production of biofuels.* Directorate for food, agriculture and fisheries; committee for agriculture.
Penaranda F. and Micola A. R. (2009). The emergence of biofuels and the co-movement between crude oil and agricultural prices.
Rapsomanikis George (2011). Price Transmission and volatility spillovers in food markets; Safeguarding food security in volatile global markets. Trade and Markets Division (FAO).
Schaffnit-Chatterjee Claire (2011). Where are food prices heading? Short term drivers, trends and implications. Deutsche Bank Research. Available at: www.dbresearch.com
Schutter Olivier (2010). Food Commodities Speculation and Food Price Crises, Regulation to reduce the risks of price volatility United Nations Special Rapporteur on the Right to Food.
Staatz and Weber (2011). Evaluating the impact on Market Performance of Investments in Market Information Systems: Methodological challenges.
Swaray, Raymond B., (2002). Volatility of primary commodity prices: some evidence from agricultural exports in Sub-Saharan Africa., Discussion Papers in Economics, The University of York, Heslington, York.
Timmer C. Peter (2009). Did Speculation Affect World Rice Prices? ESA Working Paper No. 09-07. ftp://ftp.fao.org/docrep/fao/011/ak232e/ak232e00.pdf
United Nations Conference on Trade and Development (UNCTAD 2010). The Least Developed Countries Report 2010.
United Nations Conference on Trade and Development (UNCTAD 2009). *The financialization of Commodity Market.* Trade and Development Report 2009.
Wahl Peter (2008). *Food Speculation: The Main Factor of the Price Bubble in 2008*. Briefing Paper. World Economy, Ecology & Development
World Bank (2009). *Global Economic Prospects*; *commodities at the crossroad*. Report to the 12th session of the Human Rights Council
WTO (2004). Selected Issues in trade and trade policies. World Trade Report 2004.
Zilcha I and Broll U (1992) Optimal hedging by firms with multiplesources of riskyrevenues. *Economics Letters*, 39 (1992), pp. 473–477

7 *Annex*

Table A1. 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