

PROJECT DOCUMENTS

# Speculation and price volatility in the coffee market

Javier Aliaga Lordemann  
Claudio Mora-García  
Nanno Mulder



UNITED NATIONS

ECLAC



CLAC



FAIRTRADE

# Thank you for your interest in this ECLAC publication



Please register if you would like to receive information on our editorial products and activities. When you register, you may specify your particular areas of interest and you will gain access to our products in other formats.



[www.cepal.org/en/publications](http://www.cepal.org/en/publications)



[www.cepal.org/apps](http://www.cepal.org/apps)

# Speculation and price volatility in the coffee market

Javier Aliaga Lordemann  
Claudio Mora-García  
Nanno Mulder



This document was prepared by Javier Aliaga Lordemann, Chief of the Regional Climate Change Program of the Latin American and Caribbean Network of Fair Trade Small Producers and Workers (CLAC); Claudio Mora-García, Professor at the University of Costa Rica and Senior Researcher at INCAE Business School, in Costa Rica; and Nanno Mulder, Chief of the International Trade Unit of the Division of International Trade and Integration of the Economic Commission for Latin America and the Caribbean (ECLAC). It was prepared under the 2020 cooperation agreement between CLAC and ECLAC. The authors are grateful for the comments received from the participants in a workshop held on 3 November 2020 and convey thanks to the International Coffee Organization for facilitating access to its statistics.

The views expressed in this document, which has been reproduced without formal editing, are those of the authors and do not necessarily reflect the views of the Organization.

United Nations publication  
LC/TS.2021/59  
Distribution: L  
Copyright © United Nations, 2021  
All rights reserved  
Printed at United Nations, Santiago  
S.21-00282

This publication should be cited as: J. Aliaga Lordemann, C. Mora-García and N. Mulder, "Speculation and price volatility in the coffee market", *Project Documents*, (LC/TS.2021/59), Santiago, Economic Commission for Latin America and the Caribbean (ECLAC), 2021.

Applications for authorization to reproduce this work in whole or in part should be sent to the Economic Commission for Latin America and the Caribbean (ECLAC), Documents and Publications Division, publicaciones.cepal@un.org. Member States and their governmental institutions may reproduce this work without prior authorization, but are requested to mention the source and to inform ECLAC of such reproduction.

## Contents

<b>Abstract</b> .....	5
<b>Introduction</b> .....	7
<b>I. Determinants of price volatility (second moment)</b> .....	9
A. State variables .....	9
B. Economic variables .....	9
C. Market structure variables.....	10
<b>II. Data description and sources</b> .....	13
<b>III. Description of the time series and specifications</b> .....	17
<b>IV. Methodology</b> .....	21
<b>V. Empirical results</b> .....	23
<b>VI. Discussion and conclusions</b> .....	25
<b>Bibliography</b> .....	27
<b>Annex</b> .....	31

**Tables**

Table 1	Descriptive statistics on the weekly returns on price.....	19
Table 2	Results of the baseline generalized autoregressive conditional heteroskedasticity GARCH(1,1) model on US C contract spot and futures prices .....	23
Table 3	Results of the baseline GARCH(1,1) model of volatility on spot prices by type of position held by speculators .....	24
Table 4	Results of the baseline GARCH(1,1) model of volatility on ICO composite prices .....	24
Table A1	Results of the GARCH(1,1) model of volatility on spot prices, by type of position held by speculators (includes all coefficients) .....	32
Table A2	Results of the baseline GARCH(1,1) model of volatility on ICO composite prices .....	33

**Figures**

Figure 1	Prices and open interest in the US coffee C.....	14
Figure 2	Shares of open interest by type of commodity trader .....	15
Figure 3	Weekly returns on coffee prices.....	17
Figure 4	Autocorrelation and partial autocorrelation functions for weekly coffee price returns.....	18

**Box**

Box 1	Terminology: hedgers, speculators, open interest and volume .....	11
-------	---	----

## Abstract

This study looks into the determinants of green coffee prices' conditional volatility in three different markets (spot, futures and physical). For this purpose, a generalized autoregressive conditional heteroskedasticity (GARCH) model is used. It includes weekly data on prices and control variables for state, economic, and market structure. Conditional volatility follows a GARCH(1,1) process. Moreover, speculation within futures markets decreases conditional volatility in all three prices.



## Introduction

There is extensive literature on the determinants of spot and futures' price volatility for several agricultural commodities, excluding coffee. In several developing countries, many families depend financially on green coffee farming. However, significant swings and drops in its prices have increased poverty, considering that most farmers are smallholders (ICO, 2019). Consequently, it is crucial to study what factors affect price volatility. Agricultural commodities have two characteristics that explain the importance of studying volatility in spot and futures prices. On the one hand, its prices display persistent volatility (Vivian and Wohar, 2012; Ghoshray, 2013; Karali and Power, 2013; Dawson, 2015). On the other hand, its supply and demand have a low price elasticity. This means that relatively small production or consumption changes induce rather significant price shifts (Tomek and Kaiser, 2014).

In this paper, we study the determinants of price volatility in the coffee market. In particular, we analyze the conditional volatility of three types of prices that reflect different market characteristics. These are a) weekly spot (cash), b) futures prices of the US C Coffee contracts traded at the Intercontinental Exchange (ICE), and c) weekly indicator prices for Arabica coffee on the physical market collected by the International Coffee Organization (ICO). The latter are green coffee quotations in physical markets for prompt shipment. We use a generalized autoregressive conditional heteroskedasticity (GARCH) model to analyze price volatility, assuming a generalized error distribution (GED). We examine the role of different types of variables related to states, the economy, and market structure, including speculation.

The effect of speculation on volatility has been studied for many years. Its impact ranges from positive to negative. We measure speculation in several ways and trace its impact on different markets and different supply chain levels. We found that a simple GARCH(1,1) process explains the conditional volatility of the analyzed prices, i.e. a one-period autoregressive and moving average process. We also discovered that speculation in futures markets reduces conditional price volatility in both the spot and futures markets and physical markets.

This document is structured as follows. Section I reports on the main determinants of price volatility pointed out by the literature. Section II describes the data and its sources. Section III analyzes

the stationarity of the time series and the necessary transformations to comply with this condition. Section IV describes the methodology used to analyze the data and study the relationship between volatility and its determinants. Section V presents the outcomes. Finally, section VI puts these results in the context of recent developments in the coffee industry and provides conclusions.

## I. Determinants of price volatility (second moment)

Futures or spot price volatility for agricultural commodities has been attributed to several factors. We mostly focus on the former but also look into the latter towards the end.<sup>1</sup> These factors or variables can be classified into different groups: state variables, economic variables and market structure variables. Each is reviewed below.

### A. State variables

Early studies on the volatility of futures prices focused on the time-to-maturity impact. This is also referred to as the Samuelson (1965) effect, showing that price variance increases approaching a contract's maturity. Other studies, in contrast, argued that the resolution of uncertainty about underlying supply and demand "state variables" coincides with time passing (Anderson and Danthine, 1983). Moreover, Anderson (1985) and Brorsen (1989) find that seasonality drives the volatility of daily price changes. For example, price volatility in grain markets rises in the Spring, peaks in July or August, and falls towards the end of the year. Milonas (1986) argues that other information that influences volatility is correlated with time-to-maturity.

### B. Economic variables

The second wave of studies on the volatility of futures prices examined underlying supply and demand factors. These include inventory levels (Thurman, 1988; Williams and Wright, 1991), stocks-to-use and prices-to-loans ratios (Kenyon et al., 1987), and price levels (Glauber and Heifner, 1986; Kenyon et al., 1987; Streeter and Tomek, 1992). This analysis led several papers to include economic variables as controls. For example, Kenyon et al. (1987) monitored seasonal dummies, price level, production level, a lagged volatility effect, a ratio of the futures price to the loan rate, and a year effect. Glauber and Heifner (1986); Kenyon et al. (1987); Streeter and Tomek (1992), and Goodwin and Schnepf (2000) find

---

<sup>1</sup> For references on this topic, see Streeter and Tomek (1992), Goodwin and Schnepf (2000) and da Silveira et al. (2017).

that higher prices tend to be associated with higher levels of price variability. Also, agricultural commodities' price variability depends on weather conditions (e.g. temperature and rainfall) and other stochastic elements (Hennessy and Wahl, 1996).

### C. Market structure variables

The third wave of studies includes market structure variables, such as scalping activity, market concentration, speculation, and trading volumes. Scalping activities should reduce bid-ask spreads, and thus lower price variability.<sup>2</sup> However, Brorsen (1989) argued that scalping might allow prices to adjust to information more quickly and increase price variability. Peck (1981) found that scalping had a positive effect on volatility. Market concentration may also affect price variability (Streeter and Tomek, 1992), reflecting the presence of prominent positions relative to total open interest, regardless of whether hedgers or speculators hold them. Goodwin and Schnepf (2000) pointed out that large traders' actions may reduce liquidity or cause significant price adjustments and therefore increase price volatility.

The evidence on the impact of speculation on price volatility is conflicting. On the one hand, Ward (1974), Peck (1981), Brorsen and Irwin (1987), and Irwin and Yoshimaru (1999) found that speculation reduces volatility. On the other hand, Cornell (1981), Chang, Pinegar and Schachter (1997) and Daigler and Wiley (1999) confirm the opposite.<sup>3</sup> Cornell (1981) found a positive relationship between the level of volatility and changes in daily volume. Daigler and Wiley (1999) found that the general public drives the positive volatility-volume relationship. The public has imprecise information, is uninformed, and cannot differentiate liquidity demand from fundamental value change. Interestingly, Chang, Pinegar, and Schachter (1997) highlighted a positive effect of *large* traders on futures daily volatility.<sup>4</sup>

In contrast to previous models that included only one group of variables, Streeter and Tomek (1992) developed a more comprehensive model considering all three groups' variables. They included state variables (time-to-maturity, seasonality, and price levels), economic variables (total annual supply, monthly disappearance, and mill stocks), and market structure variables (scalping, speculation, and market concentration). They found that speculation reduces price variance more than hedging, whereas scalping has the opposite effect.

The 2008 financial crisis triggered new literature on the impact of the "financialization" process of the commodity markets on price volatility, showing mixed results (Aulerich, Irwin and Garcia, 2014).<sup>5</sup> On the one hand, Bryant, Bessler and Haigh (2006), Haigh, Hranaiova and Overdahl (2007), and Brunetti, Büyükhahin and Harris (2016) confirm that speculators do not influence the volatility of futures prices. Aulerich, Irwin and Garcia (2014) found that commodity index traders (CITs) positions did not cause the massive bubbles in agricultural futures prices. Brunetti, Büyükhahin and Harris (2016) found little evidence that speculators destabilize financial markets and discovered that swap dealer activity is unrelated to contemporaneous volatility. Moreover, Bohl, Javed and Stephan (2013) did not find evidence that conditional price volatility has been affected by expected and unexpected open interest of CITs. Sanders and Irwin (2010) also found little evidence that index funds impact commodity futures returns. On the other hand, Irwin and Holt (2004), Du, Yu and Hayes (2011) and McPhail, Du and

---

<sup>2</sup> "Scalping" refers to traders entering and exiting the market often without having open positions at the end of the closing day. A standard measure of scalping is the ratio of volume to open interest.

<sup>3</sup> For a survey on the relation between price changes and trading volume in financial markets in general see Karpoff (1987).

<sup>4</sup> Bessembinder and Seguin (1993) distinguish between expected and unexpected aggregate trading volumes, while Yang, Balyeat and Leatham (2005) consider the unexpected overall volume.

<sup>5</sup> The financialization process refers to the determination of commodity prices not only by its supply and demand, but also by financial factors and investors' behavior in derivative markets (Creti, Joëts and Mignon, 2013).

Muhammad (2012) found a positive relationship. Beckmann and Czudaj (2014) also found evidence in favor of an existing short-run volatility transmission process in agricultural futures markets.<sup>6</sup>

**Box 1**

**Terminology: hedgers, speculators, open interest and volume**

According to the CFTC glossary, a **hedger** is “a trader who enters into positions in a futures market opposite to positions held in the cash market to minimize the risk of financial loss from an adverse price change; or someone who purchases or sells futures as a temporary substitute for a cash transaction that will occur later.” A **speculator** is “a trader who does not hedge, but who trades with the objective of achieving profits through the successful anticipation of price movements.” A **hedger** uses futures markets to manage and offset risk, while a **speculator** assumes market risk for profit.

**Open interest**, also called open contracts or open commitments, is the total number of futures contracts (long or short) held by market participants at the end of the day. This is a flow concept.

**Volume** counts the number of traded contracts. This is a stock concept.

Source: the CFTC glossary, see [online] <https://www.cftc.gov/LearnAndProtect/AdvisoriesAndArticles/CFTCGlossary/index.htm>.

More generally, Algieri (2016) argues that speculation is beneficial, increasing liquidity and commercial entities’ ability to transfer the risk of price changes and finance storage. However, excessive speculation may cause price deviations from supply and demand fundamentals. As excessive speculation distorts real market price dynamics, it overcomes the need to satisfy net hedging transactions and market liquidity.

Other studies on the relationship between futures markets and the volatility of spot prices found mixed results. Bohl and Stephan (2013) did not find evidence that speculation in futures markets of raw materials increased the volatility of spot prices. However, Algieri (2016) discovered speculation in the futures markets does lead to higher volatility of spot prices.

---

<sup>6</sup> According to the Commodity Futures Trading Commission (CFTC), a commodity index fund is “an investment fund that enters into futures or commodity swap positions for the purpose of replicating the return of an index of commodity prices or commodity futures prices.” In addition, a commodity index trader (CIT) can be described as “an entity that conducts futures trades on behalf of a commodity index fund or to hedge commodity index swap positions.” Two well-diversified and transparent benchmark indicators are the Standard and Poor’s-Goldman Sachs (S&P-GSCI) and the Dow Jones-UBS Commodity Index (DJ-UBSCI). The activities of CITs are also referred as the equitization or securitization of commodity futures (Bohl and Stephan, 2013).



## II. Data description and sources

This section explains the sources and features of our time series. We used weekly spot and futures prices on the US 'C' Contract for Arabica Coffee traded at the InterContinental Exchange (ICE) market from January 1990 to September 2020. This is a continuous contract for Arabica coffee.<sup>7</sup> We complemented this data with weekly averages of ICO indicator prices for Arabica coffee. Three groups make up this indicator price: Brazilian Naturals, Colombian Milds, and Other Milds. ICO indicator prices are a weighted average of daily prices of green coffee on the physical markets in the United States, France, and Germany. Prices are for prompt shipment (within 30 calendar days —instead of immediate shipment) and sales from the origin; quotations come from at least five traders and brokers. Therefore, ICO's prices are essentially spot prices. ICO indicator prices and the Coffee C Contract traded at ICE are correlated as traders and brokers often trade green coffee as Coffee C Contract including a margin.

Weekly data on open interest for each Tuesday is taken from Commitments of Traders (COT) reports issued by the Commodity Futures Trading Commission (CFTC). The COT disaggregate open interest by different market participants and outline whether they are holding long or short positions. The COT splits the number of long and short positions of major futures markets and options into commercial and non-commercial traders (i.e., hedgers and speculators) and non-reportables (i.e. small traders). A hedger uses futures markets to manage and offset risk, while a speculator assumes market risk for profit (see Box 1 below). In this respect, only data on futures markets was considered. The sample period started in October, 1992 when the weekly COT report became available.

We also use monthly inventory data for Arabica Coffee from the ICE (i.e., historical end-of-month certified Coffee C stocks by port held by ICE Futures US Licensed Warehouses measured in total bags). Inventories act as buffers that absorb shocks to demand and supply affecting spot prices (Kim, 2015, pg. 701).

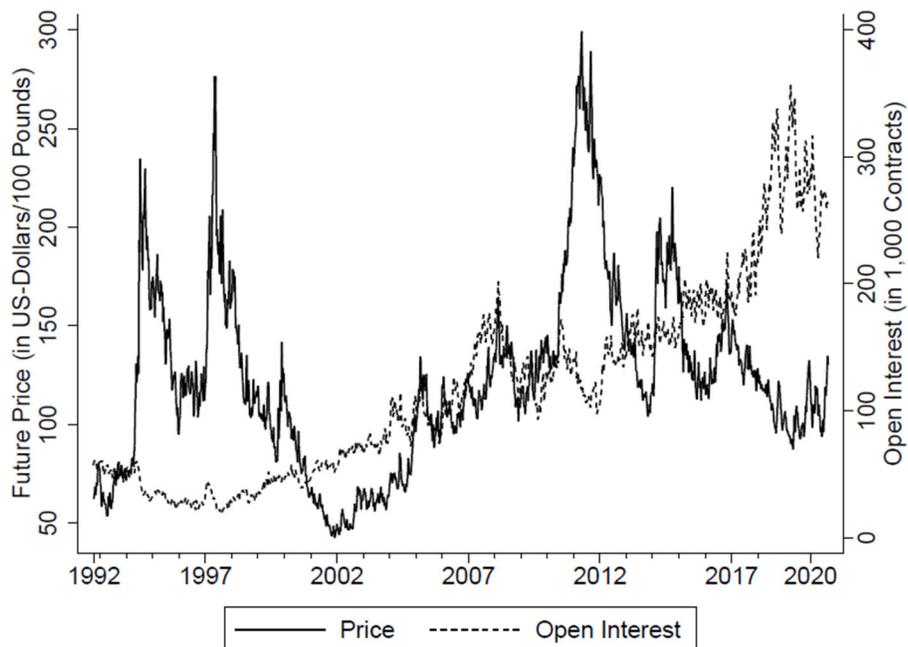
---

<sup>7</sup> The market and exchange names of the Coffee C contract changed over time. Until August 2007, it was the Coffee, Sugar and Cocoa Exchange. From September 2007 to December 2019, it was the New York Board of Trade. From January 2020 onwards, it is ICE Futures United States. Futures prices are taken from <https://www.investing.com/commodities/us-coffee-c>, which are for the contract with the nearest delivery month. Cash/spot prices are from <https://www.barchart.com/futures/quotes/KCY00/interactive-chart>.

We also included macroeconomic indicators to capture the effect of supply and demand shocks. We used quarterly gross domestic product (GDP, Billions of Dollars, Quarterly, Seasonally Adjusted) growth rate and monthly Producer Price Index for All Commodities (Not Seasonally Adjusted), and the Industrial Production Index (Seasonally Adjusted) growth rates. These variables were taken from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis' website.

Figure 1 shows weekly open interest and prices for the US Coffee C contract. Prices increased from a minimum of US\$42.6 on November 25, 2001, to a maximum of US\$164.6 on February 24, 2008. Afterward, they dropped again to a minimum of US\$108.4 on December 21, 2008. Subsequently, prices increased again, reaching a historical maximum of US\$299.35 in April 2011. Other commodities —such as corn, soybeans, sugar, and wheat — showed similar price movements.

Figure 1  
Prices and open interest in the US coffee C

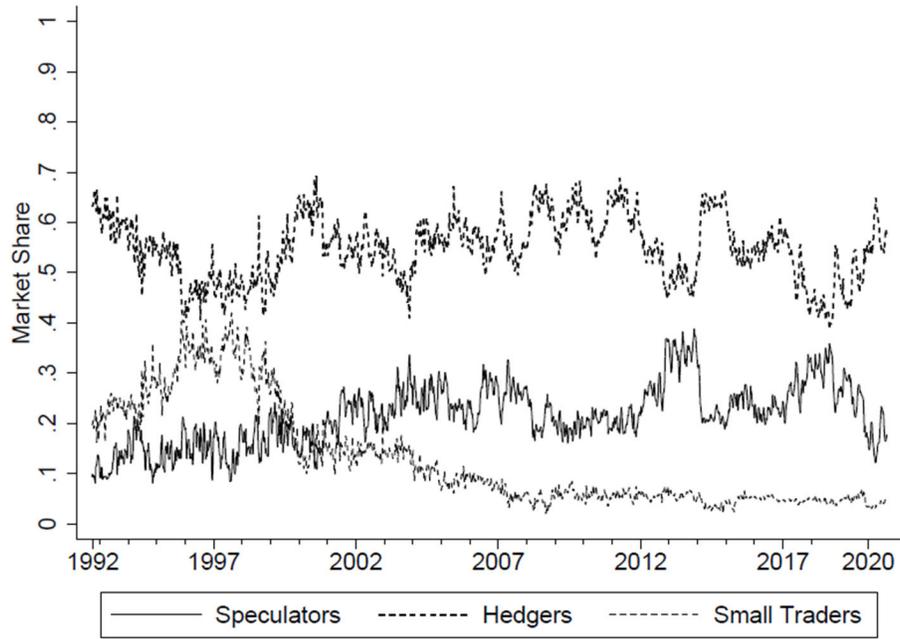


Source: Elaboration by the authors based on the cited data sources in section 3.

For its part, aggregate open interest (OI) in the Coffee C market has persistently increased over the analyzed period. This trend is referred to as “financialization of the commodity market” (Aulerich, Irwin and Garcia, 2014). Between January 2000 and March 2017, OI increased 286% for Arabica. It reached a record high during the financial crisis but plummeted until mid-2009. Later on, it consistently rose again.

Figure 2 displays the shares of open interest by type of trader. These are expressed as ratios of long plus short positions to twice the aggregate open interest. A higher share of short or long positions held by non-commercial traders reflects increased speculation. From October 1992 to November 2013, the speculators' share increased from 10% to almost 40%. In the same period, the hedgers' share fluctuated between 50% and 70%. Small traders lost more than half of their participation. Other agricultural and energy commodities show similar trends.

**Figure 2**  
**Shares of open interest by type of commodity trader**  
*(Decimals)*



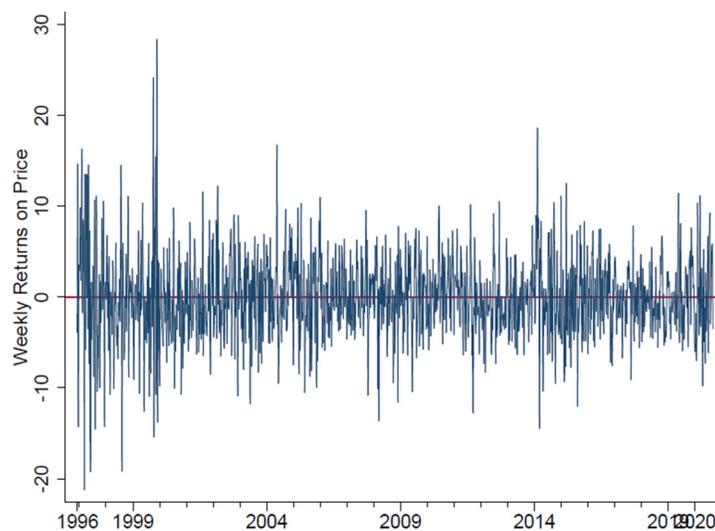
Source: Elaboration by the authors based on the cited data sources in section 3.



### III. Description of the time series and specifications

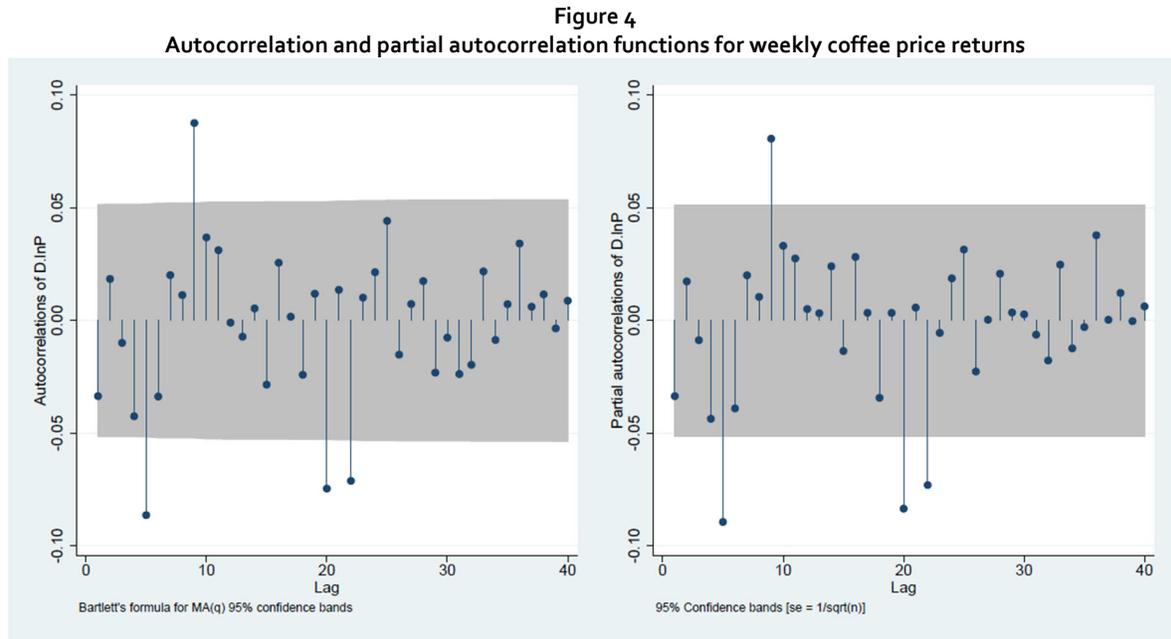
Figure 1 showed that the time series for prices and open interest are autocorrelated. The price series has no clear linear trend except for periods of large swings or instability followed by a more stable period. This feature is known as a volatility persistence. The open interest series shows a deterministic trend. As a result, we modified prices in levels and calculated price returns—defined as the weekly change on the natural logarithm of the price ( $r_t = \ln P_t - \ln P_{t-1}$ ). This is a common step made in the literature dealing with agricultural commodity prices. The main feature of  $r_t$  is that it is more similar to a stationary process than  $P_t$ , see figure 3.

Figure 3  
Weekly returns on coffee prices



Source: Elaboration by the authors based on the cited data sources in section 3.

Next, we analyzed the stationarity of  $r_t$ . The joint tests of autocorrelation were inconclusive. Portmanteau Q-statistic from Ljung and Box (1978) rejects the null of no white noise ( $Q = 62.0405$  and  $p = 0.0143$ ), while the periodogram-based test does not reject the null ( $B = 0.9743$  and  $p = 0.2986$ ). However, the autocorrelation and partial autocorrelation functions of the series  $r_t$ , shown in Figure 4, are statistically different from zero at lags 5, 9, 20 and 22.



Source: Elaboration by the authors based on the cited data sources in section 3.

The Dickey-Fuller test under different specifications (without drift or trend, with drift, with trend) rejects the existence of a unit root at the 1% level. The Augmented Dickey-Fuller test—including different lags, up to the 10th lag, the DF-GSL unit-root test, and the Phillips-Perron non-parametric test—, reject the existence of a unit root test at the 1% level. Finally, the Kwiatkowski et al. (1992) test does not contradict the existence of level stationarity at the 1% level.

We tried fitting different ARMA models for  $r_t$ , but based on simplicity, the Akaike and Schwarz information criteria, and the previous results, the preferred model is a simple  $r_t = c + \varepsilon_t$  model, i.e. the fluctuation of  $r_t$  around the long-term means price return  $c$  is given by  $\varepsilon_t$  a white noise term.

We also tested the presence of autocorrelation in the errors  $\hat{\varepsilon}_t$ . The Durbin-Watson  $d$  statistic has a value of 2.07, and the result of the Breusch-Godfrey LM test depends on the number of lags selected (for one lag, we cannot reject the null of no serial correlation, while with five lags, based on simplicity, the Akaike and Schwarz information criterions, we can reject at the 1% level).

Finally, the LM test for autoregressive conditional heteroskedasticity (ARCH) rejects no ARCH effects at the 1% level.

Table 1 shows descriptive statistics on the weekly price returns. These returns are skewed to the right, and show excess kurtosis (i.e. leptokurtosis). As a result, the Jarque-Bera test of normality is rejected. We assessed whether the errors  $\hat{\varepsilon}_t$  followed or not a normal distribution. The Shapiro-Wilk and Shapiro-Francia tests, and the Doornik-Hansen test reject the hypothesis that the errors are normally distributed. This is important for GARCH estimation by ML.

**Table 1**  
**Descriptive statistics on the weekly returns on price**

	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coffee	0.0508	42.9134	-21.2530	5.0811	0.6245	8.1054	100.8952***

Source: Elaboration by the authors based on the cited data sources in section 3.

Notes: descriptive statistics are shown for the return distributions of ICE US Coffee C. Continuously compounded weekly returns (in percent) are calculated as the change in logarithmic prices multiplied by 100. \*\*\* Statistical significance at the 1% level.



## IV. Methodology

To quantify the relation between the coffee price volatility and speculation, we used a generalized autoregressive conditional heteroscedasticity GARCH(1,1) model, and extended the volatility equation by including speculative open interest.<sup>8</sup> We also monitored the impact of aggregate trading activity by considering both overall trading volume and open interest. Given the previous analysis, price changes are modeled as a simple  $r_t = c + \varepsilon_t$  model. ARCH models were introduced by Engle (1982) and then generalized and extended by Bollerslev (1986) to the GARCH model.

Our first model (Model 1) is as follows:

$$\begin{aligned} \text{(i)} \quad r_t &= c + \varepsilon_t \\ \text{(ii)} \quad \varepsilon_t &= z_t \sqrt{\sigma_t^2} \\ \text{(iii)} \quad \sigma_t^2 &= \alpha \varepsilon_{t-1}^2 + \phi \sigma_{t-1}^2 + \mathbf{X}_t \delta \end{aligned}$$

where  $z_t$  are independent and identically distributed random variables,  $\mathbf{X}_t$  includes a vector of potential explanatory variables for the volatility of coffee price returns  $r_t$ . These variables include the weekly percentage change in: a) the aggregate futures trading volume of the Coffee C contracts ( $\% \Delta TV$ ), b) the aggregate open interest ( $\% \Delta OI$ ), and c) futures positions held by speculators ( $\% \Delta SP$ ). All three are measured using the Coffee C contracts to compare the results with those of Bohl and Stephan (2013), who use a similar specification, hence  $\mathbf{X}_t \delta = \delta_1 \% \Delta TV_t + \delta_2 \% \Delta OI_t + \theta_1 \% \Delta SP_t$ . The coefficient  $\theta_1$  measures the relationship between speculation and price volatility. A negative sign or a non-significant coefficient signals that speculators have a stabilizing to null effect on the volatility of price returns, respectively. The coefficient  $\alpha$  measures the ARCH term, and  $\phi$  the GARCH term.

However, the speculators' position is part of the total open interest. Therefore, Bohl and Stephan's estimation included two variables: futures position held by speculators and aggregate open interest in the

---

<sup>8</sup> Hansen and Lunde (2005) compare over 300 volatility models and show that the GARCH(1,1) model well describes and well predicts the conditional variance of financial assets.

conditional variance equation. This first variable is redundant as it is part of the second variable (Kim, 2015). A second specification (Model 2) excludes total open interest and instead uses aggregate trading activity by speculators, hedgers, and small traders. As part of our estimation, the trading volume captures the total trading activity in the futures market. Therefore,  $\mathbf{X}_t\delta = \delta_1\% \Delta TV_t + \theta_1\% \Delta SP_t + \theta_2\% \Delta H_t + \theta_3\% \Delta NR_t$ , where the new variables  $\% \Delta H_t$  and  $\% \Delta NR_t$  are the percentage change in futures positions held by hedgers (commercial) and non-reportable (i.e. small traders), respectively.

In Model 3, we modified equation (1) to  $r_t = a_0 + a_1 r_{t-1} + \mathbf{Z}_t \xi + \varepsilon_t$  to include an AR(1) term in weekly price returns and several control variables  $\mathbf{Z}_t \xi = c_0\% \Delta OI_t + c_1\% \Delta INV_t + c_2\% \Delta PPIACO_t$  where the new variables  $\% \Delta INV_t$  and  $\% \Delta PPIACO_t$  are the monthly percentage change in inventories and Producer Price Index for All Commodities (as a proxy for inflation), respectively. We also changed equation (3) to include  $\mathbf{X}_t\delta = \delta_1\% \Delta TV_t + \theta_1\% \Delta SP_t + \theta_2\% \Delta H_t + \theta_3\% \Delta NR_t + \gamma_1\% \Delta INV_t + \gamma_2\% \Delta PPIACO_t + \gamma_3\% \Delta GDP_t + \gamma_5\% \Delta PROD_t + \sum_{i=1}^3 (\phi s_{it})$  where the new variables  $\% \Delta GDP_t$  and  $\% \Delta PROD_t$  are the quarterly percentage change in GDP and the monthly percentage change in the Industrial Production Index, respectively. We also added a seasonality effect captured by the quarterly variables  $s_{it}$  ( $s_{1t} = 1$  for the first quarter and 0 otherwise,  $s_{2t} = 1$  for the second quarter and 0 otherwise,  $s_{3t} = 1$  for the third quarter and 0 otherwise, the fourth quarter being the omitted category).<sup>9</sup>

Our model adds  $\varepsilon_t^2 - \sigma_t^2 = u_t$  to both sides of the equation (3), obtaining  $\varepsilon_t^2 = \phi \sigma_{t-1}^2 + \alpha \varepsilon_{t-1}^2 + \mathbf{X}_t\delta + u_t$ , where  $E[u_t|F_t] = 0$  and  $var[u_t|F_t] = var(\varepsilon_t^2) = 2\sigma_t^4$ . Most GARCH models are estimated by maximum likelihood, assuming that  $\varepsilon_t$  is normally distributed and drawing on the Bollerslev and Wooldridge (1992) robust covariance matrix; however, if the spreads are highly non-normal (e.g., with negative skewness and high kurtosis), then a generalized error distribution for  $u_t$  may be used, which was introduced in the GARCH literature by Nelson (1991). Given the features of our time series highlighted in table 1, the last one is the one we used to calculate robust standard errors.<sup>10</sup>

<sup>9</sup> Huchet and Fam (2016) use different macroeconomic variables including the US inflation-indexed bonds, the VIX index of the Chicago Board Option Exchange (CBOT) and the West Texas Intermediate (WTI) oil price.

<sup>10</sup> We also tried fitting the model with a Normal and a t-distributions. For the normal distribution, the Jarque-Bera test rejected the null of a normal distribution at the 1% level, while the Kolmogorov-Smirnov test did not at the 10% level, but the Q-Q plot displayed long tails. For the t-distribution, the Kolmogorov-Smirnov test did not reject the null of a t-distribution, but the Q-Q plot also displayed long tails.

## V. Empirical results

Table 2 reports the estimation results using the GARCH(1,1) model described in equations (1) to (3), examining the relationship between price volatility and speculation. Each row shows the respective explanatory variable, where Resid<sup>2</sup> corresponds to  $\varepsilon_{t-1}^2$  and volatility to  $\sigma_{t-1}^2$ . Column (1) shows the results from Model 1. We do not report the coefficients from all control variables, such as the percentage change in trading volume and aggregate open interest. The estimate for % $\Delta SP$  indicates that there is a negative relationship between volatility and speculation, meaning that speculation tends to reduce coffee price volatility. This relationship is highly statistically significant at the 1% level.

**Table 2**  
Results of the baseline generalized autoregressive conditional heteroskedasticity GARCH(1,1) model on US C contract spot and futures prices

	Spot prices			Futures prices		
	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 1 (4)	Model 2 (5)	Model 3 (6)
Resid <sup>2</sup>	0.1104*	0.1145**	0.1293***	0.1299***	0.1290***	0.1503**
Volatility	0.7537***	0.7114**	0.3986	0.5609**	0.5569***	0.2480
% $\Delta SP$	-0.0642***	-0.0545***	-0.0441***	-0.0440*	-0.0440***	-0.0315**
% $\Delta H$		-0.0590	0.0343		-0.0741*	-0.0180
% $\Delta NR$		-0.0032	-0.0090		-0.0035	-0.0096
% $\Delta INV$			0.0043**			0.0040**
% $\Delta PPIACO$			0.0030			-0.0279
% $\Delta GDP$			0.0753			-0.0126
% $\Delta PROD$			-0.0624			-0.0378
Quarterly Fixed Effects	NO	NO	YES	NO	NO	YES

Source: Elaboration by the authors based on the cited data sources in section 3.

Notes: The dependent variables are either the weekly returns on spot/cash prices (columns 2 to 4) or futures prices of the contract with the nearest delivery month (columns 5 to 7). Results are estimated by maximum likelihood using a generalized error distribution (GED) and robust standard errors. Each column shows a different model with new covariates. In model 1, the control variables are the weekly percentage change in the aggregate futures trading volume of the Coffee C contracts (% $\Delta TV$ ) and the aggregate open interest (% $\Delta OI$ ), at the Coffee C contracts. Model 2 does not control for open interest but includes the percentage change in futures positions held by hedgers (commercial) and non-reportable (i.e. small traders). Model 3 includes an AR(1) term in weekly price returns, open interest, inventories and inflation in the price equation, and also includes quarterly GDP and monthly industrial production in the volatility equation. Statistically significant at \* 10%, \*\* 5%, and \*\*\* 1% level.

Column (2) shows the results for Model 2, after controlling for the percentage change in futures positions held by hedgers and small traders, but not controlling for open interest. The estimate for  $\% \Delta SP$  is similar, while hedgers and small traders have a statistically insignificant impact on volatility. Column (3) shows the results from Model 3, i.e. monitoring an AR(1), open interest, inventories, and inflation in the price equation, and including inventories, inflation, GDP, and industrial production. The results are similar to the previous model, suggesting that speculation reduces volatility in coffee prices. In sum, models (1), (2), and (3) seem to confirm that speculation tends to dampen coffee price volatility.

To examine if the relationship between volatility and speculative activities differs with the kind of position held by speculators, we decompose  $(\theta_1 \% \Delta SP_t + \theta_2 \% \Delta H_t + \theta_3 \% \Delta NR_t)$  into a long and short position.<sup>11</sup> Table 3 displays only the estimated coefficients for the effect of the speculators, while Annex Table A1 shows all the coefficients. The estimated coefficients for speculators' long and short positions are mostly negative or statistically insignificant. This suggests that there is no evidence that speculators' long and short positions accentuate volatility. These results also show that coefficients on speculative short positions are negative, implying that volatility tends to *decrease* when speculators are selling.

**Table 3**  
Results of the baseline GARCH(1,1) model of volatility on spot prices by type of position held by speculators

	Model 1 (1)	Model 2 (2)	Model 3 (3)
%Δ Total positions	-0.0642***	-0.0545***	-0.0441***
%Δ Long positions	0.0410**	-0.0101	-0.0014
%Δ Short positions	-0.0256***	-0.0277***	-0.0316***

Source: Elaboration by the authors based on the cited data sources in section 3.

Notes: this table follows the specification in Table 2, but decomposes the effect of speculation  $\theta_1 \% \Delta SP_t$  into long and short positions held by speculators effect in Model 1, and changes the control variables  $\theta_1 \% \Delta SP_t + \theta_2 \% \Delta H_t + \theta_3 \% \Delta NR_t$  into  $\theta_1 \% \Delta SP_{Shortt} + \theta_2 \% \Delta H_{Shortt} + \theta_3 \% \Delta NR_{Shortt}$  for the short position and  $\theta_1 \% \Delta SP_{Longt} + \theta_2 \% \Delta H_{Longt} + \theta_3 \% \Delta NR_{Longt}$  for the long position, where  $\% \Delta SP_{Shortt}$  is the percentage change in the speculators holding a short position, for example, in Models 2 and 3. Statistically significant at \* 10%, \*\* 5%, and \*\*\* 1% level.

We now examine conditional volatility in ICO composite prices as the dependent variable and keep the same specifications as in Models 1-3. For this purpose, we use a weighted average of Brazil, Colombia and Other Milds in Table 4 that we refer to as the "Arabica category". In Annex Table A1, we present the full results for each individual Arabica. According to Table 4, the speculation stabilizing effect almost doubles across the different models. The results for Colombia and Other Milds, presented in Table 4, suggest that the speculation stabilizing effect almost doubles across the different models. Annex Table A2 illustrates the results for each type of Arabica.

**Table 4**  
Results of the baseline GARCH(1,1) model of volatility on ICO composite prices

	Arabica		
	Model 1 (1)	Model 2 (2)	Model 3 (3)
Resid <sup>2</sup>	0.1119***	0.1127***	0.08787***
Volatility	0.6338***	0.6429***	0.6627***
%ΔSP	-0.1145***	0.0894***	0.0865***
%ΔH		0.0513	0.0490
%ΔNR		0.0021	-0.0010

Source: Elaboration by the authors based on the cited data sources in section 3.

Notes: Statistically significant at \* 10%, \*\* 5%, \*\*\* 1% level.

<sup>11</sup> Specifically,  $\theta_1 \% \Delta SP_{Shortt} + \theta_2 \% \Delta H_{Shortt} + \theta_3 \% \Delta NR_{Shortt}$  for the short position and  $\theta_1 \% \Delta SP_{Longt} + \theta_2 \% \Delta H_{Longt} + \theta_3 \% \Delta NR_{Longt}$  for the long position, where  $\% \Delta SP_{Shortt}$  is the percentage change in the speculators holding a short position, for example.

## VI. Discussion and conclusions

In this paper, we used a GARCH(1,1) model to identify the determinants of the conditional volatility of prices in the Coffee C market and ICO composite prices for Arabica coffee. Analyzing a comprehensive set of state, economic, and market structure variables, we found that speculation tends to reduce volatility in the coffee market. This result is similar to those of Bohl and Stephan (2013), and Kim (2015).

As speculation stabilizes prices (both during the upward and downward trends) for coffee growers, they can draw up and implement their investment plans with less risk. This is especially important for commodities such as coffee, which production cycle is relatively long (around three years). Also, investments will take place with lower expected returns compared to a scenario of higher price volatility.



## Bibliography

- Algieri, Bernardina (2016), "Conditional price volatility, speculation, and excessive speculation in commodity markets: sheep or shepherd behaviour?" *International Review of Applied Economics*, 30(2): 210–237.
- Anderson, Ronald W. (1985), "Some determinants of the volatility of futures prices." *Journal of Futures Markets*, 5(3): 331–348.
- Anderson, Ronald W. and Jean-Pierre Danthine (1983), "The Time Pattern of Hedging and the Volatility of Futures Prices." *The Review of Economic Studies*, 50(2): 249.
- Aulerich, Nicole M., Scott H. Irwin and Philip Garcia (2014), "Bubbles, Food Prices, and Speculation. Evidence from the CFTC's Daily Large Trader Data Files." In *The Economics of Food Price Volatility*, ed. Jean-Paul Chavas, David Hummels and Brian D. Wright, Chapter 6. Chicago, IL: The University of Chicago Press.
- Beckmann, Joscha, and Robert Czudaj (2014), "Volatility transmission in agricultural futures markets." *Economic Modelling*, 36: 541–546.
- Bessembinder, Hendrik and Paul J Seguin (1993), "Price Volatility, Trading Volume, and Market Depth: Evidence from Futures Markets." *The Journal of Financial and Quantitative Analysis*, 28(1): 21–39.
- Bohl, Martin T. and Patrick M. Stephan (2013), "Does Futures Speculation Destabilize Spot Prices? New Evidence for Commodity Markets." *Journal of Agricultural and Applied Economics*, 45(4): 595–616.
- Bohl, Martin T., Farrukh Javed and Patrick M. Stephan (2013), "Do Commodity Index Traders Destabilize Agricultural Futures Prices?" *Applied Economics Quarterly*, 59(2): 125–148.
- Bollerslev, Tim (1986), "Generalized autoregressive conditional heteroskedasticity." *Journal of Econometrics*, 31(3): 307–327.
- Bollerslev, Tim and Jeffrey M. Wooldridge (1992), "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances." *Econometric Reviews*, 11(2): 143–172.
- Borsten, B Wade (1989), "Liquidity costs and scalping returns in the corn futures market." *Journal of Futures Markets*, 9(3): 225–236.
- Borsten, B Wade and Scott H Irwin (1987), "Futures funds and price volatility." *Review of Futures Markets*, 6(2): 118–135.
- Brunetti, Celso, and David Reiffen (2014), "Commodity index trading and hedging costs." *Journal of Financial Markets*, 21: 153–180.

- Brunetti, Celso, Bahattin Büyükşahin and Jeffrey H. Harris (2016), "Speculators, Prices, and Market Volatility." *Journal of Financial and Quantitative Analysis*, 51(5): 1545–1574.
- Bryant, Henry L., David A. Bessler and Michael S. Haigh (2006), "Causality in futures markets." *Journal of Futures Markets*, 26(11): 1039–1057.
- Chang, Eric C., J. Michael Pinegar, and Barry Schachter (1997), "Interday variations in volume, variance and participation of large speculators." *Journal of Banking & Finance*, 21(6): 797–810.
- Cornell, Bradford (1981), "The relationship between volume and price variability in futures markets." *Journal of Futures Markets*, 1(3): 303–316.
- Creti, Anna, Marc Joëts and Valérie Mignon (2013), "On the links between stock and commodity markets' volatility." *Energy Economics*, 37: 16–28.
- Daigler, Robert T. and Marilyn K. Wiley (1999), "The impact of trader type on the futures volatility-volume relation." *Journal of Finance*, 54(6): 2297–2316.
- da Silveira, Rodrigo Lanna Franco, Leandro dos Santos Maciel, Fabio L. Mattos and Rosangela Ballini (2017), "Volatility persistence and inventory effect in grain futures markets: evidence from a recursive model." *Revista de Administração*, 52(4): 403–418.
- Dawson, P. J. (2015), "Measuring the Volatility of Wheat Futures Prices on the LIFFE." *Journal of Agricultural Economics*, 66(1): 20–35.
- Du, Xiaodong, Cindy L. Yu and Dermot J. Hayes (2011), "Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis." *Energy Economics*, 33(3): 497–503.
- Engle, Robert F. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica*, 50(4): 987–1007.
- Ghoshray, Atanu (2013), "Dynamic persistence of primary commodity prices." *American Journal of Agricultural Economics*, 95(1): 153–164.
- Glauber, Joseph W. and Richard G. Heifner (1986), "Forecasting Futures Price Variability." *Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO.*
- Goodwin, Barry K. and Randy Schnepf (2000), "Determinants of endogenous price risk in corn and wheat futures markets." *Journal of Futures Markets*, 20(8): 753–774.
- Haigh, Michael S., Jana Hranaiova and James A. Overdahl (2007), "Hedge Funds, Volatility and Liquidity Provision in Energy Futures Markets." *The Journal of Alternative Investments*, 9(4): 10–38.
- Hennessy, David A., and Thomas I. Wahl (1996), "The Effects of Decision Making on Futures Price Volatility." *American Journal of Agricultural Economics*, 78(3): 591–603.
- ICO (2019), "Growing for Prosperity. Economic viability as the catalyst for a sustainable coffee sector." International Coffee Organization September.
- Irwin, Scott H. and Bryce Holt (2004), "The Effects of Large Hedge Funds and CTA Trading on Futures Market Volatility." In *Commodity Trading Advisors: Risk, Performance Analysis and Selection*, ed. Greg N. Gregoriou, François-Serge L'Habitant, Vassilios N. Karavas and Fabrice Rouah, 151–182. New York, NY: John Wiley and Sons.
- Irwin, Scott H. and Satoko Yoshimaru (1999), "Managed futures, positive feedback trading, and futures price volatility." *Journal of Futures Markets*, 19(7): 759–776.
- Karali, Berna and Gabriel J. Power (2013), "Short- and Long-Run Determinants of Commodity Price Volatility." *American Journal of Agricultural Economics*, 95(3): 724–738.
- Karpoff, Jonathan M. (1987), "The Relation Between Price Changes and Trading Volume: A Survey." *The Journal of Financial and Quantitative Analysis*, 22(1): 109.
- Kenyon, David, Kenneth Kling, Jim Jordan, William Seale and Nancy Mc-Cabe (1987), "Factors affecting agricultural futures price variance." *Journal of Futures Markets*, 7(1): 73–91.
- Kim, Abby (2015), "Does Futures Speculation Destabilize Commodity Markets?" *Journal of Futures Markets*, 35(8): 696–714.
- Kwiatkowski, Denis, Peter C.B. Phillips, Peter Schmidt and Yongcheol Shin (1992), "Testing the null hypothesis of stationarity against the alternative of a unit root." *Journal of Econometrics*, 54(1-3): 159–178.
- Ljung, G. M. and G. E. P. Box (1978), "On a measure of lack of fit in time series models." *Biometrika*, 65(2): 297–303.

- McPhail, Lihong Lu, Xiaodong Du and Andrew Muhammad (2012), "Disentangling Corn Price Volatility: The Role of Global Demand, Speculation, and Energy." *Journal of Agricultural and Applied Economics*, 44(3): 401–410.
- Milonas, Nikolaos T. (1986), "Liquidity and Price Variability in Futures Markets." *Financial Review*, 21(2): 211–238.
- Nelson, Daniel B. (1991) "Conditional Heteroskedasticity in Asset Returns: A New Approach." *Econometrica*, 59(2): 347–370.
- Peck, Anne E. (1981), "The Adequacy of Speculation on the Wheat, Corn, and Soybean Futures Markets." *Research in Domestic and International Agribusiness Management*, 2: 17–29.
- Samuelson (1965), "Samuelson, Paul A., Proof That Properly Anticipated Prices Fluctuate Randomly, *Industrial Management Review*, 6:2 (1965: Spring) p.41." *Management*, 2.
- Sanders, Dwight R. and Scott H. Irwin (2010), "A speculative bubble in commodity futures prices? Cross-sectional evidence." *Agricultural Economics*, 41(1): 25–32.
- Streeter, Deborah H. and William G. Tomek (1992), "Variability in soybean futures prices: An integrated framework." *Journal of Futures Markets*, 12(6): 705–728.
- Thurman, Walter N. (1988), "Speculative Carryover: An Empirical Examination of the U.S. Refined Copper Market." *The RAND Journal of Economics*, 19(3): 420.
- Tomek, William G. and Harry M. Kaiser (2014), *Agricultural Product Prices*. 5 ed., Cornell University Press.
- Vivian, Andrew and Mark E. Wohar (2012), "Commodity volatility breaks." *Journal of International Financial Markets, Institutions and Money*, 22(2): 395–422.
- Ward, Ronald W. (1974), "Market Liquidity in the FCOJ Futures Market." *American Journal of Agricultural Economics*, 56(1): 150–154.
- Williams, Jeffrey C. and Brian D. Wright (1991), *Storage and Commodity Markets*. New York: Cambridge University Press.
- Yang, Jian, R. Brian Balyeat and David J. Leatham (2005), "Futures Trading Activity and Commodity Cash Price Volatility." *Journal of Business Finance & Accounting*, 32(1-2): 297–323.



## **Annex**

**Table A1**  
**Results of the GARCH(1,1) model of volatility on spot prices, by type of position held by speculators (includes all coefficients)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	BASELINE MODEL			LONG POSITIONS			SHORT POSITIONS		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
ARCH									
Resid <sup>2</sup>	0.1104**	0.1145***	0.1293***	0.1001***	0.1162**	0.1190***	0.1185***	0.1155***	0.0939***
Volatility	0.7537***	0.7114***	0.3986	0.8203***	0.7257**	0.6763***	0.7342***	0.7378***	0.5697***
HET									
% $\Delta$ SP	-0.0642***	-0.0545***	-0.0441***						
% $\Delta$ H		-0.0590	0.0343						
% $\Delta$ NR		-0.0032	-0.009						
% $\Delta$ SP Long				0.0410***	-0.0101	0.0014			
% $\Delta$ H Long					-0.0908	-0.0601**			
% $\Delta$ NR Long					0.0046	-0.0083			
% $\Delta$ SP Short							-0.0256***	-0.0277***	-0.0316***
% $\Delta$ H Short								-0.0172	-0.0156
% $\Delta$ NR Short								-0.0138**	-0.0081
% $\Delta$ OI	-0.0066			-0.1112**			-0.0148		
% $\Delta$ VOL	0.0099***	0.0111***	0.0112***	0.0102***	0.0105**	0.0119***	0.0095***	0.0104***	0.0108***
% $\Delta$ INV			0.0043**			0.0045**			0.0039**
% $\Delta$ PPIACO			0.003			-0.0137			-0.0185
% $\Delta$ GDP			0.0753			0.0465			0.0577
% $\Delta$ PROD			-0.0624			-0.0408			-0.0304
Quarterly Fixed Effects	NO	NO	YES	NO	NO	YES	NO	NO	YES

Source: Elaboration by the authors.

Notes: Statistically significant at \* 10%, \*\* 5%, \*\*\* 1% level.

**Table A2**  
**Results of the baseline GARCH(1,1) model of volatility on ICO composite prices**

	Brazil			Colombia			Others		
	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)	Model 5 (5)	Model 6 (6)	Model 7 (7)	Model 8 (8)	Model 9 (9)
Resid <sup>2</sup>	0.1060***	0.1067***	0.0888***	0.1263***	0.1265***	0.0914**	0.1254***	0.1244***	0.0870***
Volatility	0.6780***	0.6899***	0.7255***	0.6117***	0.6198***	0.6257***	0.6271***	0.6366***	0.6536***
% $\Delta$ SP	-0.1160***	-0.0882***	-0.0878***	-0.1134***	-0.0930***	-0.0895***	-0.1077***	-0.0866***	-0.0839***
% $\Delta$ H		0.0427	0.0477		0.0471	0.0426		0.0325	0.0296
% $\Delta$ NR		0.0014	-0.0026		0.0002	-0.0012		-0.0006	-0.0046

Source: Elaboration by the authors.

Note: Significant at \* 10%, \*\* 5%, \*\*\* 1% level.



Green coffee growers, most of whom are smallholders, have suffered from the significant volatility and fall in the international price of this commodity over the past decade. It is therefore crucial to understand the factors that drive price volatility, which has been studied extensively for other commodities but not for coffee. This study looks into the determinants of the conditional volatility of green coffee prices in three different markets: spot, futures and physical. For this purpose, a generalized autoregressive conditional heteroskedasticity (GARCH) model is used, drawing on weekly data on prices and control variables for the state, economic and market structure. It is shown that conditional volatility follows a GARCH(1,1) process. Moreover, it turns out that speculation within futures markets reduces conditional volatility in all three prices.

