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The main drivers of arabica coffee prices in Latin America

Javier Aliaga Lordemann
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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 A. 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 Internation 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.

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Abstract

This paper analyzes the determinants of arabica green coffee prices in Latin American countries using a time series analysis and panel data methods. For this purpose, we construct a panel of different coffee prices: Coffee Organization (ICO) composite prices for Brazilian Naturals, Colombian Milds, and Other Milds; prices paid by the *Federación Nacional de Cafeteros de Colombia* (FNC) to coffee growers; and farm gate prices by country. The results show that the Brazilian Real to USD real exchange rate, inflation, and rain in January affect prices positively. In contrast, green coffee inventories, the oil price, and the Colombian Peso to USD real exchange rate negatively affect coffee prices.

Introduction

In this paper, we study the determinants of Arabica green coffee prices in Latin America and Caribbean (LAC) using a rigorous econometric analysis. The topic is of great practical importance, as green coffee is one of the leading export products of many Latin American and Caribbean countries. This commodity is produced by hundreds of thousands of families in the region, mostly smallholder farmers. The study of the determinants of Arabica green coffee prices is essential for understanding and predicting coffee prices and the improvement of economic policymaking in these countries (Deaton and Laroque, 1992). Arabica, together with Robusta, are the two predominant coffee species produced by more than 50 countries worldwide inside the "Coffee Belt", i.e., the region located between 25°N and 30°S, between the Tropic of Cancer and the Tropic of Capricorn.

Our analysis focuses on Arabica coffee prices instead of Robusta prices in LAC for several reasons. First, Arabica and Robusta prices may have different drivers: each caters to different market segments;[1] the former is more susceptible to diseases than the latter: and each requires other farming techniques and use different inputs. In 2020, the global Arabica coffee production was 2.4 times the Robusta production (United States Department of Agriculture, USDA). Second, in 2020 Latin America accounted for 84% of the global Arabica green coffee production and 51% of the global Robusta green coffee production.

We follow a time series methodology to assess the importance of each of the determinants in explaining Arabica green coffee prices. We consider several prices at different levels of the supply chain: International Coffee Organization (ICO) composite prices for Brazilian Naturals, Colombian Milds, and Other Milds; national-level annual farm gate prices collected by ICO, a panel dataset; and prices paid by the National Federation of Coffee Producers (*Federación Nacional de Cafeteros de Colombia, FNC*) to coffee growers. We consider a comprehensive set of determinants that may shift the supply and demand curves and study how these factors influence the price in a reduced form setup. The complete set of covariates include weather shocks and national and international macroeconomic variables.

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1 Their cup roast profile is different: Arabicas are more balanced and Robustas more stringent. Their use profile also differs: Robustas are used in espressos while Arabicas are used for regular brewed and specialty coffees.

Three different econometric models are estimated: two time-series and one panel-data. The first analyzes the determinants of ICO composite prices using monthly observations from January 1997 to September 2020. The second looks into the drivers of the prices of Colombian Milds reported by ICO, those paid to coffee growers by the FNC, and the amount of coffee produced in that country from January 1997 to September 2020. The last model uses panel data to assess the determinants of farm gate prices in Latin America collected by ICO.

Our main findings from the ICO Composite model are:

(i) The BRL/USD real exchange rate has a *positive* and statistically significant effect on all ICO prices. This effect is more prominent for Brazil Naturals;

(ii) The end-of-month stocks both have a negative and statistically significant effect on all four ICO prices considered;

(iii) An increase in other commodity prices have a *positive* and statistically significant effect on the prices of Brazilian Naturals and Other Milds, but it does not affect the Colombia ICO prices;

(iv) There is no statistical evidence that the COP/USD real exchange rate, the international interest rate, nor the oil price affects ICO prices;

(v) There is no evidence that national shocks (except for the interest rate) affect Colombian Mild ICO prices.

Our main findings from the Colombian model are:

(i) The Colombian Milds international price has a *positive* and statistically significant effect on the price paid by FNC to coffee producers;

(ii) The WTI oil price and the COP/USD real exchange rate have a *positive* and statistically significant effect on prices paid to Colombian coffee growers by the FNC;

(iii) We do not find statistical evidence that other variables affect Colombian coffee growers' prices. These include national inflation, national interest rate, inventories growth, the BRL/USD real exchange rate, the international interest rate, and coffee production in Colombia.

Our main findings from the farm gate model using panel data are:

(i) The GDP per capita growth rate has a *positive* and statistically significant effect on farm gate prices;

(ii) National inflation has a *positive* and statistically significant effect on farm gate prices;

(iii) Several other variables do not seem statistically significant, including domestic consumption, stocks at the end of the year, exports nor production affects farm gate prices;

(iv) Rainfall in March and August has a significant negative effect, but rain in January has a significant *positive* impact on farm gate prices. Still, evidence for temperature is too noisy to draw any meaningful conclusion.

The following section presents an extensive literature review to identify agricultural commodities' main price drivers, including coffee. In section II, we describe the variables used in our study. In turn, data sources, their mean features and empirical relationships are discussed in section III. The methodology and regression results are presented in section IV. Finally, the last section concludes.

I. Literature review

Market prices result from the interaction between demand and supply and other macroeconomic and financial variables. Hence, factors that shift the supply and demand curves will determine the equilibrium price. The agricultural commodity price depends on market forces that alter the current or expected balance between supply and demand. Initial models (Van Meir, 1983; and Baker and Menzie, 1988) did not formulate the price formation process and used reduced-form expressions for prices through a stocks-to-use ratio. They suggest this ratio explains price variations as stocks adjust to shocks to supply and demand. Stocks will increase when production is high and prices are low, as sellers may hold on entering in new transactions waiting for a higher price and execute a new sell. Total use includes domestic consumption and exports, is generally more stable, and tends to shift gradually.

Van Meir (1983) and Baker and Menzie (1988) analyzed the relationship between stocks-to-use ratios and corn prices using annual data. Westcott, Hull, and Green (1984, 1985) used this approach in models for quarterly wheat and corn prices. Westcott and Hoffman (1999) study the determinants of farm-level prices of wheat and corn and consider as determinants: (i) the ratio of total year-end stocks to use, (ii) the percentage of publicly held stocks owned by the Government (CCC) to use, and (iii) the loan rate. Their wheat equation also included feed use and corn prices in the summer months. Their empirical results confirmed a strong inverse relationship between price and the stocks-to-use ratio. However, Goodwin, Schnepf, and Dohlman (2005) argue that the proportion of stocks to use is endogenous to prices in a study that analyze the farm gate price of soybean.

Subsequent studies provided a deeper understanding of the different factors affecting supply and demand beyond the stocks to use ratio. These factors include consumer preferences and the changing needs of end-users; factors affecting production processes (e.g., weather, input costs, pests, diseases, etc.); relative prices of crops that can substitute in either production or consumption; government policies; and factors affecting storage and transportation (Schnepf, 2006).

According to Tomek and Kaiser (2014), factors that shift the demand curve are those that affect consumer preferences and budgets:

(i) Demographic factors: population size, age distribution, ethnicity, gender, etc.;

(ii) Economic factors: income and its distribution, and the prices and availability of other products;

(iii) Consumer tastes and preferences depend on education levels, life experiences, information and advertising, and the social context in which consumers live (i.e., lifestyle effects).

Factors shifting the supply curve are those that affect marginal costs and marginal revenues are:

(i) Changes in input prices;

(ii) Changes in prices of commodities competing for the same resources or factors of production;

(iii) Changes in the prices of joint products;

(iv) Changes in the level of price faced by producers;

(v) Changes in technology that influence efficiency and the costs of production; and

(vi) Changes in institutional factors like government programs.

Cooke and Robles (2009) study the determinants of corn, rice, soybeans, and wheat prices from 2002 to 2009. These commodity prices rose rapidly from 2006 to mid-2008. They point to demand and supply explanations for this upward trend. The demand-side factors include:

(i) Rising world demand for direct consumption and animal feed: emerging nations can afford a more diversified food consumption basket;

(ii) Ethanol/biofuels significantly increased the demand for a limited supply of commodities;

(iii) Increased activity in the futures market, also referred to as the financialization of the commodity markets. In this process, commodity prices depend not only on its primary supply and demand but also on financial variables and investors' behavior in derivative markets (Creti, Joëts, and Mignon, 2013).

Supply-side factors include:

(i) Increased oil and fertilizer prices increase costs and limit production;

(ii) Low R&D investment in agriculture dampens production growth;

(iii) Trade barriers and export restrictions create scarcity and increase commodity prices;

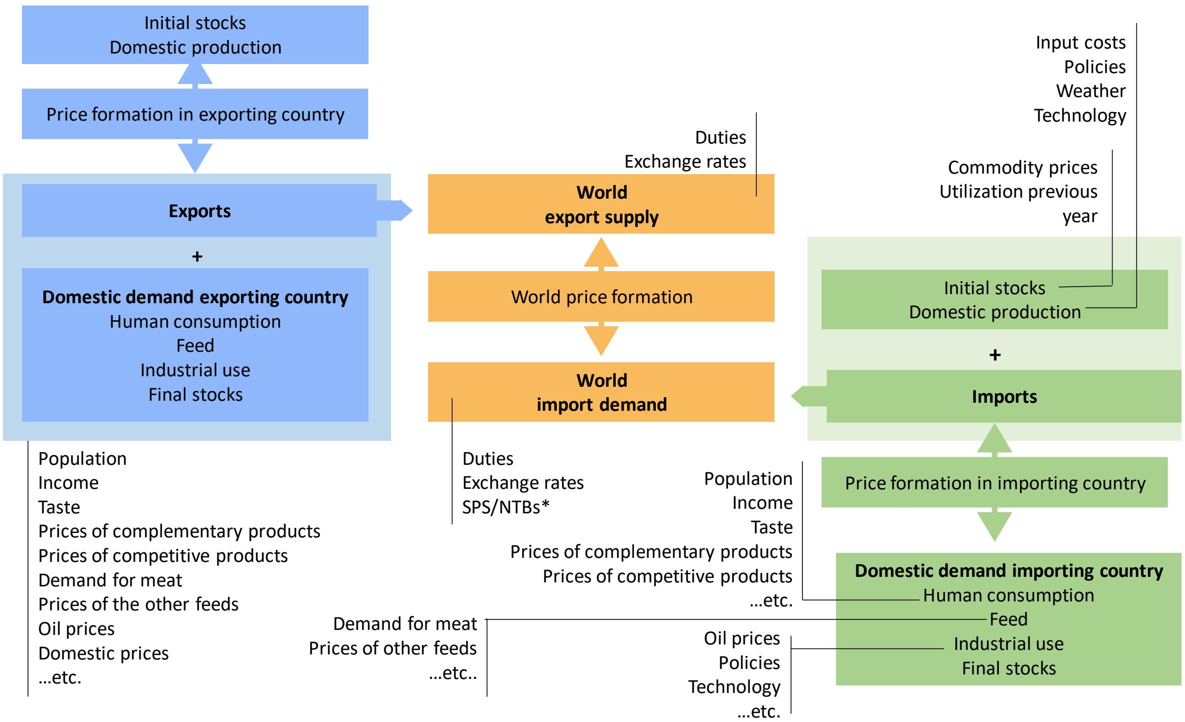
(iv) Droughts in large grain-producing nations lower global production;

(v) Dollar devaluation: most commodity prices are in USD;

Cooke and Robles (2009) find that futures markets and proxies for speculation explain changes in food prices. For their part, Aliaga, Mora-García and Mulder (2020) finds that speculation activity in the futures market for the 'C' Coffee Contract lowers price volatility.

FAO (2009) describes factors affecting agricultural commodities' price formation process in the exporting country and the world. First, price formation in the exporting region results from the interaction between domestic production and domestic demand. Factors that determine domestic production in the exporting countries include input costs, domestic policies, weather, prices, use in previous years, etc. Domestic demand in exporting countries depends on population, income, taste, prices of complementary products, prices of competitive products, meat demand, prices of other feeds, oil prices, and domestic policies. Second, price formation in the world depends on the interaction between export supply and import demand. Other factors import duties and exchange rates (see diagram 1).

Diagram 1
Factors affecting agricultural commodity prices



Source: Food and Agriculture Organization of the United Nations (FAO) (2009), The State of Agricultural Commodity Markets 2009. Rome: FAO.

Sachs et al. (2020) study the determinants of coffee prices. Overall, they find that the main drivers of the ICO Composite price are:

(i) Brazilian Real (BRL) to US Dollar (USD) exchange rate and the USD to EUR exchange rate;

(ii) The increase in productivity in Brazil and Vietnam (higher yields);

(iii) Consolidation in the roaster and retail sectors;

(iv) High price elasticity of Brazil supply (unused land may return to coffee production under the right price);

(v) Low price elasticity of the rest of the coffee producing countries;

(vi) Market power in the roast-retailer segment; and

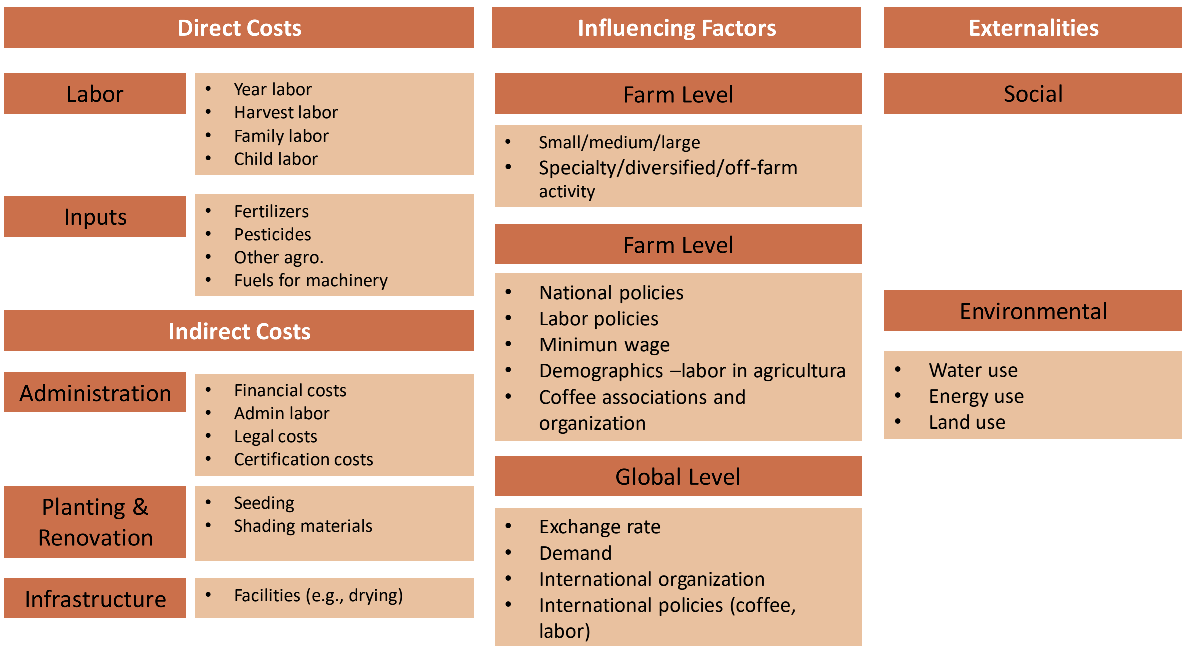
(vii) Monopsonic buyer power of coffee.

They also point out several factors contributing to direct and indirect coffee production costs. Direct costs include wages and input costs (fertilizers, pesticides, other agrochemicals, and fuels for machinery). Indirect costs refer to administrative charges (financial cost, administrative labor, legal and certification costs), cost of planting and renovation (seedling and shading maintenance), and other expenses related to infrastructure (drying facilities or depreciation rates).

They also distinguish between influencing factors at the farm, national, and global levels. At the farm level, these include land area (if the farm is small, medium, or large) and the type of coffee farm (if it is diversified, organic, or specialty-focused). At the national level, they include national policies, labor policies, minimum wage, demographics, and the existence of coffee associations or organizations or not. At the global level, they refer to the exchange rate, global demand, international organizations, and international policies related to coffee and labor.

Finally, they also distinguish between social and environmental externalities. Social externalities include child labor, gender, rural labor, forced labor, and health. Environmental externalities include water use, energy use, and land use (see diagram 2).

Diagram 2
Conceptual framework for factors contributing to coffee production costs



Source: Jeffrey Sachs, Kaitlin Y. Cordes, James Rising, Perrine Toledano, and Nicolas Maennling (2019), "Ensuring Economic Viability and Sustainability of Coffee Production," New York: Columbia Center on Sustainable Investment.

They develop six econometric coffee supply and demand models. Based on projections of income, population growth, and climate change, these models allow them to evaluate how these factors will affect the coffee industry in the following 30 years. In particular, they develop:

(i) **Demand model**: a two-staged linear econometric model. The first stage explains the international price of coffee (P_t^*) on the basis of the quantity produced (Q_{t-1}) in the previous growing season, past international price (P_{t-1}^*), and a time trend (t). The second stage explains coffee consumption (D_{it}) from the predicted international price from the first stage $(\hat{P}_t^*)$, current income (Y_{it}) and a time trend (t);

(ii) **Harvest (Yields) model**: a linear econometric model that explains domestic yields (Y_{it}) as a function of climatic variables (W_{it}). This model helps to create yield predictions $(\hat{Y}_{it})$ based on projections of climate change $(\widehat{W}_{it})$;

(iii) **Yield gaps model**: captures the relationship between model parameters in the harvest model and suitability, as estimated by the Global Agro-Ecological Zone (GAEZ) project;

(iv) **Planting model**: a linear econometric model that explains farmers' decisions to expand planted area (ΔA_{it}) from farm prices (p_{it}), yields (Y_{it}), and planted area (A_{it}). This model facilitates planted area predictions $(\Delta\hat{A}_{it})$ based on a prediction from the yields model $(\hat{Y}_{it})$ and projections of suitable land for cultivating coffee $(\hat{A}_{it})$ from GAEZ;

(v) **Production model**: combines the results from the yields model $(\hat{Y}_{it})$ and the planting model $(\hat{A}_{it})$ to obtain a forecast of domestic coffee production $(\hat{Q}_{it})$, and then combines the domestic coffee production into a global coffee production $(\hat{Q}_t = \sum_i \hat{Q}_{it})$. The combined estimated global coffee production feeds into the Demand Model to calculate the next year's international prices;

(vi) **Farm gate price model**: a linear econometric model that explains farm gate prices (p_{it}) from international prices (P_t^*), underlying trends (t), and records of differentials (γ_i). This model uses the predictions of international prices from the demand model $(\hat{P}_t^*)$ to get a forecast of farm gate prices $(\hat{p}_t^*)$ which are used for the planting model because they affect the planted area;

(vii) **Stock model**: a linear econometric model that explains stock levels (S_t) from past behavior (S_{t-1}) and the international price (P_t^*). This model provides predictions of the stock levels that influence the equilibrium price.

In sum, many commodity price movement models (particularly for grains) have employed stocks-to-use ratio, weather variables, international trade, and substitute products (Goodwin et al, 2005).

Various methods for modeling structural change have been proposed in the literature to estimate the determinants of commodities prices. Procedures vary from the use of multivariate simple linear regressions (Westcott and Hoffman, 1999) to models using most complex techniques, such as VAR models (Deaton and Laroque, 1992) or gradual switching regressions (Goodwin and Piggott, 2001). Panel regressions are also extensively used in the literature. They are used to minimize endogeneity problems arising from time variables (Rezitis, 2015; Aghion et al., 2009; Bleaney and Greenaway, 2001; Cavalcanti, Mohaddes and Raissi, 2011). These studies apply recent findings from econometric theory (Wooldridge, 2012; Kapetanios et al., 2011; Pesaran, 2006). Following these latter studies, this paper uses a heterogeneous panel analysis to shed light on the determinants of coffee prices.

II. A simple pricing model for arabica coffee

Green coffee is a storable agricultural commodity. As a result, stocks play a strategic role.[2] Green coffee producers can build supplies in periods where prices are low, and sell them on the expectation that prices recover the next year. Following Goodwin, Schenpf and Dohlman (2005), an equilibrium model for a storable commodity in a competitive market generally consists of a supply equation, a demand equation, stocks, and an identity describing equilibrium. Thus, a reduced-form expression for prices will relate prices to factors that influence supply and demand.

Supply (S) is a function of price (p) (or, more accurately, expected price) and factors (z) reflecting production shocks:

$$S_t = s(p_t, z_t)$$

Factors that shift the supply curve are those that affect marginal costs and marginal revenues:

(i) A rise in input prices increases the marginal cost of production and hence shifts the supply curve inwards, increasing the equilibrium price. The price of inputs includes wages, price of fertilizers and pesticides (including fungicides, herbicides, and insecticides), cost of land (e.g. property taxes), transportation costs (gasoline, diesel or oil), interest rate, inflation (affecting the general cost and price levels) and exchange rate (which affects the terms of trade).

(ii) An increase in the price of substitutes in production, such as other commodities, shift resources from the production of coffee towards the production of commodities with a higher profit margin. This shifts the supply curve inwards and increases the equilibrium price. An increase in the price of complementary goods has the opposite effect.

(iii) A rise in the international coffee price increases national coffee production and shifts the supply curve downwards, decreasing the equilibrium price.

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[2] Under the right conditions, green coffee can be stored between one and two years without losing quality properties.

(iv) A productivity improvement, due to changing weather conditions, GDP per capita and yield (tons per hectare), shifts the supply curve downwards, decreasing the equilibrium price.

Market equilibrium requires $S_t - D_t - K_t = 0$, where K_t are stocks. This allows for a price-dependent reduced form expression to be solved that is a function of stocks and supply and demand shifters:

$$p_t = f(K_t, z_t, y_t)$$

It is essential to differentiate between different prices (p). **Wholesale and retail market prices** of roasted/soluble coffee are prices paid by consumers to the commercial distributor or outlet. **World prices** may be the spot or future price of the Coffee 'C' contracts in USD per 100 pounds of green coffee, traded at the InterContinental Exchange (ICE). It may also be the **ICO Composite prices** for Arabica, Brazil Naturals, Colombia and Other Milds, which are prices for prompt shipment (within 30 calendar days—as opposed to immediate shipment) and sales from origin. The export price, or **free on board (FOB) price**, is the exporting price. The **farm gate prices** or producer prices are prices received by farmers at the farm gate, before transportation costs from the farm gate to the nearest market or first point of sale, excluding warehousing cost, processing cost and market charges for selling the product.

The particular interest of this work lays on the determinants of the ICO Composite prices and the farm gate price. Our focus is on Arabica coffees, as we have access to daily ICE and ICO prices, while farm gate prices are monthly. When we gathered data for each price variable, we tried to be as comprehensive as possible. The following section describes the definition of the variables data and its sources.

III. Definition of variables and data sources

This section presents the variables included in our estimated models and describes their data sources. We first list the supply variables, followed by demand variables and finally prices, our dependent variable. The frequencies are the main limitation when defining the variables, as some are available only annually, while we are interested in monthly trends.

A. Data sources for factors that shift the supply curve

Table 1 list the data sources and definitions of the factors that shift the supply curve. Also, we collected data on annual green coffee production, imports, and exports from the Production Supply and Distribution (PSD) of the United States Department of Agriculture (USDA) (annual). We used monthly data on Colombian coffee production from the FNC.

As a proxy for transportation costs, we used data on the West Texas Intermediate (WIT) oil spot price from FRED. As a proxy for the lending interest rate, we used the 3-Month Treasury Constant Maturity Rate from FRED; and monthly data on the average lending rate in Colombia ("tasa de cambio representative del mercado") from the Bank of the Republic of Colombia ("Banco de la República de Colombia"). We use the growth rate of the monthly Producer Price Index of All Commodities (PPIACO) of the United States from FRED, the monthly Consumer Price Index (CPI) from the Banco de la República de Colombia, and the annual CPI for other countries from the World Development Indicators (WDI) of the World Bank. We do not use the CPI of the United States because it is correlated with the PPIACO. As a proxy for the exchange rate, we use the Colombian Peso (COP) to United States Dollar (USD) and Brazilian Real (BRL) to USD real exchange rates from FRED. Other exchange rates are taken from the WDI.

We tried to include property taxes, wages, gasoline, and diesel prices. However, we could not find a historical data set for property taxes for the LAC countries in our sample. We found annual data for minimum wages from the International Labor Organization, but data were missing for many countries. We could also not find a good source for gasoline and diesel annual prices for all LAC countries. We also gathered data for the yearly cost of fertilizers and pesticides (fungicides, herbicides, and insecticides) from the Food and Agriculture Organization (FAO) as proxies for input prices. However, as these data contained many missing values, they were excluded to avoid a significant reduction in our country sample.

As a proxy for productivity, we use weather, GDP per capita and yield. Annual GDP per capita comes from WDI, and annual yield (in tons per hectare) from FAO. We also use the annual amount of arable land available from the WDI.

Following the literature, we define weather as a factor that shifts the supply curve.[3] We gather daily temperature and precipitation data from Climate Engine (https://clim-engine.appspot.com/climateEngine), specifically, from the CFS Reanalysis, ERA5 and CHIRPS historical datasets for coffee-producing Latin American countries. Climate Engine provides a simple average of temperature and precipitation at a given scale (computation resolution) that change from one dataset to another. We then calculate a monthly mean temperature and accumulated precipitation by country.

Table 1
Data sources and definitions of factors that shift the supply curve and its data sources

Factor	Variable	Frequency	Source	Countries	Expected Sign
Input Prices	Price of fertilizers	Annual	FAOSTAT	LAC	+
	Price of pesticides	Annual	FAOSTAT	LAC	+
	Price of WTI	Monthly	FRED		+
	3-Month Treasury Constant Maturity Rate	Monthly	FRED	United States	+
	Exchange rate	Monthly	BRPC	Colombia	+
	Producer Price Index for All Commodities (PPIACO)	Monthly	FRED	United States	+
	Consumer Price Index (CPI)	Annual	WDI	LAC	+
	Consumer Price Index (CPI)	Monthly	BRPC	Colombia	+
	COP to USD	Monthly	FRED		+
	BRL to USD	Monthly	FRED		+
	National currency exchange rate	Annual	WDI	LAC	+
Substitutes & Complements	PPIACO	Monthly	FRED	United States	+ (substitute) - (complement)
International Price	Spot Price	Daily	ICE		+
	Composite Prices	Daily	ICO		+
Factors affecting Productivity	Rain	Daily	Climate Engine	LAC	-
	Temperature	Daily	Climate Engine	LAC	-
	GDP per capita	Annual	WDI	LAC	-
	Arable Land	Annual	WDI	LAC	-
	Yield	Annual	PSD	LAC	-

Source: Elaboration by the authors.

A potential weakness of our work is that we use a simple average of our climatic variables, which means that all observations across a given grid get the same weight within a country. This method fails to consider that some areas are more suitable for cultivating coffee than others. Further research would ideally use a weighted average by the suitability for growing coffee in each cell of the grid, using some services such as the Global Agro-ecological Zones (GAEZ) services.[4]

[3] However, we also want to note that weather may also affect the demand for coffee (consumption) through seasonality with coffee consumption peaking during the colder months of the year and declining during the warmer months (http://www.futuresmag.com/2017/03/19/exploiting-coffee-seasonality).

[4] See http://www.gaez.iiasa.ac.at/w/ctrl?_flow=Vwr&_view=Welcome&idAS=0&idFS=0&fieldmain=main_&idPS=0.

B. Data sources for factors that shift the demand curve

Table 2 lists the data sources and definitions of the factors that shift the demand curve. Also, we collected annual green coffee consumption data from PSD of USDA.

(i) As proxy for demographic size, we used data on annual population from the WDI.

(ii) As proxy for income, we collected data on annual gross national income and GDP per capita from the WDI.

(iii) As a proxy for changes in the prices of substitutes and complements in coffee consumption, we use the growth rate of the monthly Producer Price Index of All Commodities (PPIACO) of the United States from FRED.

Table 2
Data sources and definitions of factors that shift the demand curve and its data sources

Factor	Variable	Frequency	Source	Countries	Expected Sign
Demographic Factors	Population Size	Annual	WDI	LAC	+
Income	Gross National Income (GNI)	Annual	WDI	LAC	+
	GDP per capita	Annual	WDI	LAC	+
	Gini Index	Annual	WDI	LAC	+
Price of Related Commodities	PPIACO	Monthly	FRED	United States	+ (substitutes) - (complements)

Source: Elaboration by the authors.

C. Stocks

We use annual end-of-year stocks of green coffee from PSD. From ICE we gather historical end of month certified Coffee C stocks by port held by ICE Futures U.S. Licensed Warehouses measured in total bags.

D. Prices

Price data comes from different sources. First, we obtain daily spot prices on the US 'C' Contract for Arabica Coffee traded at the InterContinental Exchange (ICE) market, a continuous contract based on Arabica coffee.[5]

The above data are complemented with daily ICO indicator prices for Colombian Milds, Other Milds and Brazilian Naturals that belong to the Arabicas group. 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 as opposed to immediate shipment) and sales from the origin, in USD per 100 pounds of green coffee. These quotations come from at least five traders and brokers. So ICO's prices are spot prices. There is some relationship between ICO indicator prices and the Coffee C Contract traded at ICE, because traders and brokers often trade green coffee as Coffee C Contract plus a margin. We then take a weighted average of these three, the weights are from ICO (2011) —Colombian Milds 12%, Other Milds 23% and Brazilian Naturals 31%— and construct one composite category for Arabica coffee. Appendix Table A4 show the classification of

[5] The market and exchange names of the Coffee C contract has changed over time. Until August 2007 it was the Coffee, Sugar and Cocoa Exchange. From September 2007 until December 2019 it was the New York Board of Trade. From January 2020, it is the ICE Futures U.S. The price data is taken from Barchart [online] www.barchart.com.

exporter countries by type of coffee according to ICO. When working with ICE and ICO prices, we can take averages of daily prices at weekly, monthly and annual frequencies.

We also collected monthly prices paid to Colombian coffee growers from the National Federation of Coffee Growers of Colombia (*Federación Nacional de Cafeteros de Colombia*, FNC). This data is in Colombian Pesos (COP) per 125 kilos of dry parchment coffee (a unit known in Colombia as 'carga'), and we apply the COP to USD exchange rate to transform it into USD prices.

Finally, annual farm gate prices from ICO, in USD per 100 pounds of green coffee, for many coffee-growing countries, allow us to use a panel data econometrics.

Table 3
Data sources and definitions of stocks prices

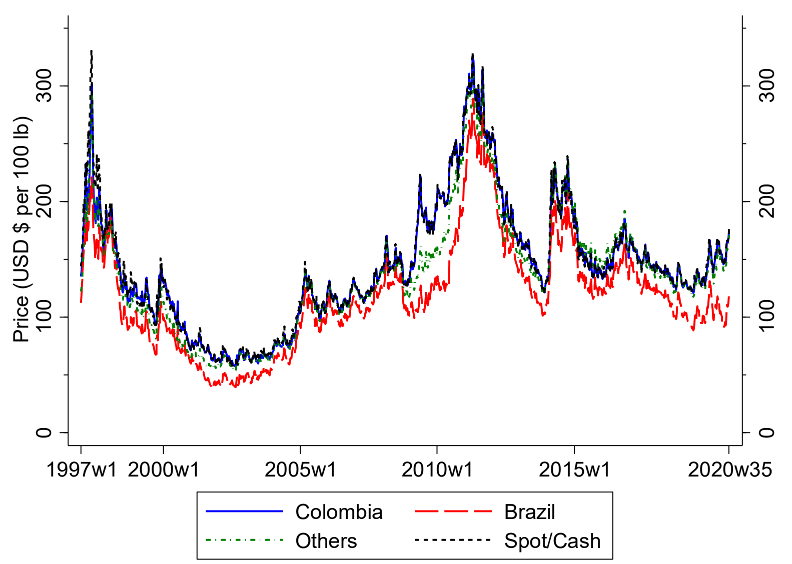
	Variable	Frequency	Source	Countries	Expected Sign
Stocks	End-of-year stocks	Annual	PSD	LAC	-
	Coffee C stocks	Monthly	ICE		-
Prices	US 'C' Contract Spot Price	Daily	ICE		
	Brazilian Naturals	Monthly	ICO		
	Colombian Milds	Monthly	ICO		
	Other Milds	Monthly	ICO		
	Prices paid to coffee growers	Monthly	FNC		
	Farm gate prices	Annual	ICO	LAC	

Source: Elaboration by the authors.

E. Data description

Figure 1 plots the spot prices for the Coffee 'C' Contract traded at the InterContinental Exchange (ICE), and the ICO composite prices for Colombia Milds, Brazil Naturals, and Other Milds. Prices for Colombian Milds closely follow the spot prices at ICE, while prices for Brazil Naturals and Other Milds have historically been under the spot price.

Figure 1
Arabica coffees: weekly spot prices for coffee 'C' contract traded at ICE and ICO composite prices for the three categories (Brazil, Colombia and other milds), 1997-2020

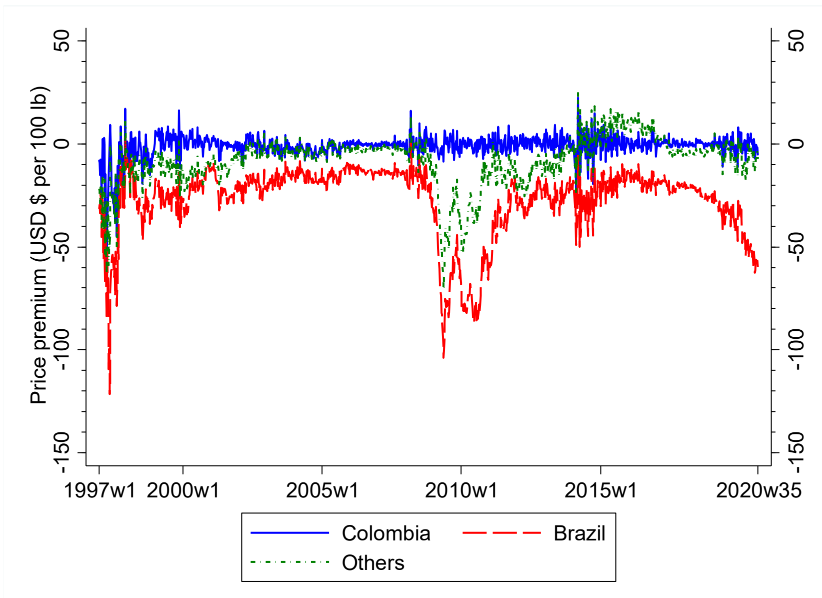


Source: Elaboration by the authors based on sources listed in section 3.

In 2019, Brazil produced 3.5 times more (Arabica) coffee than Colombia. The latter country made 6.7 times more (Arabica) coffee than the average Latin American and Caribbean nation. Exports follow a similar pattern (see Appendix Figure A1).

Figure 2 plots the price differential between the three categories of the ICO composite prices and spot prices. The price differential for Colombia fluctuates almost randomly around zero and has the typical behavior of a white noise error, while the price differential for Brazil is typically negative. The price differential for Other Milds has been negative for most of the time, except for a few weeks around the year 2015. It is also interesting to note that price differentials for Brazil and Other Mild Arabicas negatively correlate with the spot price level, meaning that price differentials decrease when prices increase. Moreover, price differentials for Brazil and Other Mild were smaller when coffee prices were at their maximum level during the period under study.

Figure 2
Arabica coffees: weekly price differentials between Coffee 'C' Contract spot prices and ICO Composite prices for the three categories, 1997-2020



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

Another important factor are yields. Many factors determine yields, such as growing techniques, topography, R&D in the development of new more productive and resistant coffee varieties, climatological variables that influence the suitability of land for growing coffee. An improvement in yield shifts the supply curve downwards, decreasing the equilibrium price. Table 4 shows average green coffee yields (hg/ha) by LAC countries in our sample, from 1961 to 2018. The second column shows the average yield during the 60s, and the other columns shows the average growth rates of yields in the following decades.

The table provides evidence on the significant productivity gains Brazil has experienced since 2000. This is important since Brazil is one of the biggest coffee producers worldwide. The increase in the Brazilian yield affects the marginal cost and production decisions of coffee farmers. The same amount of land can produce more green coffee, making it more profitable. Since Brazil is one of the biggest coffee producers worldwide, changes in its production capacity affect international spot prices. According to Sachs et al. (2019) this is one of the main factors driving global green coffee prices.

Table 4
Decade average of green coffee yields in coffee growing Latin American countries, 1961-2018

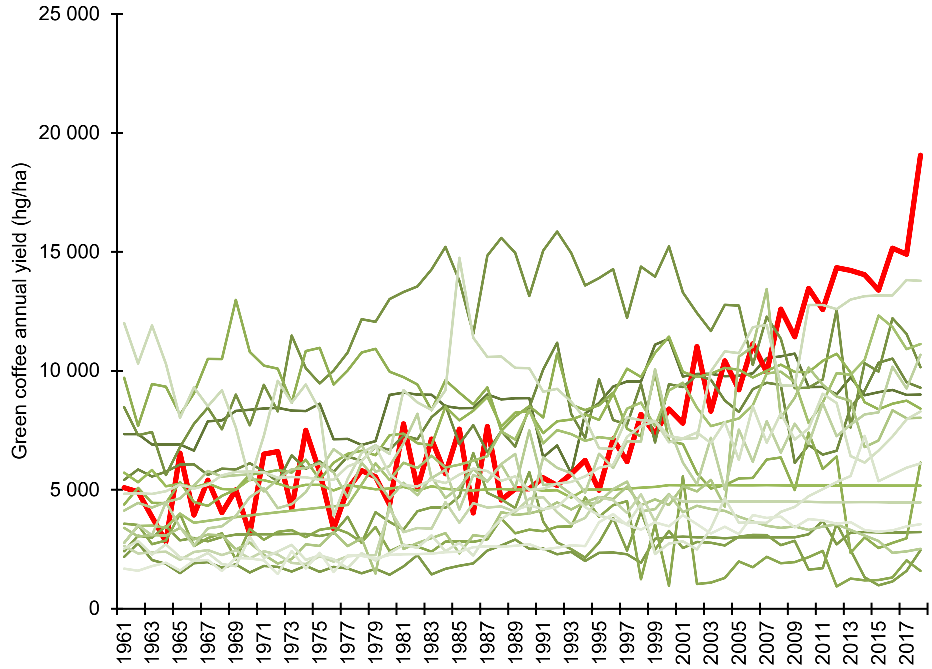
	(hg/ha)	Variation (*percentage*)				
	1961-1969	1970-1979	1980-1989	1990-1999	2000-2009	2010-2018
Brazil	4 617	15.6	10.1	4.4	63.2	45.4
Colombia	5 784	5.2	20.2	18.6	3.1	-4.0
Costa Rica	7 592	33.6	38.0	0.9	-14.2	-14.5
Cuba	1 977	-16.2	22.3	16.3	27.2	6.5
Dominican Republic	2 969	9.6	36.8	-27.2	-11.2	-34.9
Ecuador	3 052	4.5	-10.9	25.4	-44.7	-20.5
El Salvador	9 701	5.8	-12.7	-3.4	-32.5	-25.1
Guatemala	4 689	28.6	29.3	11.8	15.9	-7.9
Haiti	5 292	-2.0	-3.0	-0.8	4.0	-0.3
Honduras	3 560	24.9	41.7	21.0	16.1	16.5
Jamaica	3 062	-19.6	31.0	38.4	70.5	10.1
Mexico	4 893	14.2	-6.4	-4.0	-21.6	-24.4
Nicaragua	3 403	60.7	10.0	5.3	5.8	27.6
Panama	2 366	-9.3	83.1	8.0	6.7	-1.3
Paraguay	9 678	-26.2	39.0	-17.0	15.6	37.7
Peru	5 137	12.6	-5.1	10.9	20.9	2.4
Bolivarian Republic of Venezuela	1 817	10.8	20.9	27.8	14.7	-1.9
Puerto Rico	2 281	-0.7	28.5	36.6	-11.4	60.6

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

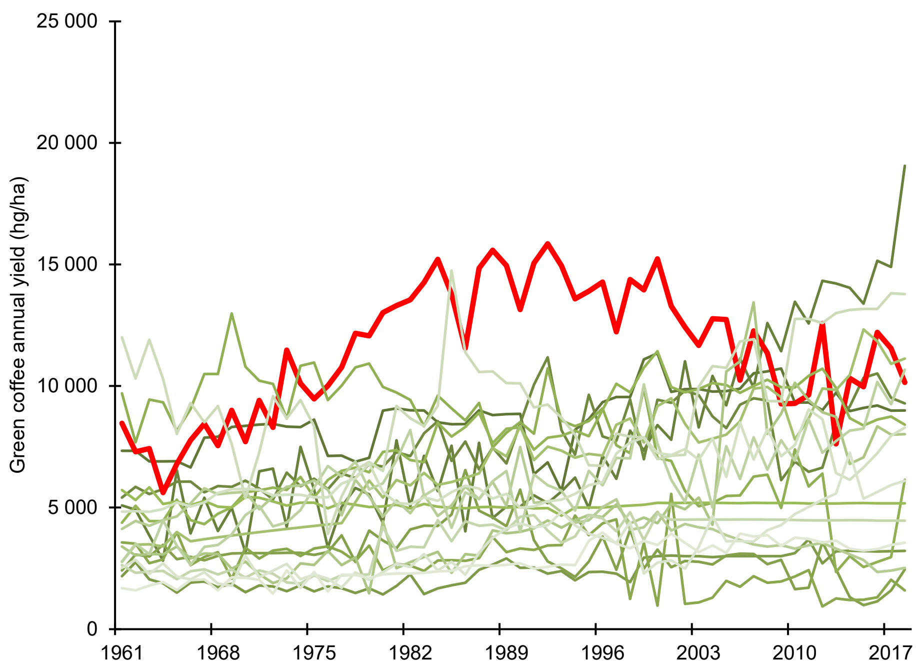
While Honduras has also experienced a constant increase in its yield, it is lower than Brazil's. Most other countries have experienced a decrease in their yield, for example Costa Rica, which experienced its highest yield growth during the 1970s. Figure 3 visualizes table 4, highlighting the cases of Brazil and Costa Rica. Nowadays Brazil is the LAC country with the highest yield, followed by Paraguay, Honduras, Nicaragua and Costa Rica.

Figure 3
Annual yield (hg/ha) of green coffee in Latin American countries, 1961-2018

A. Brazil



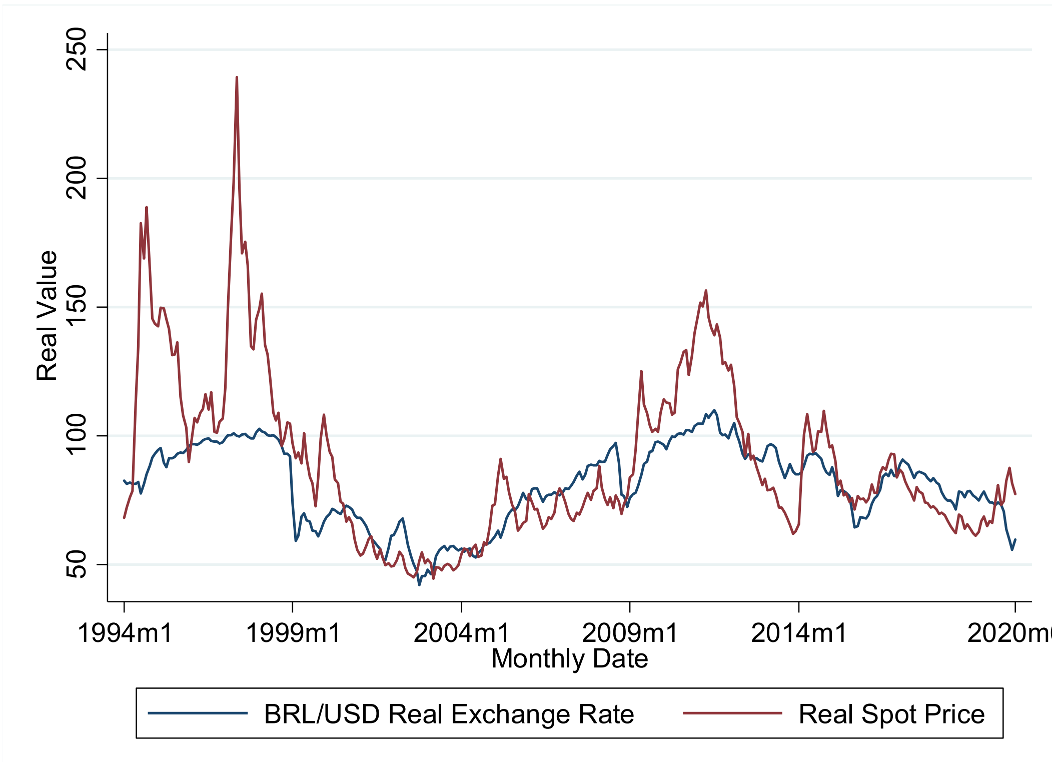
B. Costa Rica



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

The real exchange rate between the Brazilian Real and the US Dollar is another important factor that drives fluctuations in the spot price of green coffee. Figure 4 shows the monthly relationship between the real exchange rate of the Brazilian Real to the US Dollar and the real spot price from January 1994 to June 2020. Both series appear strongly related to each other (see figure 4). As explained by Sachs et al. (2019, pg. 14) "a weak Real is positively correlated with higher Brazilian coffee production and exports and consequently lower coffee prices in US dollars".

Figure 4
Monthly relationship between the real exchange rate of the Brazilian Real to the US Dollar and the real spot price, Jan 1994-Jun 2020



Source: Elaboration by the authors based on data sources listed in section 3.
Notes: The real spot price comes from dividing the nominal spot price in dollars by the producer price index of all commodities (PPIACO) and multiplying this by 100.

The previous results show correlations between time series. However, these relations simply result from the cointegration of the time series. The next section explains how we control for cointegration and explains the methodological approach we take to quantify the relationship between the different factors that drive price levels.

IV. Methods and results

The three different prices (ICE spot prices, ICO Composite prices, and FAO farm gate prices) are available at a different frequency (daily, weekly, monthly and annually). Each price frequency has its own determinants. For example, the effect of weather on prices can be analyzed for annual prices but not for monthly or weekly prices, except if we know how climatic realizations affect price formation over short time horizons. By studying annual prices, we can take advantage of a non-parametric specification that is flexible enough to allow for each month of the year to affect the annual price differently. This allows us to know which month's climatic conditions are more relevant.

Below four different models are considered: the first studies monthly ICO prices (Brazil, Colombia and Others). The second is a Colombia-specific model that analyzes monthly farm gate prices on one hand and annual farm gate prices on the other. The third model uses a fixed effects model and annual farm gate prices from ICO. Each model considers different determinants. Next, we explain the regression equation behind each model.

A. Model 1: ICO composite prices (monthly, Jan-1997 to Sep-2020)

This model fits the following equation by ordinary least squares (OLS),

$$\Delta \ln(P_t^*) = \alpha + \beta_1 \Delta \ln(STOCKS_t) + \beta_2 GS3M_t + \beta_3 \Delta \ln(BRL_t) + \beta_4 \Delta \ln(COP_t) + \beta_5 \Delta \ln(WTI_t) + \beta_7 \pi_t^* + u_t, (1)$$

where $\Delta \ln(x_t) = \ln(x_t) - \ln(x_{t-1})$ is the percentage change of any variable x_t. The dependent variables in this model are the monthly percentage change in four different international prices P_t^* from ICO composite prices (in USD/100lb of green coffee). We use the price of Brazilian Naturals, Colombian Milds, Others Milds, and our "Arabica" category—constructed as a weighted average of the former three. We add a comprehensive set of covariates to the model. Specifically, we include as control variables $STOCKS_t$ the total end of month certified Coffee 'C' stocks, $GS3M_t$ the 3-Month Treasury Constant Maturity Rate (a proxy for the international rate), WTI_t the West Texas Intermediate oil price, and π_t^* the monthly growth rate of the Producer Price Index of All Commodities (inflation). In addition to the BRL_t the BRL-USD real exchange rate we also included the COP_t the COP-USD real exchange rate. Both the BRL/USD and COP/USD have a very similar behavior and we wanted to test where the effect was coming from. All variables are measured monthly and we correct standard errors by using a robust covariance matrix (Eicker-Hubert-White).

Table 5 show the results from equation (1). The first column shows results for the weighted average of all ICO Arabica price categories; the second column focuses on Brazil Naturals; the third on Colombian Mild; and the last column on Other Milds. We find that (i) the growth in the BRL/USD real exchange rate has a positive and statistically significant effect at the 1% level on the growth rate of all four ICO prices, but this effect is bigger for Brazil Naturals. This means that an increase (depreciation) in the BRL/USD real exchange rate increases all Arabica ICO prices. (ii) regardless of the ICO price considered, the rate of growth of end-of-month stocks both have a negative and statistically significant effect at the 5% to 10% level on the growth rate of all four ICO prices considered. This means that stocks acts as a buffer to price variations, an increase in stocks decreases prices. (ii) we do not find statistical evidence that the growth in the COP/USD real exchange rate affects the growth rate of any of the Arabica ICO prices, as the share of Colombia in coffee sales is not sufficiently large to affect coffee prices. (iii) Inflation in commodity prices also affects prices positively and has a statistically significant effect at the 5% to 10% level on the growth rate of Arabica, Brazil and Others, but it does not affect the Colombia ICO prices. (iv) Neither the interest rate nor the oil price have any effect on any of the ICO prices.

Table 5
Determinants of monthly ICO prices from Arabica coffee (our Arabica category, Brazilian Naturals, Colombian Naturals, and Other Milds) using Model 1

	(1) Arabica	(2) Brazil	(3) Colombia	(4) Others
$GS3M_t$	-0.2098	-0.2333	-0.1839	-0.1891
	(0.2478)	(0.2403)	(0.2778)	(0.2311)
$\Delta\ln(COP_t)$	0.1032	0.0325	0.1467	0.1653
	(0.1553)	(0.1682)	(0.1532)	(0.1475)
$\Delta\ln(WTI_t)$	-0.0600	-0.0785	-0.0306	-0.0682
	(0.0539)	(0.0573)	(0.0559)	(0.0507)
π^*	0.8520*	0.9976**	0.6349	0.8473**
	(0.4391)	(0.4787)	(0.4311)	(0.4221)
$\Delta\ln(STOCKS_t)$	-0.0603***	-0.0687***	-0.0470*	-0.0632***
	(0.0221)	(0.0210)	(0.0258)	(0.0239)
$\Delta\ln(BRL_t)$	0.4420***	0.5690***	0.3523***	0.3668***
	(0.1165)	(0.1260)	(0.1108)	(0.1148)
Constant	0.3439	0.2947	0.3462	0.3816
	(0.5165)	(0.5502)	(0.5269)	(0.4965)
N	274	274	274	274
R^2	0.09	0.12	0.06	0.09
Adjusted R^2	0.07	0.10	0.04	0.07
F-statistic	5.55	7.74	3.58	4.95
AIC	1 829.13	1 842.74	1 859.28	1 797.14
BIC	1 854.43	1 868.03	1 884.57	1 822.43
p-JB	0.00	0.00	0.00	0.00
Durbin-Watson d	1.77	1.69	1.88	1.67

Source: Elaboration by the authors based on data sources listed in section III.
Notes: This table shows coefficient estimations using Model 1 and equation (1). The first column show results when using as dependent variable the monthly growth rate in our ICO Arabica composite price, the second uses the monthly growth rate in the ICO Brazilian Naturals price, the third uses the monthly growth rate in ICO Colombian Milds price, and the fourth uses the monthly growth rate in Other Milds price. The row called p-value Normal is the p-value for the D'Agostino, Belanger, and D'Agostino (1990) Normal Distribution test of the residuals. Robust standard errors, i.e. Huber (1967) and White (1980, 1982), are in parentheses. Significant at * 10%, ** 5%, *** 1%.

Specification Checks. The last rows in Table 5 shows the Durbin-Watson d statistics for first order autocorrelation that range from 1.67 to 1.88; it also shows the p-value for the D'Agostino, Belanger, and D'Agostino (1990) test and provides evidence against a Normal Distribution of the residuals. Table A2 show variance inflation factors of multicollinearity, that are lower than 1.77 in all cases. It also shows the Dickey-Fuller statistic for the presence of a unit root in each of the variables (both dependent and independent) in the model. The results show that we can reject the null hypothesis of a unit root at all common significance levels, except for the international interest rate. The R^2 range from 0.06 to 0.12, but increases to 0.77 to 0.83 if we control for the spot prices (results are available upon request to the authors). The F-statistics range from 4.95 to 7.74 and are highly significant.

B. Model 2: colombian prices and production (monthly, Jan-1997 to Jun-2020)

This model attempts to bring forward the most important factors correlated to the Colombian coffee prices. We take advantage that the ICO composite price for Colombian Milds consists mostly of coffee grown in Colombia (although Kenya and Tanzania also trade coffee under this category). Moreover, we have data on prices paid to coffee growers from FNC. Therefore, this model attempts to quantify if national shocks occurring in Colombia affect (a) prices at warehouses outside of Colombia and (b) the pricing process by the FNC. We fit the following equation by ordinary least squares (OLS),

$$\Delta\ln(y_t^c) = \alpha + \beta_1\Delta\ln(STOCKS_t) + \beta_2 GS3M_t + \beta_3\Delta\ln(BRL_t) + \beta_4\Delta\ln(COP_t) + \beta_5\Delta\ln(WTI_t) + \beta_7\pi_t^* + \beta_8 i_t + \beta_9\pi_t + \beta_{10}RAIN_t + \beta_{11}TEMP_t + \beta_{12}\Delta\ln(P_t^*) + u_t, (2)$$

where the dependent variable y_t^c in this model is either the Colombian Mild ICO Composite price, the price paid to coffee growers in Colombia, or the Colombian coffee production in month t. We dollarize the prices paid to Colombian coffee growers by dividing the price reported by the FNC by the COP/USD real exchange rate.

Equation (2) includes the same covariates from equation (1), in addition to i_t the Colombian interest rate and π_t the growth rate in the Colombian CPI (inflation). We also add $RAIN_t$ the average cumulative rain and $TEMP_t$ the average temperature in the Colombian territory. When the outcome of interest is the price paid to Colombian coffee growers or the Colombian production, we included P_t^* the ICO Composite Colombian Mild international price. In this context, we use the WTI_t variable as a proxy to represents transportation costs and other processing activities that requires the use of gasoline or diesel. All variables have a monthly frequency. Moreover, we correct standard errors by using a robust covariance matrix (Eicker-Hubert-White).

Table 6 presents results from equation (2). The first column shows results for the ICO Colombian Mild prices, the second for the price paid to coffee growers from FNC, and the third for FNC coffee production. The results in column (1) confirm the results from column (3) of Table 5. We also find that (i) there is no statistically significant effect of national shocks (except for the interest rate) on Colombia Mild ICO prices. Regarding column (2), we find that (ii) the Colombian Milds international price has a *positive* and statistically significant effect at the 1% level on the price that producers receive when they sell their coffee to the FNC. This means that there is a certain degree of pass-through from international markets to national markets, that is below unity (a pass-through of 79.4% of the Colombian Mild price in a given month). A future study could examine how this this pass-through has evolved over time.

Table 6
Determinants of the monthly prices of colombian coffee (Colombian Milds, price paid to Colombian coffee growers) and quantity produced using Model 2

	(1) ICO Price	(2) Producer Price	(3) National Production
i^*	-0.3995*	0.0225	0.1526
	(0.2213)	(0.1285)	(0.8827)
$\Delta \ln(COP_t)$	0.1317	0.7829***	-0.4126
	(0.1613)	(0.1013)	(0.4969)
$\Delta \ln(WTI_t)$	-0.0129	0.0899***	-0.0404
	(0.0539)	(0.0300)	(0.1887)
π^*	0.4338	0.3074	0.1846
	(0.4708)	(0.2958)	(1.6920)
$\Delta \ln(STOCKS_t)$	0.0173	0.0104	-0.0200
	(0.0113)	(0.0167)	(0.0336)
$\Delta \ln(BRL_t)$	0.3492***	0.0195	0.1197
	(0.0956)	(0.0664)	(0.3520)
Temperature	-0.2365	-0.2064	1.5211
	(0.4563)	(0.2269)	(1.5586)
Rain	-0.1469	-0.0520	3.2058***
	(0.2434)	(0.1482)	(0.6297)
π	1.4931	0.9121	-2.7206
	(1.6255)	(0.7538)	(3.5811)
i	-0.7964**	0.1423	0.1144
	(0.3085)	(0.2187)	(1.3394)
$\Delta \ln(P_t^*)$		0.7935***	-0.0631
		(0.1150)	(0.1748)
Constant	6.6470	5.1363	-59.3936
	(10.7952)	(5.3669)	(37.8010)
N	281	281	280
R^2	0.09	0.68	0.12
Adjusted R^2	0.05	0.67	0.08
F-statistic	3.36	15.83	3.85
AIC	1 912.65	1 621.83	2 559.13
BIC	1 952.67	1 665.49	2 602.74
p-value Normal	0.00	0.00	0.00
Durbin Watson d	1.92	2.47	2.16

Source: Elaboration by the authors based on data sources listed in section III.
Notes: This table shows coefficient estimations using Model 2 and equation (2). The first column show results when using as a dependent variable the monthly growth rate in ICO Colombian Mild prices, the second uses the monthly growth rate in the price paid to coffee growers and the third uses the monthly growth rate of the national coffee production. The row called p-value Normal is the p-value for the D'Agostino, Belanger, and D'Agostino (1990) Normal Distribution test of the residuals. Robust standard errors i.e. Huber (1967) and White (1980, 1982), are in parentheses. Significant at * 10%, ** 5%, *** 1%.

Columns (2) and (3) show (iii) a *positive* and statistically significant relationship at the 1% level between the WTI oil price, the COP/USD real and prices paid to Colombian coffee growers by the FNC. This means that an increase in the WTI price, which captures transportation costs and other processing activities that require gasoline or diesel, and an increase (depreciation) in the COP/USD real exchange rate increases the price paid to growers. We find that (iv) monthly rain has a positive and statistically significant relationship at the 1% level with the amount of coffee produced in Colombia in the same month. This means that more rain is linked to more Colombian coffee production. (v) We do not find statistical evidence that national inflation, national interest rate, inventories growth, the BRL/USD real exchange rate and the international interest rate affect prices paid to Colombian coffee growers nor the amount of coffee produced in Colombia.

The coefficient of determination (R^2) in Model 2 is much higher than the R^2 in Model 1 because Model 2 includes the international price as an explanatory variable, while Model 1 does not.

Specification Checks. Table A3 show variance inflation factors of multicollinearity, they are lower than 2. It also shows the Dickey-Fuller statistic for the presence of a unit root in each of the variables (both dependent and independent) in the model. The results show that we can reject the null hypothesis of a unit root at all common significance levels for all variables except for the international interest rate. The F-statistics range from 3.36 (using as dependent variable the Colombian Milds price from ICO without controlling for the international spot price at the ICE) to 15.83 (using as dependent variable the producer price and controlling for the interntional Colombian Milds price from ICO), all F-statistics in this model are highly significant.

C. Model 3: panel data for farm gate prices (annual, panel data, 1979 to 2019)

This model uses the fact that we have access to a rich panel data set from ICO on annual farm gate prices paid to coffee growers, in USD per 100 lb, for all the coffee growing countries. We focus on Latin American coffee growing countries and farm gate prices for Arabica coffee only, and fit the following model using a fixed effects model for panel data:

$$\Delta\ln(p_{it}) = \boldsymbol{\alpha}_i + \sum_{j=1}^{12}\beta_j TEMP_{ijt} + \sum_{j=1}^{12}\gamma_j RAIN_{ijt} + \tau\boldsymbol{X}_{it} + \epsilon_{it}, (3)$$

where p_{it} is the farm gate price at country i during year t, $TEMP_{ijt}$ is the average temperature during month j (January,…, December), $RAIN_{ijt}$ is the cumulative rain during month j (January,…, December). We adopt a novel approach to measure the effect of rain and temperature on farm gate prices that is flexible enough as to identify the effect of weather shocks realization in each month on farm gate prices. This is captured by the terms $\sum_j \beta_j TEMP_{ijt}$ and $\sum_j \gamma_j RAIN_{ijt}$ that measure the average effect of weather realizations by month on farm gate prices.[6] We also included in our covariate vector $\boldsymbol{X}_{it}$ the percentage change in arable land, inflation, percentage change in exchange rate to USD, growth in GDP per capita, population growth, domestic consumption of coffee, coffee end-of-year stocks, coffee exports, coffee production, and yield. We also include a set of country fixed effects ($\boldsymbol{\alpha}_i$) to capture time-invariant characteristics of the countries in our panel. Some of these characteristics include land fertility, the location with respect to the Equator which affects weather, topography, distance to markets and transportation costs, and many other things that affects practices for growing coffee and the biology of the plant itself.

Table 7 shows results from estimating equation (3) using a fixed effects model. All regressions in this table include country fixed effects. The first column of Table 7 estimates all coefficients on equation (3) and shows all those except for the coefficients on rain and temperature (to save space). We find that (i) the growth rate of the GDP per capita has a positive and statistically significant effect at the 5% level on farm gate prices. The coefficient implies that for each additional percentage point in GDP per capita growth, the growth rate of farm gate prices increases by 1.1 percentage points. (ii) We also find a positive and statistically significant effect at the 5% level of inflation on farm gate prices. However, we do not find statistical evidence that any of the other variables, including domestic consumption, stocks at the end of year, exports nor production affects farm gate prices.

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6 Unfortunately, the data sources from Climate Engine only cover rain and temperature for Brazil in a meaningful way since 2014, so most of the data for this country is left out of our estimating sample in the panel data.

Table 7
Determinants of annual farm gate prices using panel data for Latin American countries, 1979-2019 and Model 3

	(1) $\Delta\ln(PP_t)$	(2) $\Delta\ln(PP_t)$	(3) $\Delta\ln(PP_t)$	(4) $\Delta\ln(PP_t)$	(5) $\Delta\ln(PP_t)$
$\Delta\ln(\text{Arable Land}_t)$	-0.6198***		-0.2853		-0.2606**
	(0.1842)		(0.1888)		(0.1068)
π	0.0268***		0.0195***		0.0199***
	(0.0052)		(0.0041)		(0.0046)
$\Delta\ln(\text{Exchange Rate}_t)$	-0.0014		-0.0013		-0.0004
	(0.0013)		(0.0008)		(0.0010)
$\Delta\ln(\text{GDP per capita}_t)$	2.1606***		0.9151**		1.0730***
	(0.3778)		(0.3223)		(0.3257)
$\Delta\ln(\text{Population Growth}_t)$	-0.4256*		-0.1411		-0.0535
	(0.2189)		(0.1019)		(0.0719)
$\Delta\ln(\text{Yield}_t)$	-0.0548	-0.0057			-0.0485
	(0.1449)	(0.0514)			(0.1162)
$\Delta\ln(\text{Consumption}_t)$	0.0331			-0.0161	-0.0234
	(0.0779)			(0.0201)	(0.0150)
$\Delta\ln(\text{Stocks}_t)$	0.0024			-0.0071	-0.0055
	(0.0066)			(0.0047)	(0.0056)
$\Delta\ln(\text{Exports}_t)$	-0.0249			0.0334	0.0388
	(0.0866)			(0.0626)	(0.0627)
$\Delta\ln(\text{Production}_t)$	0.3519***			0.1302*	0.1189*
	(0.0874)			(0.0655)	(0.0636)
N	266	266	266	266	266
R^2	0.24	0.67	0.68	0.68	0.75
Adjusted R^2	0.09	0.64	0.65	0.65	0.68
F-statistic	77.82	739.60	3 940.68	524.52	9 500.21
AIC	2 565.36	2 301.45	2 295.24	2 297.46	2 293.80
BIC	2 723.04	2 376.70	2 384.83	2 383.46	2 487.31
p-value Normal	0.23	0.00	0.00	0.00	0.00
Country F.E.	Yes	Yes	Yes	Yes	Yes
$\boldsymbol{\delta}_i\Delta\ln(P_t^*)$	No	Yes	Yes	Yes	Yes

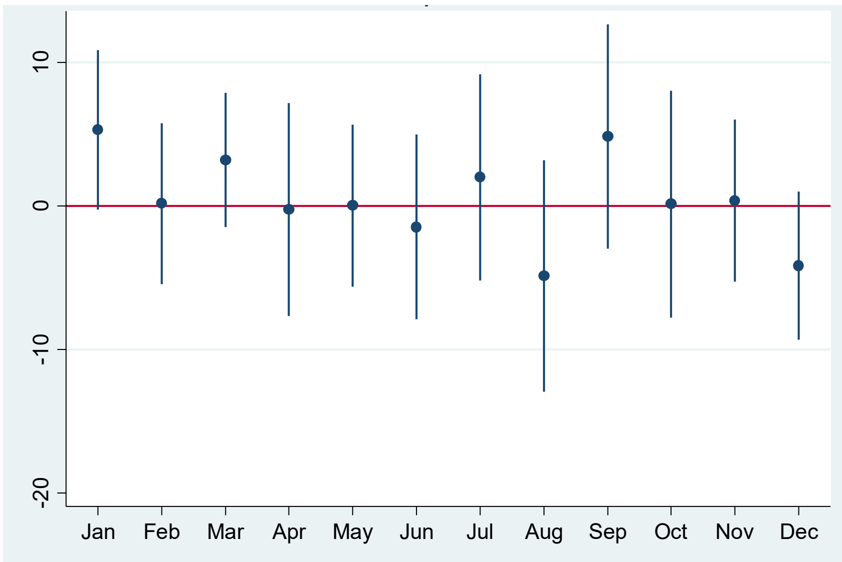
Source: Elaboration by the authors based on data sources listed in section III.
Notes: This table shows coefficient estimations using Model 3 and equation (3), with panel data and a country fixed effects model. The dependent variable is the annual growth rate of the national farm gate prices. The difference between columns (1) and (2) is that column (1) does not control for δ_i Δ ln (P_t^*), the differentiated pass-through by country of the international spot price from the ICE, while column (2) does. Clustered standard errors in parentheses. Significant at * 10%, ** 5%, *** 1%.

Our preferred specification is shown in Column (5) according to the Akaike criterion, the Adjusted R^2, and the F statistic. This specification include an interaction term between country fixed effects and the growth rate of the international spot price from the ICE ($\boldsymbol{\delta}_i\Delta\ln(P_t^*)$) to account for a differentiated pass-through by country. After controlling for the spot price, we now find that (i) the relationship between GDP per capita and farm gate prices still holds, but its elasticity is lower: for each additional percentage point in GDP per capita growth, the growth rate of farm gate prices increases by 1.1 percentage points. (ii) We still find a positive and statistically significant relationship between national inflation and farm gate price.

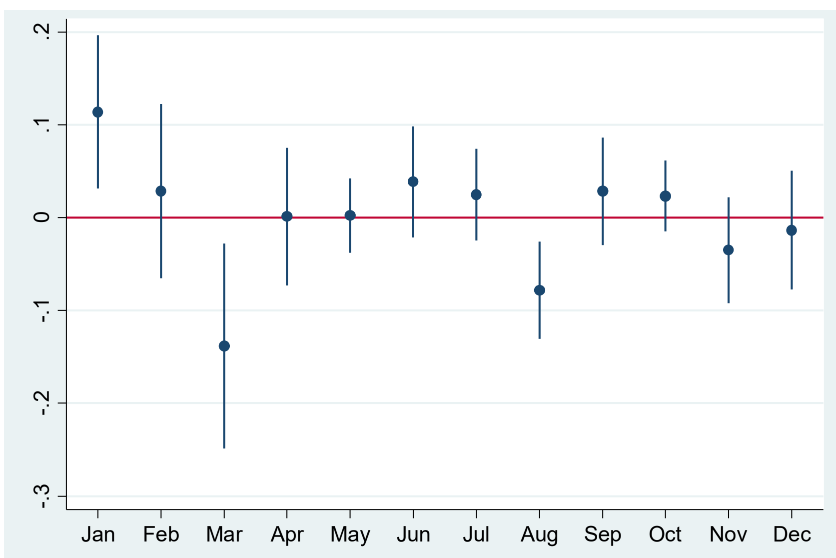
Figure 5 show results for the coefficients, by month, on temperature (the β_j in Panel A) and on rain (the γ_j in Panel B) from our flexible specification with their 95% confidence intervals. According to our model, there is a *positive* and statistically significant relationship at the 10% level between temperature in September and farm gate prices. Regarding rain, we find a *negative* and statistically significant relationship at the 5% level between the amount of rain in March and the farm gate prices.

Figure 5
The effect of temperature and rain on farm gate prices using Model 3

A. Temperature



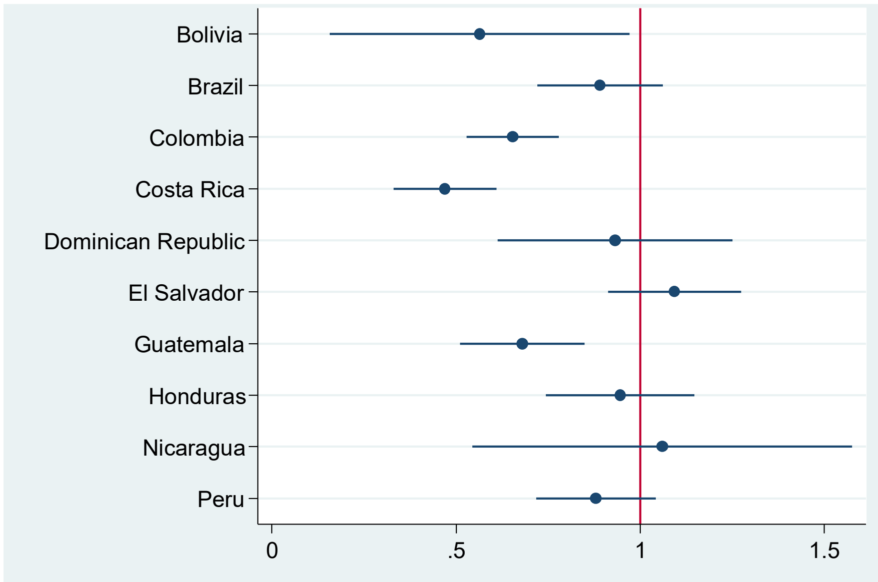
B. Rain



Source: Elaboration by the authors based on data sources listed in section III.
Notes: The dots represents the coefficients and the whiskers are the 95% confidence intervals on the monthly temperature (Panel A) and rain (Panel B) from estimating equation (3), based on robust standard errors.

Figure 6 show the pass-through results by country on the interaction terms $\boldsymbol{\delta}_i \Delta \ln(P_t^*)$. We find evidence of a *positive* and statistically significant pass-through at the 1% level for all countries. We also find that Costa Rica has the lowest pass-through, which is roughly 0.5, while El Salvador has the highest pass-through which is 1.1.

Figure 6
Heterogeneity in the pass-through coefficients from international spot prices to national farm gate prices using Model 3



Source: Elaboration by the authors based on data sources listed in section III.
Notes: The dots represents the coefficients and the whiskers are the 95% confidence intervals for the coefficients $\boldsymbol{\delta}_i \Delta \ln(P_t^*)$ of the heterogeneous pass-through of the international spot price to national farm gate prices, based on robust standard errors.

Specification Checks. Columns (2)-(4) on Table 7 show robustness checks from Model 3. All columns include country fixed effects and the country-specific pass-through $\boldsymbol{\delta}_i \Delta \ln(P_t^*)$. We start our robustness checks by excluding a group of controls variable at a time. Column (2) includes FAO variables only, column (3) includes WDI variables only and column (4) includes PSD USDA variables only. The coefficients on GDP per capita and inflation remain almost similar and significant compared to the results from our preferred model shown in column (5). The F-statistic in this model ranges from 77.82 to 9,500.21 once we control for for $\boldsymbol{\delta}_i \Delta \ln(P_t^*)$, the differentiated pass-through by country of the international spot price from the ICE.

We test for our fixed effects model specification and test for random effects. An F-test does not reject that the fixed effects are jointly equal to zero and the Hausman test provides evidence in favor of using a random effects model. As a result, we estimated a random effects model, but obtained similar results (that are available upon request from the authors). This probably reflects the fact that the market prices do not perceive differences in coffee from different sources.

Table A4 show variance inflation factors of multicollinearity with mixed results, the macroeconomic variables have low Variance Inflation Factors (VIF) and are not correlated, but the VIF for rain is somewhat higher and appear to be moderately correlated, and the VIF for temperature show that they are highly correlated.

V. Discussion and conclusions

This document analyzes the different determinants of Arabica green coffee prices produced by Latin America and Caribbean countries. We use linear regressions of time series to quantify the importance of each of the determinants in explaining Arabica green coffee prices. We consider different prices: International Coffee Organization (ICO) composite prices for Brazilian Naturals, Colombian Milds, and Other Milds; prices paid by the Federación Nacional de Cafeteros de Colombia (FNC) to coffee growers, and farm gate prices by country. The latter allows us to build a balanced panel dataset. We consider a comprehensive set of determinants that include weather shocks and national and international macroeconomic variables that may shift the supply and demand curves and study how these factors influence the price in a reduced form setup.

Our main findings from the ICO Composite model are:

(i) The BRL/USD real exchange rate has a *positive* and statistically significant effect on the growth rate of all four ICO prices, but this effect is bigger for Brazil Naturals;

(ii) The of end-of-month stocks both have a *negative* and statistically significant effect on the growth rate of all four ICO prices considered;

(iii) Inflation in commodity prices have a positive and statistically significant effect on the prices of Brazilian Naturals and Other Milds, but it does not affect the Colombia ICO prices;

(iv) We do not find statistical evidence that the COP/USD real exchange rate, the international interest rate nor the oil price affects ICO prices;

(v) We do not find statistical evidence that national shocks (except for the interest rate) affects Colombia Mild ICO prices.

Our main findings from the Colombian model are:

(i) The Colombian Milds international price have a positive and statistically significant effect on the price paid by FNC to coffee producers;

(ii) The WTI oil price and the COP/USD real exchange rate have a positive and statistically significant effect on prices paid to Colombian coffee growers by the FNC;

(iii) Monthly rain increase the ammount of coffee produced in Colombia;

(iv) We do not find statistical evidence that national inflation, national interest rate, inventories growth, the BRL/USD real exchange rate and the international interest rate affects prices paid to Colombian coffee growers nor the ammount of coffee produced in Colombia.

Our main findings from the farm gate model using panel data are:

(i) The GDP per capita growth rate has a positive and statistically significant effect on farm gate prices;

(ii) National inflation has a positive and statistically significant effect on farm gate prices;

(iii) We do not find statistical evidence that any of the other variables, including domestic consumption, stocks at the end of year, exports nor production affects farm gate prices;

(iv) Temperature in September has a positive and statistically significant effect on farm gate prices;

(v) Rain in March and December has a negative and statistically significant effect on farm gate prices;

These results confirm findings from previous studies. In particular, we find that:

(i) stocks are an important determinant of international coffee prices as in Baker and Menzie (1988), Van Meir (1983), Westcott, Hull, and Green (1984, 1985), Westcott and Hoffman (1999), Goodwin et al. (2001) and Goodwin, Schnepf and Dohlman (2005);

(ii) weather shocks, especially the distribution of rains along the year, are an important determinant of coffee prices, as in Sachs et al. (2019). This highlights the importance of adapting to climate change and developing new coffee varieties that are resistant to droughts, frosts and other extreme weather.

(iii) pass-through rates from international prices to producer prices vary much across countries. This highlights the importance of building price stabilization funds that build-up when prices are above a medium term average but distribute when prices are below that average. Costa Rica is the country with the smallest pass-through rate. It is also the only country in our sample who has an institute (ICAFE) with the authority to reject a coffee transaction between a buyer and a seller in situations when, for example, considers that the price is lower than it should be. This highlights the importance of improving institutional channels that might act as a buffer to fluctuations in the international coffee price. By reducing the exposure of small farmers to high fluctuations in the international coffee price, small farmers will be able to protect themselves against unexpected fluctuations in the price, which provides opportunities to make safer investment decisions.

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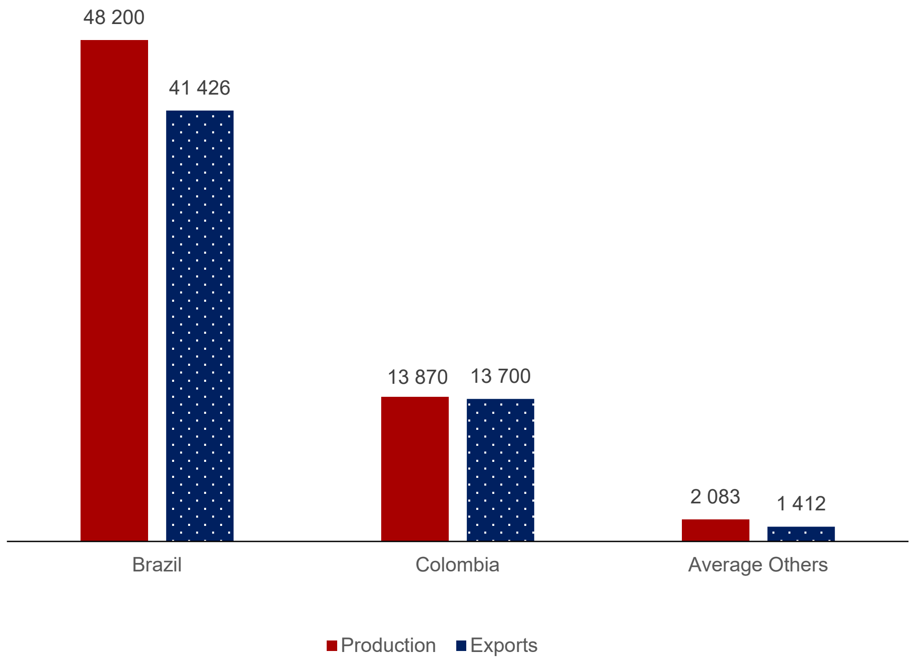
Annex

Figure A1
Arabica green coffee production and exports (in 1,000 60 kg bags) by Latin American and Caribbean (LAC) countries during the 2018/2019 harvest



Source: Elaboration by the authors.
Notes: This graph shows the amount of Arabica production and exports by Brazil and Colombia and the average amount of production and exports by the rest of LAC countries, during the 2018/2019 harvest, in 1,000 60 kg bags, according to the Production, Supply and Distribution (PSA) of USDA.

Table A1
Summary of the literature, methods and significant variables affecting coffee prices

Panel A: supply

Variable	Methodology	Source
Loan rate	OLS with logs, OLS and hierarchical Bayesian method	Westcott and Hoffman (1999), Sachs et al. (2020)
Input prices	Theory, OLS and hierarchical Bayesian method	Tomek and Kaiser (2014), Sachs et al. (2020)
Prices of commodities competing for the same resources or factors of production	Theory, ECM, first difference model, OLS and hierarchical Bayesian	Tomek and Kaiser (2014), Cooke and Robles (2009), Sachs et al. (2020)
Prices of joint products	Theory, OLS and hierarchical Bayesian method	Tomek and Kaiser (2014), Sachs et al. (2020)
Changes in technology	Theory, ECM and first difference model	Tomek and Kaiser (2014), Cooke and Robles (2009)
Institutional factors	Theory, ECM, first difference model, OLS and hierarchical Bayesian	Tomek and Kaiser (2014), Sachs et al. (2020), Cooke and Robles (2009)
Input prices	Theory, descriptive data, ECM, first difference model, OLS and hierarchical Bayesian method	Cooke and Robles (2009), Sachs et al. (2020), FAO (2009)
Climatic condicions	Theory, descriptive data, ECM, first difference model, OLS and hierarchical Bayesian method	Cooke and Robles (2009), FAO (2009), Sachs et al. (2020)
Exchange rate	ECM, first difference model, OLS and hierarchical Bayesian method	Cooke and Robles (2009), Sachs et al. (2020)
Administrative costs financial costs, administration labor, legal costs and certification costs)	OLS and hierarchical Bayesian method	Sachs et al. (2020)
Land area	OLS and hierarchical Bayesian method	Sachs et al. (2020)
Yield per hectare	OLS and hierarchical Bayesian method	Sachs et al. (2020)
Inflation	OLS and hierarchical Bayesian method	Sachs et al. (2020)
Type of cofee farm (diversified, organic or specialty-focused)	OLS and hierarchical Bayesian method	Sachs et al. (2020)
Social and environmental externalities	OLS and hierarchical Bayesian method	Sachs et al. (2020)

Panel B: demand

Variable	Methodology	Source
Population size	Descriptive data, OLS and hierarchical Bayesian method	Tomek and Kaiser (2014), FAO (2009), Sachs et al. (2020)
Income	OLS, hierarchical Bayesian, ECM and first difference model	Tomek and Kaiser (2014), Cooke and Robles (2009), FAO (2009), Sachs et al. (2020)
Consumer tastes and preferences	Theory, descriptive data, ECM and first difference model	Tomek and Kaiser (2014), Cooke and Robles (2009), FAO (2009)
Oil, Ethanol/biofuels prices and use	Theory, descriptive data, ECM and first difference model	Cooke and Robles (2009), FAO (2009)
Activity in futures market	ECM and first difference model	Cooke and Robles (2009)
Prices of complementary products	Theory and descriptive data	FAO (2009)
Institutional factors	Theory and descriptive data	FAO (2009)
Wheather	OLS and hierarchical Bayesian method	Sachs et al. (2020)
Monopsonistic buyer	OLS and hierarchical Bayesian method	Sachs et al. (2020)

Panel C: stocks

Variable	Methodology	Source
Stocks to use	General equilibrium model, OLS and Gradual Switching Model	Van Meir (1983), Baker and Menzie (1988), Westcott, Hull, and Green (1984, 1985), Westcott and Hoffman (1999)
Ratio of publicly held stocks owned by the Government	OLS with logs	Westcott and Hoffman (1999)

Source: Elaboration by the authors.
Note: ECM stands for Error Correction Model.

Table A2
Variance Inflation Factors (VIF) and Dickey-Fuller statistics for the variables in Model 1

	(1) VIF	(2) D-F
$\Delta\ln(WTI_t)$	1.77	-12.797***
π^*	1.73	-12.229***
$\Delta\ln(BRL_t)$	1.22	-12.210***
$\Delta\ln(COP_t)$	1.20	-12.056***
$\Delta\ln(STOCKS_t)$	1.05	-16.547***
i_t^*	1.05	-1.308
$\Delta\ln(\mathrm{P}_t^{\mathrm{Arabica}})$		-14.536***
$\Delta\ln(\mathrm{P}_t^{\mathrm{Brazil}})$		-13.846***
$\Delta\ln(\mathrm{P}_t^{\mathrm{Colombia}})$		-15.852***
$\Delta\ln(\mathrm{P}_t^{\mathrm{Others}})$		-13.867***
Mean VIF	1.34	

Source: Elaboration by the authors.
Note: Significant at * 10%, ** 5%, *** 1%.

Table A3
Variance Inflation Factors (VIF) and Dickey-Fuller statistics for the variables in Model 2

Variable	(1)	(2) VIF	(3)	(4) D-F
	ICO	Producer	Production	
$\Delta\ln(WTI_t)$	1.79	1.79	1.79	-12.907***
π	1.75	1.75	1.76	-12.312***
π^*	1.54	1.55	1.54	-8.162***
i^*	1.28	1.29	1.29	-1.257
Rain_t	1.28	1.28	1.28	-10.296***
$\mathrm{Temperature}_t$	1.22	1.22	1.22	-6.909***
$\Delta\ln(BRL_t)$	1.17	1.21	1.20	-11.532***
$\Delta\ln(COP_t)$	1.20	1.20	1.20	-12.181***
$\Delta\ln(P_t^*)$		1.10	1.10	-16.272***
$\Delta\ln(STOCKS_t)$	1.06	1.07	1.07	-18.129***
i	1.02	1.03	1.03	-18.958***
$\Delta\ln(Producer\ Price_t)$				-18.694***
$\Delta\ln(Production_t)$				-24.029***
Mean VIF	1.33	1.32	1.32	

Source: Elaboration by the authors.
Note: Significant at * 10%, ** 5%, *** 1%.

Table A4
Variance Inflation Factors (VIF) for the variables in Model 3

	(1) $\Delta\ln(PP_t)$	(2) $\Delta\ln(PP_t)$
$\Delta\ln(\mathrm{Arable\ Land}_t)$	1.29	1.32
π	1.25	1.25
$\Delta\ln(\mathrm{Exchange\ Rate}_t)$	1.28	1.30
$\Delta\ln(\mathrm{GDP\ per\ capita}_t)$	1.39	1.47
$\Delta\ln(\mathrm{Population\ Growth}_t)$	1.16	1.17
$\Delta\ln(\mathrm{Yield}_t)$	1.33	1.36
$\Delta\ln(\mathrm{Consumption}_t)$	1.17	1.25
$\Delta\ln(\mathrm{Stocks}_t)$	1.43	1.69
$\Delta\ln(\mathrm{Exports}_t)$	1.75	1.78
$\Delta\ln(\mathrm{Production}_t)$	1.95	2.17

	(1) $\Delta \ln(PP_t)$	(2) $\Delta \ln(PP_t)$
Temperature		
January	33.58	34.16
February	48.70	49.35
March	34.60	35.30
April	79.76	84.10
May	65.51	67.46
June	94.06	96.73
July	92.64	94.86
August	68.77	70.41
September	55.04	59.72
October	44.01	46.82
November	30.52	31.23
December	29.04	30.50
Rain		
January	9.28	9.45
February	9.76	9.87
March	15.55	15.71
April	10.87	11.10
May	4.85	4.92
June	9.56	9.75
July	8.39	9.08
August	8.55	8.86
September	8.24	8.52
October	4.71	4.83
November	5.62	5.86
December	5.64	5.98
Mean VIF	31.09	26.32

Source: Elaboration by the authors.

Table A5
Classification of exporter countries by type of coffee according to ICO

Variety		Latin America and Caribbean	Africa and Asia
Arabica	Colombian Milds	Colombia.	Kenya and Tanzania.
	Other Milds	Bolivia (P.S of), Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Jamaica, México, Nicaragua, Panama, Peru and Venezuela.	Burundi, India, Malawi, Nepal, Papua New Guinea, Rwanda, Zambia and Zimbabwe.
	Brazilian Naturals	Brazil and Paraguay.	Ethiopia, Timor-Leste and Yemen.
Robusta	Robustas		Angola, Benin, Cameroon, Central African Republic, Congo Dem. Rep. of, Congo Rep., Côte d'Ivoire, Equatorial Guinea, Gabon, Ghana, Guinea, Guyana, Indonesia, Lao, People's Dem. Rep., Liberia, Madagascar, Nigeria, Philippines, Sierra Leone, Sri Lanka, Thailand, Togo, Trinidad & Tobago, Uganda and Vietnam.

Source: Elaboration by the authors based on [online] http://www.ico.org/documents/cy2014-15/sc-59e-data-concepts.pdf.

This paper analyses the determinants of arabica green coffee prices in Latin America using a time series analysis and panel data methodology. A panel of different coffee prices was constructed based on International Coffee Organization composite prices for Brazilian naturals, Colombian milds and other milds, prices paid to farmers by the Colombian Coffee Growers' Federation (FNC) and farm gate prices by country. The results confirm that stocks are key determinants of international coffee prices; the same is true of real exchange rates of Brazilian and Colombian currencies against the United States dollar, inflation, oil prices and weather-related shocks, especially annual rainfall distribution. In addition, the pass-through from international prices to producer prices varies across countries. These findings highlight the importance of climate change adaptation and of breeding coffee varieties resistant to droughts, frosts and extreme weather. Lastly, the study underlines each country's need for institutional trade and price stabilization arrangements.

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