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Price dynamics and interaction of international cash crop and staple food markets

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Kurzfassung

Plötzliche Änderungen in globalen Grundnahrungsmittelpreisen tragen häufig zu wirtschaftlicher Instabilität in vom Import abhängigen Entwicklungsländern (NFIDC) bei. Volkwirtschaftliche Theorien besagen, dass Länder mit instabilen Leistungsbilanzen aufgrund schwankender Exporterlöse und/oder Lebensmittelimportausgaben, versuchen sollten, Sparguthaben aufzubauen um ihren Verbrauch im Zeitablauf glätten zu können. In vielen einkommensschwachen NFIDCs sind die Sparmöglichkeiten jedoch durch unzureichende inländische Finanzsysteme begrenzt. Diese Länder verfügen wegen ihres hohen Ausfallrisikos auch nur über eingeschränkte Möglichkeiten Kredite von den Weltmärkten zur Finanzierung von Lebensmittelimporten aufzunehmen.

Eine Analyse der Preise für Grundnahrungsmittel und Exportprodukte (cash crops) bestätigt, dass sich diese tendenziell synchron bewegen. Dies zeigte sich insbesondere in den Jahren 2007-2011, als die Rohstoffpreise auf einem hohen Niveau schwankten. Dadurch könnten Exporteinnahmen aus dem Verkauf von Exportprodukten als Absicherung gegen einen Anstieg der Importausgaben für Grundnahrungsmittel genutzt werden und somit die Instabilität der Leistungsbilanz verringern. Unterstützend wirkt, dass die internationale Nachfrage nach Agrarrohstoffen im Allgemeinen unelastisch ist, und somit die Preisbewegungen die Mengenschwankungen übersteigen.

In dieser Arbeit werden die Beziehungen zwischen den Preisen für Exportprodukte und Grundnahrungsmittel in Bezug auf ihre Höhe und Schwankungen untersucht. Der Fokus dieser Forschung liegt dabei auf der Preiskomponente der Exporteinnahmen eines Landes. Diese Studie wendet eine Reihe ökonometrischer Methoden an, darunter die GARCH-Schätzung, die Wavelet-Analyse, einen Volatilitäts-Spillover-Index, die allgemeine Varianzzerlegung der Vorhersagefehler und die Bayes'sche Modellmittelung um die Beziehungen zwischen den internationalen Preisen wichtiger Exportprdukte und Grundnahrungsmittel zu beschreiben.

Die Ergebnisse zeigen, dass die Stärke der Wechselwirkungen zwischen den Preisen für Exportprodukte und Grundnahrungsmittel erheblich variiert. Im Zeitraum 2007-2011 jedoch waren sie deutlich und positiv, was mit hohen Rohstoffpreisen und Problemen auf den Finanzmärkten zu begründen ist. Die Ergebnisse deuten ebenfalls darauf hin, dass die Preise für Grundnahrungsmittel die der Exportprodukte eher lang- als kurzfristig beeinflussen. Ausserdem bestätigt eine Analyse des internationalen Zuckermarktes, unter Verwendung der Bayes'schen Modellmittelung, die Rolle der Grundnahrungsmittelpreise als bestimmenden Faktor der internationalen Referenzpreise für Zucker.

Eine positive bedingte Korrelation zwischen den Preisen für Exportprodukte und Grundnahrungsmittel bedeutet, dass die Regierungen der NFIDCs ihren Finanzbedarf besser einschätzen können, indem sie die Einnahmen aus Lebensmittelexporten den Ausgaben für die Einfuhr von Grundnahrungmitteln gegenüberstellen. Globale Preisinformationen für

Grundnahrungsmittel können auch bei der Konzeption und Planung von Investitionen im Exportproduktsektor Verwendung finden.

Abstract

For a number of net food importing developing countries (NFIDCs), abrupt changes in international staple food prices constitute an important source of macroeconomic instability. Theory suggests that in the face of instable current accounts, due to relatively volatile export earnings and/or food import bills, agents should seek to boost savings, a move that enables smoothing consumption over time. Yet, the ability to increase the level of savings is rather limited in many poor NFIDCs, mainly due to weak domestic financial systems. Their capacity to borrow funds from world markets to finance food imports is also limited because of generally elevated levels of default risks.

A casual review of staple foods and cash crops price series shows that they tend to display a synchronized behavior. This was particularly evident during 2007-2011, corresponding to the period of high and volatile commodity prices. This coordinated price movement means that export revenues, from the sales of cash crops that many NFIDCs rely on, could act as a good hedge against surges in food import bills, and hence, contribute to reducing current account instability. This is because international demand for agricultural commodities is generally inelastic, implying that movements in prices outweigh those of quantities.

This thesis explores the relationship between cash crop and staple food prices by examining co-movements and dynamics in terms of level and volatility. While movements in quantities together with prices determine the direction and magnitude of export earnings, the focus of this research is exclusively on the price component of the equation, given its relative importance. This study applies a series of econometric techniques, including GARCH estimation, wavelet analysis, volatility spillover index, general forecast error variance decomposition, and Bayesian model averaging, to characterize the interdependence between a selection of major international cash crop and staple food price series.

Results show that the intensity of interaction between cash crop and staple food quotations varies considerably, but is generally positive and stronger during the period 2007-2011 associated with high commodity prices and financial market stress. Results also indicate that the level of co-movement and volatility linkages are strongest at lower frequencies (i.e. longer run) than at higher time scales (i.e. short run), with information running from staple food to the cash crop markets. Finally, an analysis of the international sugar market, using a Bayesian model averaging technique, confirms the importance of staple food prices as key determinants of international sugar quotations.

Positive conditional correlation between cash crop and staple food markets means that Governments of NFIDCs can evaluate more accurately their financial needs in the face of current account imbalances due to import bills by taking into consideration the fact that revenues from cash crop exports can reduce funding requirements, and hence borrowing costs. They can also use price information relevant to international staple foods in the design and planning of investment strategies for the cash crop sub-sector.

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Abbreviations

ADF	Augmented Dickey-Fuller
AIC	Akaike information criterion
ARCH	Autoregressive Conditional Heteroscedasticity
BMA	Bayesian model averaging
CCC	Constant Conditional Correlation
CWT	Continuous Wavelet Transform
DCC	Dynamic Conditional Correlation
DWT	Discrete Wavelet Transform
FAO	Food and Agriculture Organization of the United Nations
FEVD	Forecast Error Variance Decomposition
GARCH	General Autoregressive Conditional Heteroscedasticity
GFEV	Generalized forecast error variance
HFCS	High fructose corn syrup
LIFDCs	Low Income Food Deficit Developing Countries
MCMC	Markov Chain Monte Carlo
MRA	Multiresolution Analysis
NFIDCs	Net Food Importing Developing Countries
OLS	Ordinary least squares
PIP	Posterior inclusion probability
PMP	Posterior model probability
PP	Phillips-Perron
RMSPEs	Root mean square prediction errors
RSPEs	Root square prediction errors
RW	Random walk
SIC	Schwarz information criterion
UIP	Unit information prior
VAR	Vector Autoregression
VCM	Variance contribution matrix
VMA	Vector moving average

Chapter 1

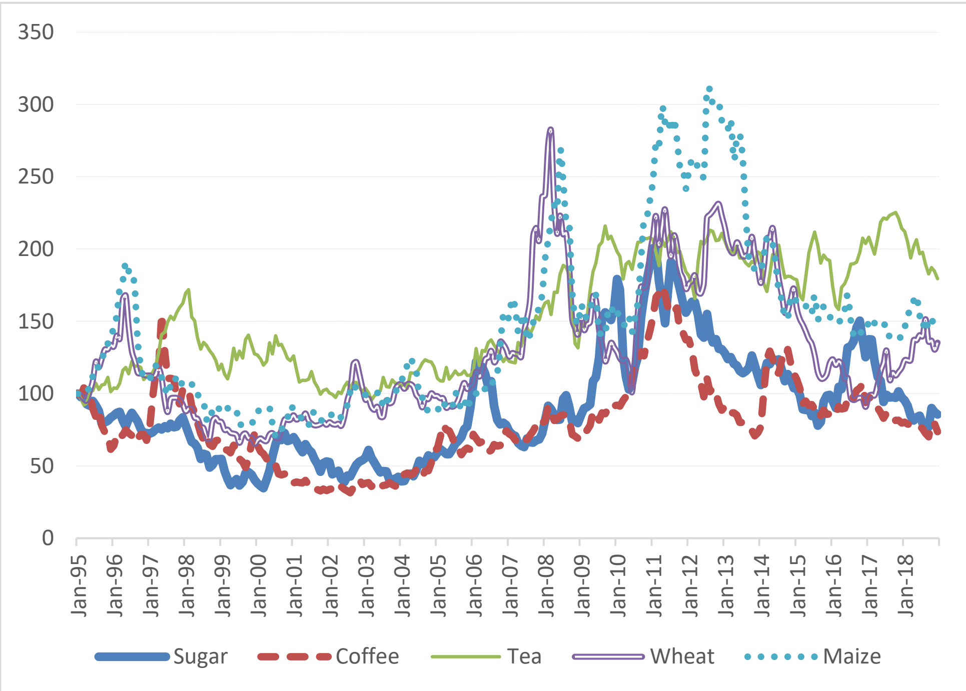
Introduction and overview of the thesis

1.1 Introduction and motivation

In the midst of the unfolding world food crisis (2007-2011), commentators and observers contended that increasing staple food prices threatened food security and the economic welfare of poor developing countries. The concerns were legitimate when considering the economic evidence. First, many of these countries were net food importers, which implied that changes in staple food prices required higher import costs. Between 2006 and 2008, the world food import bill was estimated to have reached a record level of 1 trillion dollar (FAO, 2009). Second, food expenditure accounted for the largest share of total household purchases for net food importing developing countries (NFIDCs), as opposed to households in developed countries where that share was relatively limited (e.g. 9.6 percent in the United States (USDA, 2016)). Third, transactions in international staple food often take place in hard currencies, namely the United States dollar (USD), and that meant if the cost of food were to remain elevated for a protracted period, net food importing developing countries with inadequate foreign currency reserves would not be able to sustain imports (Independent Evaluation Group, 2013).

Concomitant with an inflationary global food price environment, the market value of the commodities that many net food importing developing countries relied on for export earnings was also on the rise (see Figure 1.1). Interestingly, this fact did not benefit from similar wide spread media coverage. Indeed, aside from increasing international energy and metal quotations, world cash crop prices were also fluctuating around an upward trend. In several instances, increases in cash crop export earnings were sufficient to partially, or fully, offset the surge in food prices. For Kenya, wheat import cost went up by 39 percent between 2007 and 2008, while at the same time tea export earnings increased by 33 percent. Similarly, in Uganda, coffee export earnings rose by 61 percent while import costs of food and animal products grew by 9 percent. As such, terms of trade in favor of cash crop exporting countries helped compensate for some of the fallouts resulting from higher food prices (Hossain and Green, 2011).

Figure 1.1: International prices for a selection of cash crop and staple food products



Note: Price refer to ICE No. 11 for sugar, ICE Other mild Arabicas for coffee, average auction prices for tea, US No. 2 for wheat, and US No. 2 for maize.

A question that emerges is whether the simultaneous increase in cash crop and international staple food prices between 2007 and 2012 is mere coincidence or the result of some underlying structure that is worth exploring. This question guides the overall objective of this research by examining the interaction effects and possible linkages between both commodity sub-groups in terms of volatility and level aspects. No doubt, there is a great deal of research that looks at the interaction of cash crops and staple foods, but these studies mostly focus on exploring the economic trade-off that emanates from resource allocation at the farm or national level. There are also several studies that discuss the contribution of cash crops to food security, economic development, value chain upgrading, and poverty alleviation. Analysis examining the interaction between these commodities from an international level perspective is, however, relatively limited despite its implication on net food importing developing countries' balance of payments and commodity policy. The present thesis contributes to filling this research gap, focusing on some of the facets that govern the relationship between cash crop and staple food prices. It should be noted, however, while movements in quantities together with prices determine the direction and magnitude of export earnings and food import costs, the emphasis in this research is exclusively on the price component of the equation amid its relative importance. Research shows that international markets for agricultural commodities (including cash crops) are generally inelastic, meaning that changes in prices outweigh those of quantities (FAO, 2004).

1.2 The importance of the cash crop sub-sector

As mentioned previously, many developing countries rely on the production and export of cash crops such as coffee, cocoa, tea, and sugar, as a basis for economic and rural development. Cash crop export earnings bring in much needed hard currency that allows the procurement of food imports from the world markets. Given that international transactions of agricultural products often take place mostly in USD, and not in local currencies, net food importing country are drawn to manage the amount of foreign currency reserves in order to sustain imports. That is the reason many Governments in developing countries provide support to sectors of the economy that contribute to building foreign currency stocks. The cash crop export sector is often a significant provider of hard currency and can act as an automatic consumption smoothing mechanism. As can be seen in Table 1.1, despite the fact that the contribution of cash crop exports to total agricultural exports and to total merchandise exports declined between 1997 and 2017, the shares remained relatively significant.

Table 1.1: An illustration of the contribution of cash crop exports

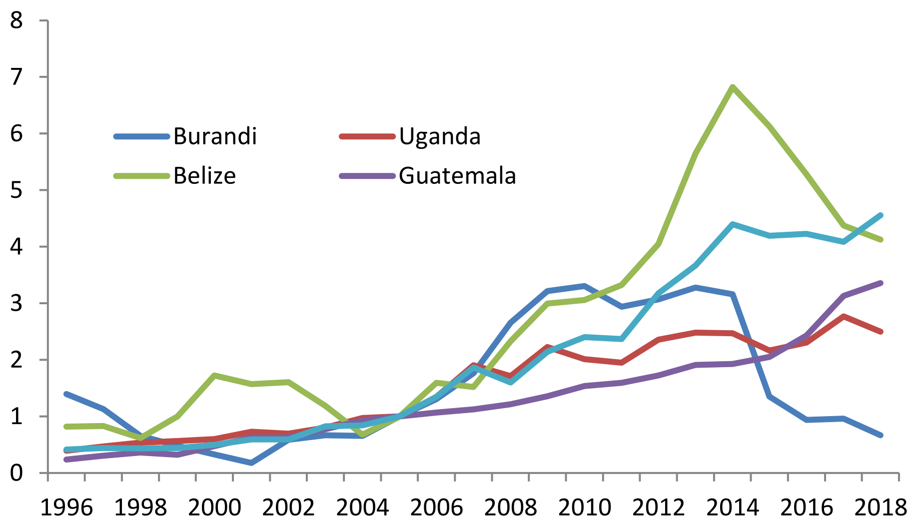
	Tropical beverage crops, fruits and sugar[1/] as a percentage of total agricultural products			**Tropical beverage crops, fruits and sugar[1/] as a percentage of total merchandise trade**		
	1997	**2007**	**2017**	**1997**	**2007**	**2017**
Burundi	99.5	93.8	72.8	66.7	89.0	35.1
Belize	59.6	43.5	66.0	45.5	24.3	27.8
Uganda	78.9	48.1	48.1	55.3	19.2	26.9
Kenya	61.9	39.8	48.2	34.8	21.3	28.8
Guatemala	66.9	45.9	44.6	41.7	18.1	21.7
Ethiopia	77.7	42.4	42.5	65.3	33.9	29.8
Eswatini	52.0	71.6	67.4	22.3	6.5	16.8
Côte d'Ivoire	70.7	51.4	46.5	40.9	21.1	31.6
Costa Rica	69.2	56.7	53.0	27.3	15.7	27.2
Malawi	16.5	16.1	14.2	15.4	14.8	12.2
Cameroon	60.7	55.5	53.5	15.2	10.1	15.7
Sri Lanka	66.6	45.5	51.4	15.8	7.1	13.4

1/ Includes tea, coffee, and cocoa, 2/ Includes bananas and pineapples

Source: FAO

For example, in Burundi, cash crop export accounted for 73 percent of agricultural export and 35 percent of the total merchandize trade of the country in 2017. Coffee accounts for 90 percent of agricultural export in that country. Similar observation can be made for Belize, Uganda, and Kenya, among others. The contribution of cash crops is not only limited to attracting foreign currency, but it also enables governments to strengthen their fiscal position as a result of taxes levied on exports. Figure 1.2 shows that during the recent food crisis episode, total reserves, excluding gold, for a sample of cash crop exporting developing countries rose, reflecting the increase in earnings underpinned by higher cash crop returns. When world prices of cash crops go up, it is often associated with greater export earnings, because of the inelastic nature of cash crop markets (see Figure 1.3). We should also note that the contribution of cash crops goes beyond its effects on the balance of payments, as it induces positive outcomes at the microeconomic level as well. The sector is a provider of employment opportunities at the farm and various stages of the value chain, including the processing and transportation sectors. Most importantly, the proceeds from cash crops allow smallholders to access basic foods as well as other products and services from their local markets (FAO, 2016).

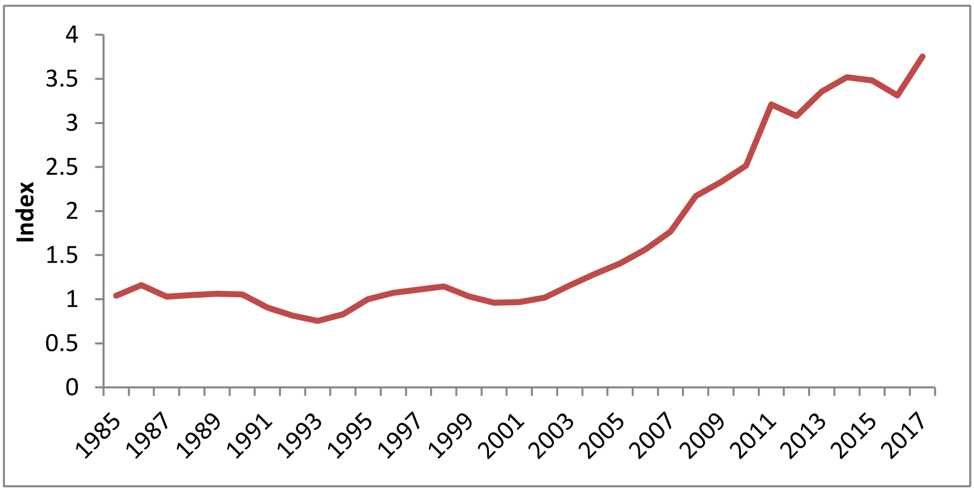
Figure 1.2: Total reserves excluding gold, US Dollars (index 2005=1)



Source: IMF

There are a couple of reasons that motivate the study of the interdependence between cash crop and staple food prices from a global perspective, as opposed to carrying out a research at the farm or national level. First, knowing that cash crop and staple food prices exhibit similar stochastic behavior can help net food importing developing countries forecast foreign currency reserve needs more accurately. Positive correlation means that when international food prices increase, it is likely that cash crop export earnings will increase as well. Second, cash crop exporting countries that participate in hedging through futures markets can take into account movements in staple futures prices in their hedging strategies. With staple food and cash crop prices moving together, knowing, for instance, that the market expects futures prices of staples to rise, can enable cash crop exporting countries to consider reducing the volume of hedged cash crops, and hence save on costs associated with futures market transactions. Third, assuming that international prices transmit to domestic markets, the fact that cash crop and staple food prices are correlated means that crop diversification at the smallholder farm level is unlikely to lower price risks. On the contrary, smallholders holding a comparative advantage in the production of cash crops may be better off specializing in these crops and using the earnings to buy food from local markets.

Figure 1.3: Evolution of agricultural export earnings of net food importing developing countries (1995=1)



Source: FAO

The apparent positive correlation between cash crop and staple food prices is rather challenging to explain on the basis of market fundamentals only, at least in the short run. This is because the substitution possibilities in consumption and production between cash and staple food crops in the physical markets are rather limited and therefore cannot justify the extent of price correlation. Still, macroeconomic and financial related factors (e.g. interest rates, GDP growth, value of USD currency, etc.), weather shocks affecting major producers of both commodity groups, and movements in energy prices constitute some of the common factors that can explain correlated price movements in the short term. Another factor that can be responsible for correlated price movements, and which has received a lot of attention since the recent food crisis, is the influence of institutional investors seeking to diversify their portfolio assets away from equities. The latter is commonly associated with the financialization phenomenon of commodities and can justify short term co-movements between seemingly unrelated futures price quotations such as those of wheat and cocoa (Grosche and Heckelei, 2016). Futures prices, which are negotiated at markets like the Intercontinental Exchange (ICE) and the Chicago Board of Trade (CBOT), are important because they are often considered as the world price benchmark for commodities. As such, they can influence border prices, and hence, the value of import bills and export earnings (Chen et al., 2009). Empirical evidence dates the start of the financialization of commodity futures around 2004 (Tang and Xiong, 2012; Basak and Pavlova, 2016). Holdings by institutional investors increased from USD 15 billion in 2003 to more than USD 200 billion in 2008. Institutional investors often take positions in the commodities through commodity futures index such as the S&P Commodity index (SPCI), the Goldman Sachs Commodity Index (GSCI), or the Dow Jones UBS Commodity Index (DJ-UBS) (Bohl et al., 2013).

The creation of exchange-traded products (ETPs) linked to commodity indices, the spread of electronic trading, falling financial transactions costs, and readily accessible information about commodity markets contribute to facilitating access to a broad range of commodity markets. Because investors hold both equities and commodities in their portfolio, these two asset classes become intertwined, as shown by a growing body of empirical evidence (Basak and Pavlova, 2016). Shocks in equity markets can 'spill over' to commodity markets, and vice-versa, as investors adjust their asset portfolios. Consequently, commodity sub-groups, such as cash crops and staple foods, co-move not only with one another but also with equity markets because of financial investment activities.

The effect of financialization on commodity market remains, however, a subject of ongoing debate and research. For instance, studies by Irwin and Sanders (2011), Fattouh et al. (2012), and Hamilton and Wu (2015) argue against the view that institutional investors, and speculators in particular, have any impact of commodity futures prices. Generally, they view market fundamentals as the primary cause underlying the recent boom and bust in commodity futures markets. Concerning the price co-movement between staple foods and cash crops, it is difficult to attribute it solely to fundamentals, at least in the short run, as discussed earlier. In the long run, however, changes in factor input costs, most notably energy and labor cost, technological improvements, and changes in agricultural trade policies could play a role in driving co-movement (Pingali and Rosegrant, 1995), as it is illustrated in the next section. We should note, however, that the overall objective of this research is not to assign causal effects behind the cash crop-staple food price movement but rather to estimate the magnitude of the interdependence and unveil the nature of the price dynamics.

1.3 Some hypothesis explaining the co-movement between staple and cash crop prices

As previously mentioned, the co-movement between cash crop prices and staple food prices can be explained by common reaction patterns to global macroeconomic shocks (Frankel, 2006) as well as financialization phenomenon of commodity markets. In this section, we briefly examine five other possible drivers of co-movement, namely, 1) substitution possibilities in production and consumption, 2) changes in the cost of labor and other factors of production, 3) technological improvements, 4) trade and domestic policies, and 5) commodity investment and market regulations. Figure A3.2

summarizes the discussion in this section about the linkages between cash crop and staple food prices.

1.3.1 *Substitution possibilities in production and consumption*

Substitution possibilities in production between staple foods and cash crops at the farm level can cause prices to correlate. Farmers can decide to change the output mix in response to changes in relative prices of farm products. Hence, as food prices decline relative to cash crops, more resources are likely to go into cash crop production within what is permissible in terms of market and agro-ecological characteristics. In practice, however, substitution in production is rather limited, especially as farming systems become more market oriented and diversified. Quiroz and Valdes (1994) note that the larger the positive correlation between commodity prices, the less profitable farm diversification becomes.

In the case of commercially oriented farms, because of the necessity to invest in product specific assets, the long gestation period (e.g. coffee, cocoa, tea), and the specific skills and techniques required, diversifying the farm output mix becomes less viable (Pingali and Rosegrant, 1995). Commercial estates are therefore less likely to substitute staple food production for cash crop production when food prices increase relative to perennial crop prices, at least in the short to medium term. Similarly, for subsistence farms, the extent of substitution possibilities in production is also weak. This is because subsistence farmers rely on non-traded inputs (e.g. family labor) and have limited access to product and factor input markets. For semi-commercial farms, some degree of substitution can be expected to occur but staple food production remains the dominant farm household enterprise. Often, semi-commercial farmers choose to substitute some level of cash crop production for food production to gain access to credit, fertilizers, and other factor input that are made available as part of a contract arrangement with the cash crop processor (von Braun, 1995). Likewise, substitution possibilities in consumption between cash crop and staple food crops are rather limited. An increase in the price of rice is not an indication that a surge in coffee consumption is likely to take place. That is, the assumption of separability applies between both commodity sub-groups.

1.3.2 *Changes in the cost of factors of production*

When food prices increase, the cost of living for agricultural laborers goes up as well because of the importance of food expenditure in household budgets. As it is often the case in rural areas of developing countries, higher food inflation raises labor costs and discourages production, which then creates an upward pressure on cash crop prices (Pingali and Rosegrant, 1995). Also, higher cash crop prices tend to lead to increased labor demand for cash crop production, raising the opportunity cost of food production. The transmission of labor cost changes between staple foods and cash crops constitutes a channel through which price shocks can filter from one market to another generating positive co-movement between prices. This channel of transmission is also relevant for other factor of production common to both commodity sub-groups. For example, a surge in food prices can create an increase in the demand for fertilizers, land, water, capital, boosting the value of these inputs, particularly when rural input markets are inflexible. Hence, changes in factor input costs, in particular labor costs, create a positive correlation between food and cash crop prices.

1.3.3 *Technology and new crops*

Technology improvements that boost total factor productivity can affect agricultural input and output markets. In the case where the new technology is non-commodity specific, such as precision farming technologies, it is expected that both cash and food crops benefit as productivity increases. This leads to correlated changes in output prices. If, on the other hand, the new technology is commodity specific, such as the introduction of an improved cash crop variety, or an innovative agronomic practice, it can end up altering the farm input mix for cash crop production. Changes in the use of inputs will affect their values, at least in the short term, and spill over to the staple food crop production and prices.

Also, the introduction of a new farm enterprise in a region can prompt a shift in resource allocation away from the regional traditional crops. Often, the construction of a road linking a rural area with other regional markets can motivate local farmers, or outside investors, to introduce new crops. When the additional crop is a cash crop, then it will bid up the cost of factors of production, including for staples, as demand for input increases (Pingali and Rosegrant, 1995).

1.3.4 *Trade and domestic policies*

The introduction of non-commodity specific domestic, regional, and international trade policies can generate price correlation among agricultural markets. Even in the case where these agreements cover non-agricultural sectors, they may have second round effects on agriculture output and input markets. Non-commodity specific trade policies cover a full set of instruments, ranging from border measures - e.g. import tariffs, tariff-rate-quotas, export taxes, etc. - to non-tariff-measures. The implementation of these policies can change the value of production factors, aside from altering the relative prices between agricultural products. Input cost changes can then be transmitted to cash crop and staple food prices, causing price co-movements.

Specific-commodity trade measures, such as a reduction of export levies for cash crops, can stimulate cash crop commercialization, biding up demand for factor inputs and raising their market value, particularly when input markets are relatively inflexible (Pingali and Rosegrant, 1995). The subsequent increases in input cost can spill over to staple food production and prices. Similarly, domestic policies can trigger co-movements between cash crop and staple food prices. An input subsidy program targeted towards the agriculture sector can end up modifying the opportunity cost of factor inputs.

1.3.5 *Investment and market regulations*

Public investments targeted at improving rural infrastructure such as roads, communication, rural electrification, and market infrastructure tend to benefit commodities across the board, by reducing input costs and marketing margins. As a result, these investments in rural areas can cause prices for cash crops and staple foods to correlate. Also, non-commodity specific market regulations which lead to reductions in the level of risks associated with input and output markets can stimulate price co-movements. This is because public market regulations that address property rights, land and water access rights, and contract enforcement rules, have a direct effect on the profitability of farm products, by lowering, inter alia, marketing costs.

1.4 Research objective and structure of the thesis

The main objective of this thesis is to examine the price interaction effects between cash crop and staple food futures prices at a global level. As discussed, this price relationship is of particular relevance to developing countries that depend on cash crop export earnings to finance their staple food import bills. The price dynamics between these agricultural commodity sub-groups can help with cash crop price forecasting or with the estimation of foreign currency and borrowing needs, particularly during periods of high international food prices. Also, understanding the relationship between cash crop-staple food price pairs can support countries develop pragmatic sectoral strategies and formulate sound investment decisions. The overall emphasis of the thesis is on the price interdependence in terms of level and volatility and is not about explaining empirically the causal effects of such interdependence. Further, the focus is on international prices captured in terms of futures markets. The analysis covers the following cash crops: cocoa, coffee, sugar, and cotton, while the selected staple foods are: maize, wheat, and soybeans. The choice and the process of sampling these commodities are discussed later in the data and methodology section. Some of the research hypotheses that the study sets out to explore include:

1. The level of interdependence and the dynamics of volatility across staple-cash crops price pairs are significant.
2. Information transmission takes place mostly from staple food to cash crop markets at the international level.
3. The time dimension is important in the assessment of volatility dynamics.
4. Volatility transmission is bidirectional and asymmetric.
5. Movements in international food prices contain information that can guide predicting changes in international cash crop quotations.

1.4.1 *Research questions*

In this thesis, the elaborated research hypotheses are examined by addressing three main questions:

(I) *How do we characterize the level of interdependence and the volatility dynamics between cash crop and staple food futures prices?*

Many developing countries depend on the production and export of cash crop as a source of export earnings and economic development. At the same time, many of these countries are net food importers, which means that they depend on the fluctuations of international food prices. Casual observation of data indicates that movements in cash crop and staple food prices show some coherence across time. This is particularly evident during the period 2004-2011, when prices of both commodity sub-groups increased rather significantly. Can this be pure coincidence or the result of some underlying relationship? The implication is that during episodes of high food prices cash crop export earnings could actually help offset some, or all, rises in food import bills.

(II) *Does the time dimension matter in characterizing the level of interdependence and the volatility dynamics between cash crop and staple food futures prices? How significant is the transmission of information across both cash crop-staple food commodity pairs?*

While the previous research question characterizes the time-varying correlation between cash crops and staple food futures prices, the second research question seeks to explore the strength of the correlation at different time-scale (or frequency) level. That is, by considering the time dimension the analysis aims to locate precisely marked periods of volatility bouts and to assess at what frequency (i.e. short run vs long run) the level of correlation and volatility linkages are the strongest. Policy implications differ depending on the nature of the price linkages at each time horizon. For example, if the price dynamics is stronger in the long run, as opposed to the short run, cash crop earnings could potentially limit, or offset, rises in international food prices, while in the short run, measures may be required to address current account imbalances.

(III) *What are the key explanatory variables of international sugar prices and their relative importance?*

The third research question seeks to understand the underlying factors, beyond changes in staple food prices, driving price movements of a specific cash crop, namely sugar. Sugar is taken as a case study because of its importance for many developing countries, both as a source of export earnings and as a contributor to food import bills. Understanding movements in world sugar prices helps policy-makers and participants in the sugar value chain formulate effective investment strategies and better forecast the impact of market shocks.

1.4.2 *Structure*

The rest of this introductory chapter first discusses the data and methodologies used in the research, and then it describes the main results and implications for the three main research questions of the thesis (chapter 2-4). Finally, the last section of the chapter draws some overall conclusions with suggestions for future research.

The chapters contained in this thesis can each be read separately and are only connected through their examination of aspects related to commodity markets and cash crops in particular. The article contained in chapter two is entitled “Interdependence between cash crop and staple food international prices across periods of varying financial market stress”, and looks at research question 1 by characterizing the nature of the relationship between cash crop and staple food futures prices as well as reviewing the latest literature on the use of GARCH and the rolling spillover index approach. Chapter 3 presents an article entitled "International interdependence between cash crop and staple food futures prices indices: A dynamic assessment", and discusses research question 2, by focusing on the magnitude of the interdependence between cash crop and staple food price indices at different time-frequency levels. In addition, the wavelet approach used in the article allows an assessment of the extent to which each scale (or frequency) contributes to the overall variance of the food and cash crop price futures price indices. The article contains a review of the principals of wavelet analysis as well as an analysis of the conditional correlation between cash crop and staple food price indices. Chapter 4 presents an article entitled "Forecasting international sugar prices: A Bayesian Model Averaging Analysis", and covers research question 3. The chapter reviews some of the main characteristics of sugar markets and discusses methodological aspects related to model averaging techniques, model performance, and model-based price predictability. The effects of changing model and parameter priors are also simulated.

1.5 Data and methodologies

The methods applied in this research are in the domain of time series analysis and draw from the latest empirical approaches applied to price analysis, including copula estimation, wavelet analysis, volatility spillover index, general forecast error variance decomposition, and Bayesian model averaging. The various approaches address specific research questions, as described previously. After a brief discussion about the main sources of data, this section looks at the main elements of the methodology pertaining to the research questions.

1.5.1 *Data sources*

Futures price series for the selected commodities are collected from Bloomberg Terminal. Prices refer to active contracts, which are contracts that are next to expiration. The rolling procedure ensures a continuation of the price series and implies rolling expiring active contracts to the first deferred contract on the last trading day. The cash crop futures index is derived by taking the weighted average of the daily closing futures prices recorded at the Intercontinental Exchange (ICE) for sugar No. 11 (SB) futures, cocoa (CC) futures, coffee “C” (KC) futures, and cotton No.2 (CT) futures. Prices are normalized first, and then the daily traded volumes are used as weights to construct the daily futures price index. A similar procedure is adopted for the staple food futures prices, where the daily closing futures prices quoted at the Chicago Board of Trade (CBOT) for corn (C1) futures, soybeans (SB1) futures and wheat (W1) futures are used. Also in this case, traded volumes are used as weights. For both indices, daily futures prices and volume data are extracted from Bloomberg Terminal and cover the period of 3 January 1990 to 30 August 2016. The analysis is undertaken using the returns of the index series by taking the differences in the logarithm of two consecutive price indices, as it is often done in the literature. Series expressed in returns are often stationary.

The decision to use the CBOT and the ICE as the reference markets for international prices is based on a general assessment from the literature and expert knowledge. Changes in these markets are relevant because they often determine movements in domestic prices. For instance, coffee prices received by farmers in Ghana are dependent, to some extent, on futures prices realized at the Intercontinental Exchange (ICE) market in New York. Similarly, wheat import prices paid by Egypt, the world’s largest wheat importer, are associated with wheat futures prices negotiated at the Chicago Board of trade (CBOT) or EURONEXT/MATIF in Paris (Janzen and Adjemian, 2017). Yet, it is important to keep in mind that the primary focus of this research is on movements in international prices. These movements may actually differ from those of FOB or domestic prices, depending on the extent to which border prices/domestic prices are linked with international prices. Border measures, such as high import/export tariffs, tariff rate quotas, price support polices, subsidies, etc., are examples of factors that can impede a full and instantaneous transmission of price shocks in international markets.

The selection of the cash crop and staple food used in the analysis is based on a pre-analysis phase which consisted of ranking the top five net food imported commodities and the top five net cash crop exported commodities by value for the group of NFIDCs. From this sample, commodifies that are traded in the CBOT and/or ICE are then chosen. The idea from this is to identify commodities that are very much relevant to food importing developing countries that rely on the proceeds from cash crop exports to finance food import bills. For Chapter 4, data for sugar international prices is sourced from Bloomberg Terminal, while the series associated with financial markets, sugar world supply and utilization accounts, and macroeconomic variables, are extracted from the following sources: Bloomberg Terminal, the United States Department of Agriculture (USDA) database, FAOSTAT, the Federal Reserve Economic (FRED) database, and the Brazilian sugarcane industry association (UNICA). A preliminary analysis of the cash and staple crop futures price series shows that they are consistent with the commonly acknowledged commodity price behavior. Specifically, the series are rather volatile, with occasional price peaks followed by equally sharp declines. Overall, the series are asymmetric, negatively skewed, and leptokurtic. The non-normality of the futures prices distribution is confirmed by the Jarque-Bera test. Further, the structure of the series is characterized by the presence of autocorrelation and heteroscedasticity. Tests for the stationarity property of the series confirm the presence of unit root. These statistical characteristics are in line with the underlying nature of commodity price movements, as described in Deaton and Laroque (1992).

1.5.2 *Methodology*

To address research question (I), two main methodologies are applied. First, the computation of the time varying conditional correlation estimates between cash crops and staple foods are obtained by using a Dynamic Conditional Correlation (DCC)-Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, as developed by Engle (2002). The use of this model is motivated by its flexibility and the fact that it converges to a solution given the relatively large number of variables. Full-BEKK-

GARCH models, for instance, suffer from convergence issues beyond a bivariate or trivariate specification. There are a number of correlation estimators that can be used (e.g. Pearson product-moment correlation coefficient, rolling correlation coefficient, etc.), but there is a great amount of subjectivity in these estimators. Given two random variables r_1 and r_2 each with zero mean and variance of one, it can be shown that the conditional correlation is also equal to the conditional covariance between the standardized disturbances; that is $\rho_{12,t} = E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t})$. Consequently, a GARCH specification can be used to estimate conditional time-varying correlations, implicitly estimating the weights assigned to past observations. It is this relationship that is framed into the DCC-GARCH model. The estimation of the DCC model assumes that the multivariate joint distribution follows a Student-t copula. This is to account for the leptokurtic distribution of the price series. Models estimated using joint copula distributions provide a better empirical fit than standard normal multivariate distributions (Breymann et al., 2003; Demarta and McNeil, 2005). While the DCC-GARCH model yields estimates for own ARCH and GARCH effects as well as estimates for conditional correlations, it does not give a measure of cross-market transmission or spillover effects. For that, the study uses an approach by Diebold and Yilmaz (2009) calculating total and directional (pairwise) rolling-sample volatility indices to identify the direction of the volatility transmission. The computation of the spillover indices relies on the generalized forecast error variance decomposition specified within a Vector Autoregressive (VAR) representation.

Research question (II) is explored using wavelet analysis in combination with a BEKK-MGARCH model. To address the convergence issue that is often associated with BEKK-GARCH parameterization, two price indices are calculated. The first price index captures daily futures price changes for cash crops, while the second index depicts daily futures price changes for staple foods. Both price indices are volume weighted, with data on daily volumes obtained from the futures markets where the respective commodities are traded.

To examine the relevance of the time horizon for the level of interdependence between cash crop and staple food price series, a wavelet analysis is applied. A wavelet approach decomposes a signal into basic time scale components, allowing a focus on fluctuations belonging to specific frequencies. Wavelets are small waves that grow and decay over a limited period. There are a number of wavelet functional forms for representing irregular, discontinuous, and non-stationary signals. In this research, the Daubechies' "extremal phase wavelets" (Daubechies, 1992) are used. In practice, a wavelet with some desired properties is convoluted with a time series to extract the various frequencies that are contained in that series. It is then possible to rebuild the series by excluding, for example, certain frequencies, to locate with precision stretches of volatility. After denoising the series, bivariate BEKK-GARCH models are estimated for three frequency bands, corresponding to the short, medium, and long run. The application of a GARCH framework allows an estimation of own and cross-market ARCH and GARCH effects, hence shedding some light on the significance of volatility spillover and persistence.

Research question (III) is investigated by applying a combination of time series techniques. Univariate and multivariate estimations are carried out to describe international sugar prices on the basis of a selection of key variables capturing changes in supply and demand fundamentals, macroeconomic, and financial markets. Given the large number of possible model specifications stemming from the many possible combinations between explanatory variables, we use a Bayesian model averaging (BMA) approach. Making inferences on the basis of one particular model specification without consideration for model uncertainty can result in biased inferences. The BMA method gives insights into the effect of a series of regressors on a dependent variable, in this case world sugar prices, on the basis of a weighted average of the estimated parameters obtained from the different model specifications. In the BMA method, the weighting rule relies on the posterior model probability (PMP) derived from the different model specifications. Given the large number of regressors, a Markov Chain Monte Carlo (MCMC) method with the Metropolis-Hastings algorithm is implemented to approximate posterior model distributions.

An out-of-sample analysis is also undertaken to compare the predictive ability of the BMA against a sample of benchmark time series models. The comparison is based on standard loss measures: the root mean square prediction errors (RMSPEs) and the root square prediction errors (RSPEs). The sensitivity of the predictive ability of the BMA is tested by computing the RSPEs and the RMSPEs resulting from altering the assumptions on model and parameter priors. Considering that these various BMA-based forecasts could represent one possible realization, the question of whether there are any differences in predictability among the BMA models is tested using bootstrapping techniques. Finally, the analysis adds a dummy explanatory variable accounting for the EU major sugar reform introduced in 2006. The objective is to evaluate to what extent the reform had an effect on international sugar prices. This could serve as an indication of the potential effect of the EU's decision to eliminate domestic sugar quota production, which entered into force in 2017/2018 marketing season.

1.6 Summary of main results

In this section, a summary of the main results for each of the articles included in this thesis is discussed, before examining their main implications and some ideas for future research in the next section.

(I) *How do we characterize the level of interdependence and the volatility dynamics between cash crop and staple food futures prices?*

The estimation of the DCC-GARCH model is carried out based on the likelihood estimation technique. The estimation yields 15 time-dependent correlation series, corresponding to the combination of four cash crops with three staple foods, in addition to three time-varying correlation series for staple foods. In general, the conditional variance estimates indicate that ARCH coefficients are generally lower than those obtained for GARCH, implying that lagged shocks do not influence current conditional variance as much as lagged values of volatility for these markets. The estimated conditional correlation present three general characteristics: 1) they are relatively highly volatile for much of the sample period, 2) they are generally positive, yet relatively low and with occasional spikes (e.g. 2009 and 2011), and 3) their values start to rise in 2004, reaching a peak in 2009, before falling and surging again around 2011. In most cases, following 2011, the conditional correlation values revert back to their pre-2004 levels. Note that a change in the value of the conditional variances implies a change in the value of one of the residuals, or both, by assumption. During 2004-2009, the positive increase in the conditional correlations is attributed to a rise in the conditional variance of both cash crop and staple food commodity groups. With respect to the conditional mean return equation, results indicate that in the cases of bidirectional mean transmission, the estimated coefficients are larger for the staples than for cash crops, suggesting that information transmission flows mostly from staple food to the cash crop markets.

The direction of the transmission of information is looked at by computing spillover indices based on the generalized forecast error variance decomposition, as described by Diebold and Yilmaz (2012). Three observations can be formulated based on the results: 1) overall, the net spillovers are generally negative, meaning that the volatility runs from the staple food to the cash crop markets, 2) the spillovers are also found generally larger during the recent period of the soaring commodity prices and the global financial crisis (2007-2012), in line with the results obtained by the DCC-GARCH approach, and 3) the results are sensitive to the cross-market coefficient estimates of the vector moving average (VMA). Increases in the spillover indices reflect greater unpredictability in the staple food markets, which eventually transmits to cash crop markets.

For the full sample (1990-2016), the spillover indices indicate that 20 percent of the forecast error variance of the VMA system is accounted for by volatility spillovers among the seven markets, with

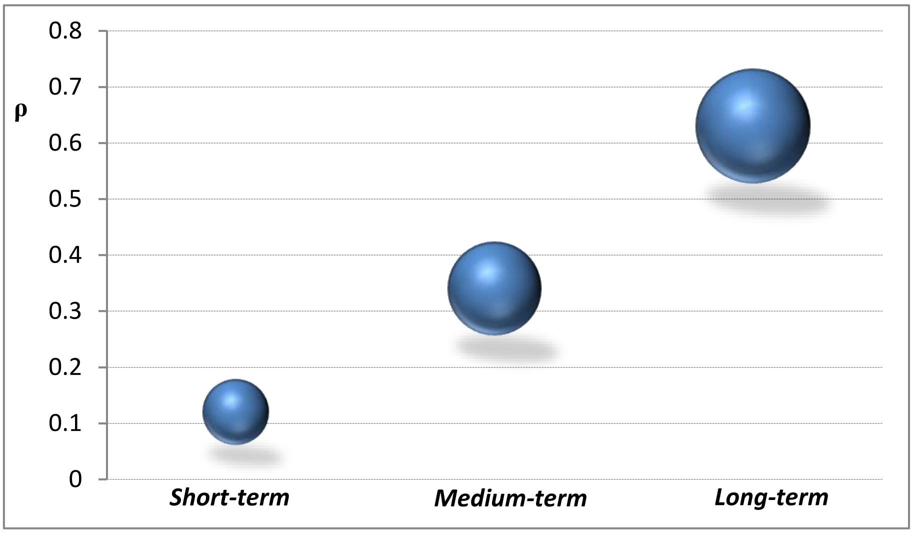
18 percent of the forecast error variance of cash crop markets explained by spillover effects from the staple food markets (directional spillover). When the sample is restricted to 2007-2012, 38 percent of the forecast error variance of the VMA system is due to volatility transmission among the various markets, with 61.4 percent of the forecast error variance of cash crop series explained by spillover effects from the staple food markets.

(II) *Does the time dimension matter in characterizing the level of interdependence and the volatility dynamics between cash crop and staple food futures prices? How significant is the transmission of information between the cash crop-staple food commodity pairs?*

Overall, the outcome of the wavelet analysis illustrates that the cash crop-staple food index series have common trends and volatility patterns, yet differences in volatility subsist at specific scale levels. This indicates that the level of interdependence and the dynamics of volatility between cash crop and staple food price indices depends on the time scale (e.g. 2 days) at which the analysis is undertaken. Low frequencies measure variations at a time scale of 512 days; medium-frequency: 32 days, while high frequencies measure fluctuations at a time scale of 2 days. Results show that the cash crop index series displays a relatively much higher level of volatility than the food index at both the medium and high frequencies scales. Three stretches of highly volatile periods are identified. The first one expands from around 1995 to 2001, while the second long period of volatility runs from 2007 to 2012, which coincides with the global financial crisis and the surge in international food prices. The third period of volatility runs from about 2014 to 2016, concurring with the period of high and volatile cocoa and coffee prices. In the case of the food index, a stretch of extreme fluctuations spans from about 2007 to 2012, corresponding to the period of the recent financial crisis and food crisis, and from 1995 to 1997, which coincides with a period of high cereal prices following tightness in world supplies.

To account for the heterogeneity in the variance dynamics across time-frequency domains as revealed by the wavelet analysis, a bivariate model VAR(3)-Full-Bekk-GARCH(1,1) is estimated for three scale levels: low-frequency (scale=9), medium-frequency (scale=5), and high-frequency (scale=1). The estimation results for the conditional mean show that own autoregressive parameters are significant for both cash crops and staples. Further, four observations can be made: 1) the transmission of volatility is generally bidirectional, with GARCH parameters greater than ARCH; 2) volatility spillovers are asymmetric as the magnitude of the transmission of volatility from staples to cash crop futures is larger than the reverse; 3) own ARCH and own GARCH estimates are larger than cross-market estimates, meaning that intrinsic factors mostly dominate as a source of volatility; 4) the estimated model corresponding to low frequency levels reveals that for the long term fluctuations, the relationship between cash crops and staple foods is tighter - it has mostly higher spillover estimates (in absolute value), and higher and significant Pearson correlation values (see Figure 1.4). Finally, the wavelet variance decomposition shows that the largest contribution to the sample variance is accounted for by variations at the largest scale (long run variations) for both the cash crop and food future price indices.

Figure 1.4: Correlation and volatility transmission between cash crops and staple foods at different time horizons



Note: The size of the bubbles represents the magnitude of volatility transmission

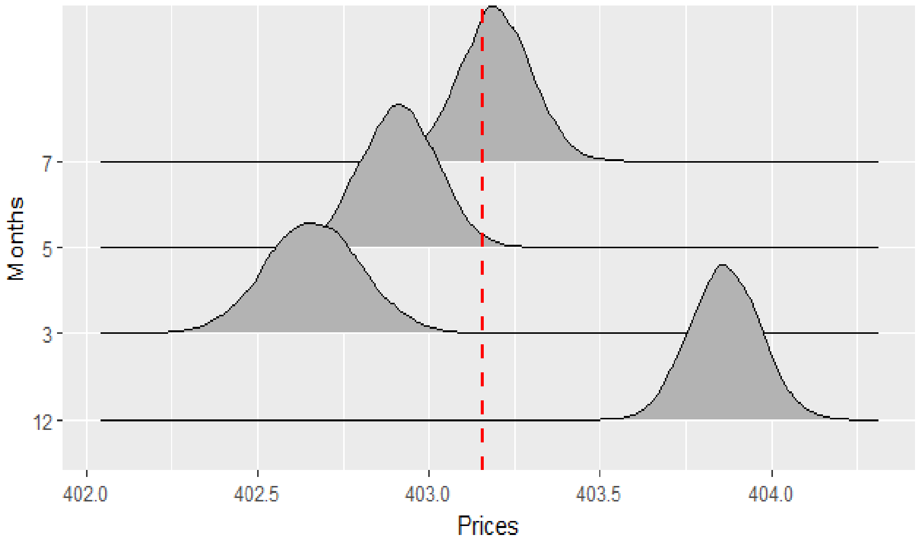
(III) What are the key explanatory variables of international sugar prices and their relative importance?

Considering the number of explanatory variables included in this study, a total of $2^{18} = 262144$ models are evaluated by the BMA approach. The baseline model assumes that models have uniform priors, and that regression parameters follow Zellner's g-prior structure, with g = UIP (unit information prior). The BMA results show that sugar price movements are mostly associated with changes in the lagged value of world sugar prices, the price of a basket of international food commodities, the cost of producing sugar in Brazil, movements in the value of the Brazilian currency (Real) against the United States dollar, and lagged value of the world sugar production. Other variables such as sugar stock-to-use ratio, the price of high-fructose corn syrup (HFCS) - which is the main alternative sweetener - net sugar exports of India, the world's second largest sugar producer, are relatively less important in explaining sugar prices. Interestingly, the policy variable, which captures the introduction of a large set of reforms to the sugar sub-sector by the EU in 2006, does not seem to be important in explaining the data.

Overall, these results stay relatively unchanged to alternative assumptions with respect to the shrinkage value g and the model priors. The only recurrent observation that emerges is that, in some scenarios, the variable associated with India net sugar exports gains in importance, with ethanol losing some of its weight as its posterior inclusion probability (PIP) falls. The results are relatively comparable when the assumption of uniform model priors is changed to binomial and beta-binomial. One noticeable difference is the importance, in terms of higher PIPs, assigned to the variable representing international crude oil prices, and a smaller PIP assigned to the value of lagged sugar production. The root mean square prediction errors and the monthly square prediction errors computed over the pseudo out-of-sample show that the forecasting errors fall as the hyperparameter g increases, but only to a certain point, when it starts to increase again. As compared to a sample of benchmark time series model, the BMA baseline model performs as well as an autoregressive model of order 1 (AR(1)) specification, but outperforms VAR(2), Ordinary least squares (OLS), and a random walk (RW) model. Similar results are obtained when the model prior is changed from uniform to a binomial or a beta-binomial.

The estimation of the BMA model enables the elicitation of a joint posterior probability distribution for the coefficients. Drawing from this distribution, and using auxiliary ARIMA-based forecasts of the selected regressors, one obtains time-varying distributions of price forecasts. Results of this exercise suggest, for example, that the distribution of the forecasted sugar price revolves around a mean of USD 402.6 per ton and USD 403.8 per ton in the 3rd and 12th month of the forecasting period, respectively (Figure 1.5).

Figure 1.5: A selection of time-varying distributions of forecasted sugar prices based on BMA analysis



Note: The vertical dashed line represents the forecasted sample mean

1.7 Conclusion

The main objective of this thesis is to explore the level of interdependence and the dynamics of volatility between cash crop and staple food futures prices. The idea comes from the observation that during the recent food crisis (2007-2011), a number of observers highlighted that increasing food prices posed a great threat to the economies of developing countries. However, little attention was given to the fact that international prices of the commodities that these countries relied on for export earnings were also on the rise during the same period. In several instances, increases in cash crop export earnings were sufficient to partially, or fully, offset the surge in food prices. Therefore, the basic idea of this thesis is to study the interaction between cash crop and stale food prices from an international perspective and to understand their linkages from a volatility and level aspect. It is important to note that this research only looks at the price component of export earnings. The other element, i.e. quantity, is not addressed. Research shows that cash crop and staple food markets are generally inelastic, so that changes in export earnings are positively correlated with changes in prices. Studies looking at the interaction between cash crop and staple food international prices remain very much limited. This thesis contributes to filling this research gap.

Why is it relevant to investigate the interaction between cash crop and staple food prices? One of the reasons is that many developing countries rely on the production and export of cash crops for economic development. In 2017, for example, export of tropical beverage crops, fruits, and sugar as a percentage of total agricultural products was evaluated at 73 percent, 66 percent, and 67 percent for Burundi, Mauritius, and Eswatini, respectively, while these products represented about 35 percent, 27 percent, and 29 percent of total merchandise export for Burundi, Uganda, and Kenya, respectively (FAO, 2018). These figures highlight the influence of cash crop products on macroeconomic and financial stability of developing countries. Further, cash crop export earnings bring in hard currencies that enable the procurement of food from international markets. Often, the cash crop export sub-sector is the largest provider of hard currency reserves.

With a focus on international markets, this thesis provides some insights into cash crops and staple foods price behavior by addressing three research questions that examine specific issues: (I) the characterization of the level of interdependence and the volatility dynamics between cash crop and staple food futures prices, (II) the influence of the time dimension in characterizing the level of interdependence and the volatility dynamics between cash crop and staple food futures prices, and (III) the influence of factors related to market fundamentals, macroeconomics, and financial markets, on international cash crop prices. The third research question uses sugar as a case study to investigate the importance of a set of key variables, beyond staple food prices, in explaining movements in world sugar prices. These research questions are addressed using econometric time series techniques that allow insights into the dynamics of price level and volatility.

When looking at the interaction effects and dynamics of volatility, results from the time series assessment indicate that the conditional correlation between staples and cash crop futures price returns is relatively low, generally positive, yet highly volatile, with the correlation estimates being greater in 2007-2012 - a period associated with the recent commodity boom cycle and financial market stress. The volatility spillover indices confirm an increase in the volatility linkages between cash crop and staple food commodity pairs, while noting that the volatility transmission is asymmetric, running mostly from staple food futures to cash crop futures. A change in volatility spillover does not automatically mean a change in the estimated conditional correlation. In fact, changes in estimated conditional correlations are often driven by own volatility shocks. When considering the time dimension in the analysis, the resulting outcome shows the level of correlation and volatility linkages being the strongest at lower frequencies (i.e. longer run). The largest contribution to the variance of the cash crop and staple food price series originates from fluctuations at the largest scale (long run variations). Using sugar as a case study, a Bayesian model averaging analysis highlights the importance of international staple food prices in predicting movements in sugar prices, in addition to fundamental and financial factors.

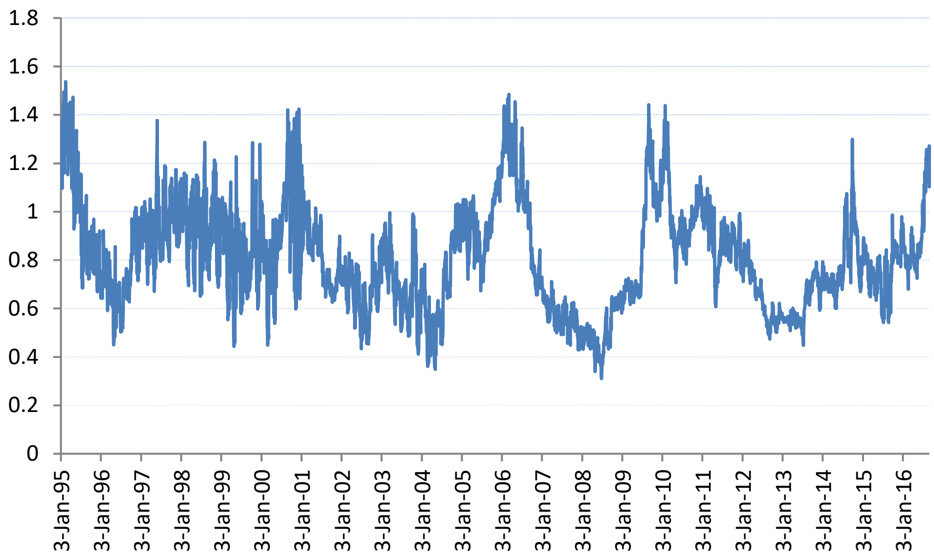
These findings entail some policy implications from both an investment and policy making perspective. Given that the correlation between cash crops and staples is estimated to be relatively weak in the short run (i.e. high frequency), investors can include cash crop futures in their portfolio to reduce the risk of holding staple foods as investment assets. In addition, since significant cross-market effects run mostly from staples to cash crops, information provided by staples futures can be used to forecast cash crop futures returns. From a policy perspective, the weak correlation found in the short run means that cash crop export earnings cannot significantly compensate for the impact of short term surges in international food prices. Therefore, short term measures are needed to finance import bills in the case where a cash crop exporting developing country uses the earnings to pay for food imports. In the long run, estimation results suggest relatively high correlation and significant cross-market effects, meaning that investors would not benefit by including cash crop futures to offset risk associated with holding staple food related assets. From a policy perspective, the stronger correlation means that cash crops earnings could potentially limit, or offset, increases in international staple food prices. Indeed, research shows that because cash crops are inelastic, the rate of increase in cash crop prices more than offset the decline in export quantities. The stronger interdependence in the long run also suggests that governments in cash crop exporting countries could implement support policies targeted at the cash crop sub-sector when staple food prices rise relative to those of cash crops, and then relax these policy measures when cash prices begin to move higher sustained by staple food quotations.

At the smallholder level, and assuming full transmission of international prices to domestic markets, the correlation between staple food and cash crop prices in the long run means that crop diversification at the farm level is not likely to lower price risks. Therefore, the results seem to suggest that smallholders holding a comparative advantage in the production of cash crops are better off specializing in these crops and using the proceeds to buy food from the local markets. The behavior of smallholders seems, however, to contradict these findings. In fact, smallholders devote a large share of their farm resources to food and livestock production, despite holding a comparative advantage in cash crop production (Govereh and Jayne 2003). This can be explained by the fact that local markets often do not function adequately, in the sense that they are not well integrated markets. In addition, the higher degree of farm production diversification results from the need to mitigate risks associated with the perennial nature of most of the cash crops, as well as the prevalence of pests and diseases, and extreme weather events, which affect smallholders' revenue. There is some scope for public intervention to lessen these constraints and foster a greater level of specialization. For example, measures to enhance access to factor inputs, including pest and disease resistant crop varieties, technology, knowledge, and access to credit markets. These steps can help alleviate production risks and create the right amount of incentives to maximize the comparative advantage derived from cash crop production and export.

What do these results mean for a country like Burundi, which relies on cash crop exports and imports of staple foods? Strong and positive conditional correlation between cash crop and staple food markets means that the Government can evaluate more accurately its financial needs in the face of current account imbalances due to import bills, by taking into consideration the fact that revenues from cash crop exports can reduce funding requirements, and hence borrowing costs. Second, the Government can also use price information relevant to international staple foods in the design and planning of investment strategies for the cash crop sub-sector, given the linkages between both commodity sub-sectors. For example, information on staple food price prospects can be utilized to strengthen the accuracy of national cash crop price projections.

It seems, however, that the perceived benefit of cash crop production is not shared by all. There is a belief held by some development experts and analysts that developing countries should diversify away from commodity production and export (UNCTAD/FAO, 2017; Derosa, 1992). Their argument is based on the observation that real commodity prices have been on a declining trend relative to the prices of manufactures. The Prebisch-Singer hypothesis provides the theoretical background behind the decline in relative prices which translates into deteriorating terms of trade for developing countries (UNCTAD/FAO, 2017). The recommended solution is to move away from the production and export of commodities, such as cash crops, and into more value added products and services. The problem with this argument is that it is highly sensitive to the price index, such as the manufactures unit value index, and to the empirical approach used in testing for the presence of a trend. On this basis, some studies actually question the existence of a downward trend in relative prices (Cuddington and Urzúa, 1989). Perhaps, the conclusion on whether to move away from commodity production and export should be looked at from several perspectives. As an example, the results of this research indicate that when comparing the cash crop price index relative to the staple food index, there is no obvious downward trend, in fact the relationship between the indices seems to remain relatively steady in the long run, with prevailing short-lived peaks (see Figure 1.6). Hence, when considering the movements of cash crop prices relative to staple foods, it appears that cash crop earnings have a role to play in limiting the negative impact of higher staple food prices and the resulting potential drawdown of foreign currency reserves. Looking at it from this angle, the argument of moving away from cash crop production and export is questionable. Perhaps a better policy advice to cash crop producing developing countries would be to argue for the implementation of measures to render the commodity sector more resilient and efficient, while at the same time, expanding the mix of exported products, particularly into more value added products.

Figure 1.6: Cash crop price index relative to staple food price index



Future research should focus on three major areas. First, there is clearly a need for additional research into the theoretical and empirical aspects of large dimension MGARCH models. The vast majority of MGARCH do not exceed a trivariate specification, given the prevailing convergence issues, particularly when exogenous variables are added in the mean and/or variance equations. Also, considerable knowledge gaps remain about the statistical and asymptotic properties of higher dimension MGARCH. More research is warrant in this direction as well. Second, effort should be devoted to exploring the theoretical linkages between estimates of volatility based on GARCH and volatility indices based on the general forecast error variance decomposition. This thesis addresses some of the linkages, but this work can be supplemented by an approach that formally unifies both methods. Finally, since our study on the interaction effects between cash crop and staple futures prices is carried out from an international standpoint, the next natural step is to examine if the integration holds at the country level. For that, higher frequency observations for cash crop export prices and food import prices are needed together with updated estimates of trade elasticities for both commodity sub-groups. The analysis at the country level should help anticipate the magnitude and direction of export earnings amid volatile international agricultural commodity markets.

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Chapter 2
Interdependence between cash crop and staple food international prices across periods of varying financial market stress[1]

Abstract

This paper investigates the price dynamics between a selection of international staple food and cash crop futures prices. This price interaction is particularly relevant for developing countries that rely on cash crop export earnings to finance their staple food import requirements. We employ a multivariate Copula-DCC-GARCH model to characterize the cash crop and staple food price interaction over time and a rolling-sample volatility index to identify the direction of the volatility spillover for staple-cash commodity pairs. Results show that the intensity of interaction varies considerably over the sample time, but is, generally positive, and stronger during the period 2007-2012 associated with high commodity prices and financial market stress.

Keywords: Volatility spillover, Copula-DCC-GARCH, forecast error variance decompositions, cash crops, staple food crops

JEL classification: Q13, C13, G11, G01

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2.1 **Introduction**

The run-up in world agricultural commodity prices over the past decade remains a subject of debates and vivid research. One of the questions relates to the ability of net food importing developing countries (NFIDCs) to secure food procurements amid growing food import bills and the resulting pressures on the balance of payments (IMF 2008). Foreign direct investments, borrowings from foreign capital markets, and available foreign reserves, are possible sources that can alleviate those pressures. For many NFIDCs, a sizeable share of capital inflows comes from exports of cash crops. For example, exports of tropical beverage crops, fruits, and sugar accounted for 77 percent and 74 percent of total agricultural products in 2013 for Burundi and Mauritius, respectively. Similarly, in that year, these products amounted to 43 percent, 27 percent, and 24 percent of total merchandise export for Burundi, Uganda, and Kenya, respectively (FAO 2016). Mostly, movements in prices determine changes in the value of these exports as well as those of food import bills because cash crop and staple food international markets are generally inelastic (FAO 2004).

A casual review of the price series for cash crops and staple foods shows that they are positively correlated over time (see Figure 2.1)[2]. Given the inelastic nature of both markets, the observed co-movement means that higher cash crop and staple food prices lead to higher export earnings and import bills (FAO 2004)[3]. This apparent correlation is difficult to explain on the basis of market fundamentals only, at least in the short run. The substitution possibilities in consumption and production between cash crops and staple foods in the physical market are rather limited and therefore cannot describe the full extent of the co-movement. On the other hand,

[2] During the 2007-2011 food price crisis, the World Bank non-energy index increased by 136.8 percent, including a 102.9 percent increase for the agricultural sub-index. Cash crop quotations also rose sharply. For example, coffee prices went up by 26 percent between 2006 and 2009, while prices for tea and sugar increased by 45 percent and 23 percent, respectively.

[3] The extent to which rising cash crop earnings can offset increasing food import bills depends, inter-alia, on their contribution to a country's GDP, the price elasticities of the international demand and supply for cash crops, currency movements, and the transmission of world futures to local markets.

macroeconomic related factors, weather shocks, movements in energy prices, and institutional investors diversifying own assets away from equities by investing in commodity futures, are possible drivers underlying the synchronized behaviour. The effect of financial investments on commodity market remains, however, a subject of ongoing debate. Irwin and Sanders (2011), Fattouh et al. (2012), and Hamilton and Wu (2015), argue that institutional investors don't have any impact on commodity futures prices. Possible linkages underlying the relationship between cash crop and staple food markets are discussed in Amrouk et al. (2019).

In this paper, we examine the magnitude of interdependence and the dynamics, in terms of level and volatility, across a selected sample of four cash crops (sugar, coffee, cocoa, and cotton) and three staple foods (maize, wheat, and soybeans) international futures prices[4]. Daily prices are obtained from Bloomberg and cover the period of January 2, 1990 to August 30, 2016 for a total of 6740 observations. The examination of volatility transmission is important because it provides insights into the direction of market information, which helps anticipate price movements. Anticipating price volatility helps commodity-dependent developing countries design realistic budgets that are resilient to price shocks, and also improve predictions of funding needs and borrowing costs. Previous research also shows that volatility is a key variable in investment decisions. We use a Dynamic Conditional Correlation (DCC)-Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to assess the extent of the interaction across our sample of commodities. Other more flexible multivariate GARCH specifications exist, such as the Baba, Engle, Kraft and Kroner (BEKK)-GARCH, but problems of model convergence linked with dimensionality issues renders them difficult to use. We augment the DCC-GARCH specification with a Student-t copula to account for tail dependence that often characterizes commodity price series. Because a DCC-GARCH model does not yield estimates of volatility transmission across markets, we compute spillover indices based on the generalized forecast error variance

[4] Futures prices, such as those negotiated at the Intercontinental Exchange (ICE) and the Chicago Board of Trade (CBOT), are relevant because they are often taken as the world reference price. They influence border prices, and hence, the value of import bills and export earnings (Chen et al., 2010).

(GFEV) decompositions, as suggested in Diebold and Yilmaz (2012). The interaction in terms of level is investigated using a vector autoregressive (VAR) representation.

Our analysis contributes to the existing research in several ways. First, the trade-off between cash crops and staple foods has been extensively researched at farm level (Govereh and Jayne 2003), but analysis at international market level is lacking. We contribute to filling this gap by characterizing the interdependence and volatility dynamics between these commodity sub-groups, thus helping to assess whether export earnings can contribute to alleviate current account instability resulting from rising import bills. Second, the analysis covers a period extending from 1990 to 2016, which allows assessing the impact of the recent surge in food prices 2007/2008 and 2011, the global financial crisis of 2007/2008, as well as the period of end-1990 and beginning 2000 when cash crop futures prices were depressed and touched historical lows in real terms (e.g. coffee). Third, we combine two different methodologies for assessing volatility dynamics, namely the DCC-GARCH and the rolling-sample volatility index and relate their results. A rolling-sample enables the examination of the extent and nature of the spillovers over time through the associated time series of spillover indices. Also, the technique allows to take into account potentially different regimes, or structural breaks, over the sample period.

The remainder of the paper is structured as follows: the next section provides a review of methodologies to investigate short-term market interdependence, followed by a discussion on the methodology and data used in our empirical analysis. Subsequently, we present and discuss the main results. The final section provides a summary of the main conclusions and some ideas for future research.

2.2 Methodologies for investigating short-term commodity market interdependence

The literature on the relationship between international prices of cash crop and staple food is limited. Most of the studies involving cash crops and staples are concerned with medium-to-long-term relations, with a particular focus on farm resource allocation in the presence of input constraints (Norton and Hazell 1986). The focus on cash crop vs staple food production is motivated by food security concerns. On one hand, food security of smallholders may be at risk when farm resources are assigned to cash crop production (Maxwell and Fernando 1989; Mittal and others 2009), while, on the other, cash crop production provides the means to secure food access - i.e. the access dimension of food security (Timmer 1997; Von Braun and Kennedy 1986; Weber et al. 1988). Recent research shows that cash crop and staple food can actually play a complementary role (Govereh and Jayne 2003; Theriault and Tschirley 2014).

While the literature on the linkages between cash crop and staple food international prices remains scarce, the use of GARCH framework to investigate the interdependence among markets has been quite extensive. For example, Olson et al. (2014) use a BEKK-GARCH framework to analyse the volatility integration between energy and equity markets and find that equity markets response modestly to shocks in the energy markets, and that correlation is low between these markets, with the exception during the financial crisis (2008-2010). Using a VAR-GARCH model, introduced by Ling and McAleer (2003), Mensi et al. (2013) study the price return and volatility ties between the S&P 500 index and commodity price indices for energy, food, gold, and beverages over the period from 2000 to 2011. They estimate the effects of unexpected shocks, or news, on the S&P 500 index and the impact on the agricultural markets.

Gao and Liu (2014) also apply bivariate GARCH models to investigate the volatility connection between the S&P 500 index and a set of commodities. Results show that regime switches in the energy complex appear to be driven by volatility in the equity market rather than volatility in the grains market. They also reveal significant scope for risk diversification between certain commodity groups. Gardebroek and Hernandez (2013) use a BEKK and a dynamic conditional correlation (DCC) trivariate GARCH approach to evaluate the volatility spillover among maize, crude oil, and ethanol spot prices. Model results indicate a unidirectional volatility spillover running from maize to ethanol. Similar results are obtained by Trujillo-Barrera et al. (2012) with the use of a BEKK-GARCH specification.

Other studies employing a GARCH approach to assess price volatility between various commodities include Chang and Su (2010), Ji and Fan (2012), and Harri and Hudson (2009). Likewise, Serra (2011) examines the relationship between food and energy market, with a focus on the price linkages among crude oil, ethanol and sugar and detects only a limited effect of ethanol on price movements of sugar and crude oil. Also, using a multivariate GARCH applied to a sample of 28 commodities, Vivian and Wohar (2012) identify significant volatility linkages and volatility persistence even after accounting for structural breaks. A similar research is undertaken by Al-Maadid et al. (2017) to look at the mean and volatility spillover between food and energy markets. Similarly, Nazlioglu et al. (2013) undertake an examination of price volatility between crude oil and a sample of commodities including wheat, maize, sugar, and soybeans. On the other hand, Aepli et al. (2017) use multivariate dynamic copulas DCC-based models to explore the time-varying dependence structure of commodity futures portfolios. They find that copula functions are most suitable specifications to model dynamic dependence across markets. Other studies using a DCC approach include Chiang et al. (2007), Celık (2012), Bicchetti and Maystre (2013), Lombardi and Ravazzolo (2016), and Roy and Sinha Roy (2017).

Most of the GARCH studies mentioned so far are estimated under the assumption of a multivariate normal distribution of the variables. However, distributions of asset price returns, and those of commodities in particular, are generally skewed and leptokurtic - features that a joint normal distribution does not capture. The use of joint copula distribution methods can account for these specific data characteristics, and provide a better empirical fit than standard normal multivariate distributions (Breymann et al. 2003; Demarta and McNeil 2005). The concept of copulas was introduced by Sklar (1959), but only applied recently to a wider range of areas including environmental and financial studies. Patton (2006) introduced copulas with time-dependent parameters to model exchange rate dependency, while Jondeau and Rockinger (2006) used the skewed Student-t copula to investigate the daily market returns. Bartram et al. (2007) use time-varying copula to model the dependency among 17 European stock markets. A number of convenient copula functions have been developed to address certain distributional features. A complete review of copulas can be found in Manner and Reznikova (2012).

2.3 **Methodology and data**

2.3.1 *GARCH approach*

The Autoregressive Conditional Heteroscedasticity (ARCH) and GARCH models are known methodologies for modelling volatility. In this study, the empirical approach is based on estimating a DCC-GARCH model for three staple food futures price returns series (maize, wheat, and soybeans) and four cash crop futures price returns series (coffee, cocoa, cotton, and sugar). We begin by specifying the conditional mean equation, commonly represented as a reduced form of a VAR[5]:

$$A(L)r_t = \varepsilon_t \ , \tag{2.1}$$

with

$$\varepsilon_t|\omega_{t-1} \sim N(0, H_t)$$

where $A(L)$ refers to a 7 x 7 polynomial matrix in the lag operator L, r_t is a 7 x 1 daily return vector at time t, and ε_t a 7 x 1 corresponding vector of random errors, representing the shocks, or innovations. H_t represents a 7 x 7 conditional variance-covariance matrix conditional on market information

[5] To take into account potential cointegration relationships, a series of Johansen cointegration tests are carried out. These reject, at the 1 percent level, the null hypothesis of a cointegration relationship between cash crop and staple food price series, suggesting that a VAR specification, without an error correction term, is appropriate.

ω_{t-1} available at t-1. Given the large number of variables involved in the analysis, and to facilitate parameter estimation, we select a DCC-GARCH type model. This specification enables the measurement of conditional variances and conditional correlations, while ensuring the positive definiteness of $\mathrm{H_t}$ and easing model conversion. As in Engle (2002) and Gardebroek and Hernandez (2013), we apply the DCC model to parameterize the conditional variance-covariance matrix $\mathrm{H_t}$ as:

$$\mathrm{H_t = D_t R_t D_t}, \tag{2.2}$$

where

$$\mathrm{D_t = diag(h_{11t}^{\frac{1}{2}}+, \dots, h_{77t}^{\frac{1}{2}})},$$

and each $\mathrm{h_{ii,t}}$ is described by a univariate GARCH model such as a GARCH(1,1) where $\mathrm{h_{ii,t} = w_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}}$. Further,

$$\mathrm{R_t = diag(q_{iit}^{\frac{1}{2}}+, \dots, q_{NNt}^{\frac{1}{2}})^{-1/2} Q_t diag(q_{iit}^{\frac{1}{2}}+, \dots, q_{NNt}^{\frac{1}{2}})^{-1/2}}, \tag{2.3}$$

where $\mathrm{Q_t}$ is a 7x7 symmetric positive definite matrix and is specified as:

$$\mathrm{Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha(}u_{\mathrm{t-1}} u'_{\mathrm{t-1}}\mathrm{) + \beta Q_{t-1}}, \tag{2.4}$$

with the standardized residuals defined as $u_{\mathrm{t}} = D_t^{-1}\varepsilon_t$, and the positive adjustment parameters $\alpha + \beta < 1$, and $\overline{\mathrm{Q}}$ being a 7x7 unconditional correlation of $\mathrm{u_t}$. The estimation of the DCC model is carried out by maximum likelihood and, hence, requires the specification of a likelihood function. We choose a multivariate joint distribution that follows a Student-t copula in order to account for the leptokurtic distribution of the price series (see Table 2.1). It is possible to choose a copula offering the best fit based on the Bayesian information criterion (BIC) and the Akaike information criterion (AIC), using the VineCopula package available for the R software. The application of the algorithm leads to the selection of the Student-t copula, as the best fit among a set of possible copulas. As in Kim and Jung (2016), the density function of the Student-t copula can be expressed as:

$$c_t(\mathrm{u_{it}}, \ldots, \mathrm{u_{nt}} | \mathrm{R_t}, \delta) = \frac{\mathrm{f_t}(\mathrm{F_i^{-1}}(\mathrm{u_i}|\delta), \ldots, \mathrm{F_n^{-1}}(\mathrm{u_{nt}}|\delta)|\mathrm{R_t}, \delta)}{\prod_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{f_i}(\mathrm{F_i^{-1}}(\mathrm{u_i}|\delta)|\delta)} \tag{2.5}$$

where $\mathrm{u_{it}} = F_{it}(r_{\mathrm{it}}|\mu_{\mathrm{it}}, h_{\mathrm{it}}, \varphi_{\mathrm{t}}, \delta_{\mathrm{it}})$ is the probability integral transformed values by F_{it} estimated with the first stage GARCH process, $F_i^{-1}(u_i|\delta)$ refers to the quantile transformation, $f_t(.|R_{\mathrm{t}}, \delta)$ is the multivariate density of the student distribution with conditional correlation R_{t} and shape parameter δ, and $f_i(.|\delta)$ are the univariate margins of the multivariate student distribution with δ taken as the common shape (Kim and Jung 2016; Ghalanos 2015). Finally, the joint density is composed of (1) the copula density function and (2) the marginal distribution functions associated with the univariate GARCH estimation and can be expressed as in Kim and Jung (2016):

$$\mathrm{f}(r_{\mathrm{t}}|\mu_{\mathrm{t}}, h_{\mathrm{t}}, R_{\mathrm{t}}, \delta) = c_t(\mathrm{u_{it}}, \ldots, \mathrm{u_{nt}}|R_{\mathrm{t}}, \delta) \prod_{i=1}^{n} \frac{1}{\sqrt{h_{it}}} f_{it}\,(u_{it}|v_{\mathrm{i}}, \varphi_{\mathrm{i}}) \tag{2.6}$$

We use the R package rmgarch (Ghalanos 2015) to implement and estimate the Copula-DCC-GARCH model and select the solver *solnp* developed by Ye (1987) for general nonlinear programming problems.

2.3.2 *Spillover indices*

To estimate the volatility transmission across markets, we compute spillover indices based on the generalized forecast error variance decomposition, as described by Diebold and Yilmaz (2009). The generalized form of the FEVD does not depend on variable ordering, as illustrated by Koop et al. (1996) and Pesaran and Shin (1998). For every h-step-ahead forecast, we can decompose the total variance of the error forecast for variable i into shocks due to i and those due to variable j. The variance contribution matrix (VCM) contains these estimates, θ_{ij}, and where the row elements of the matrix add to unity:

$$\theta_{ij}(h) = \begin{bmatrix} \theta_{ii}^{h} & \cdots & \theta_{ij}^{h} \\ \vdots & \ddots & \vdots \\ \theta_{ji}^{h} & \cdots & \theta_{jj}^{h} \end{bmatrix}, \qquad \text{and i, j} = 1,2,3,\ldots,\text{N}. \tag{2.7}$$

The diagonal elements of $\theta_{ij}(h)$ show the contribution of own shocks to the variance of the forecast error of variable i, while the elements off-diagonal show the contribution of the various shocks due to j, or spillover, with j≠i. As defined by Diebold and Yilmaz (2012), and illustrated by Grosche and Heckelei (2016), a series of time-varying volatility spillover indices can be computed. In this paper, we make use of two main indices: 1) total spillover, and 2) net pairwise spillovers, as described in the following:

$$S(h) = \frac{\sum_{i,j=1,i\neq j}^{N} \theta_{ij}(h)}{N} * 100 \tag{2.8}$$

Equation (2.8) represents the *total spillover* index $S(h)$, which calculates the share of volatility spillovers across N variables h-step ahead in relation to the total forecast error variance. On the other hand, *net pairwise spillover* between market i and market j is the difference between the gross volatility shocks from market i to market j and those originating from market j to market i and is described as:

$$S_{ij}(h) = \frac{\theta_{ij}(h) - \theta_{ji}(h)}{N} * 100 \tag{2.9}$$

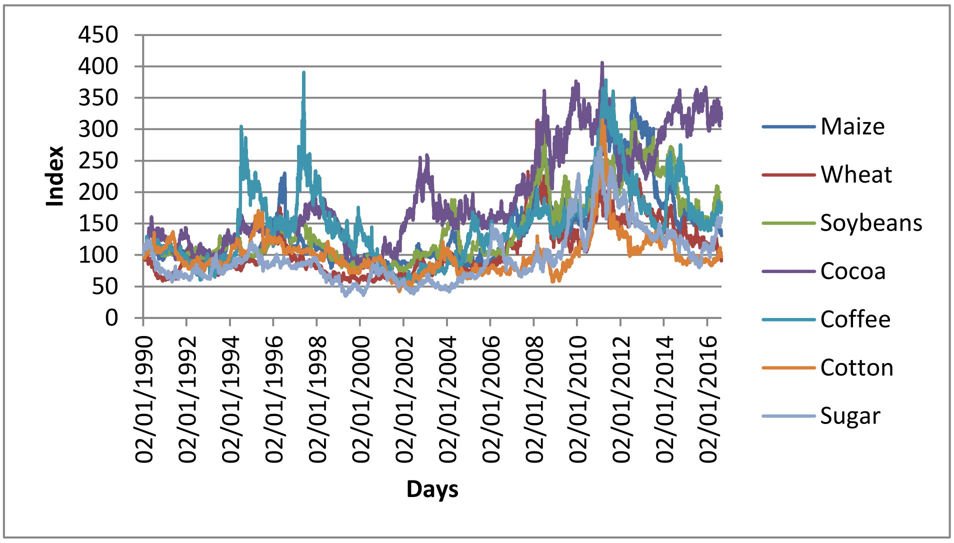
As opposed to the DCC-GARCH approach, the main advantage of the rolling-sample volatility index method is that it produces spillover estimates across different markets.

2.4 **Data**

Using the FAOSTAT[6] database, the choice of the commodities included in this study is based on a pre-analysis that involves identifying the top exported cash crops and the top imported staple foods by the NFIDCs group. We then select those crops for which an international futures contract exists. On this basis, coffee, cocoa, cotton, and sugar futures prices are selected to represent the group of cash crops, while wheat, corn, and soybeans futures prices are chosen to represent the staple food group. We consider a sample composed of the Chicago Board of Trade (CBOT) corn (C1) futures, soybeans (SB1) futures and wheat (W1) futures, and the Intercontinental Exchange (ICE) sugar No. 11 (SB) futures, cocoa (CC) futures, coffee "C" (KC) futures, and cotton No.2 (CT) futures. Futures prices are historical first generic price series, with expiring active futures contracts rolled to the successive deferred contract following the last trading day of the front month. The DCC-GARCH formulation is carried out on the returns of the series by taking the difference in the logarithm of two consecutive futures prices. This logarithmic transformation, which is a standard procedure for this type of empirical work, addresses the presence of unit roots in the price levels, as depicted by the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. This transformation also ensures the stationarity of the VAR system. The descriptive statistics of the price return series are reported in Table 2.1, while Figure 2.2 illustrates the changes in daily price returns for each of the commodities.

[6] http://www.fao.org/faostat/en/#data

Figure 2.1: Daily prices of selected cash crop and staple food commodities (01/01/1990 = 100).



Source: Bloomberg

Figure 2.2: Daily price returns of selected cash crop and staple food commodities.

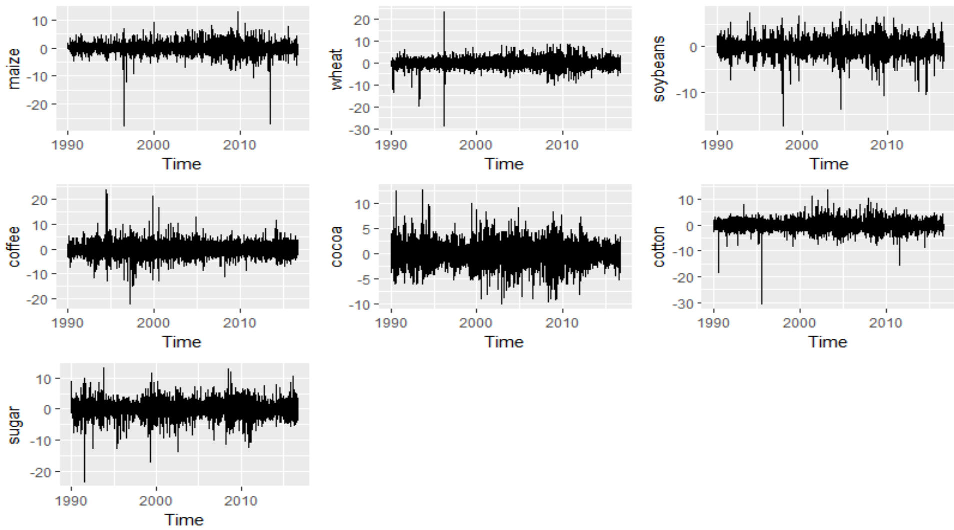


Table 2.1: Descriptive statistics of futures price return series

	Maize	Wheat	Soybeans	Cotton	Coffee	Cocoa	Sugar
Mean (%)	0.004	-0.001	0.008	0.000	0.009	0.017	0.007
Median (%)	0.000	0.000	0.046	0.000	0.000	0.000	0.000
Maximum	12.760	23.300	7.629	13.620	23.770	12.740	13.210
Minimum	-27.620	-28.610	-17.430	-30.440	-22.060	-10.010	-23.490
Standard deviation (%)	1.710	1.930	1.550	1.810	2.400	1.910	2.160
Skewness	-1.140	-0.490	-0.930	-0.850	0.170	0.080	-0.430
Kurtosis	21.210	14.720	7.850	16.840	7.470	2.680	5.830
Jarque-Bera	127820	61199	18275	80455	15724	2027	9755
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Q(14)	28.540	24.141	27.252	37.319	31.158	27.578	44.571
P-value	0.012	0.044	0.018	0.000	0.005	0.016	0.000
ARCH(14)	42.191	711.320	321.700	46.878	445.520	185.420	150.110
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ADF	-57.840	-59.400	-57.490	-56.980	-60.020	-58.650	-61.380
P-value	0.010	0.010	0.010	0.010	0.010	0.010	0.010
PP	-78.948	-83.443	-80.438	-77.192	-83.285	-82.701	-83.138
P-value	0.010	0.010	0.010	0.010	0.010	0.010	0.010

Note: Q(14) refers to the Ljung-Box test for autocorrelation of order 14, while ARCH(14) is the Engle (1982) test for conditional heteroscedasticity of order 14. Normality is tested using the Jarque-Bera test for normality. Test for non-stationarity is carried out using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test.

2.5 **Empirical results**

2.5.1 *Results of the Copula-DCC-GARCH model*

Using the three staple food price return series (maize, wheat, and soybeans) and the four cash crop price return series (coffee, cocoa, cotton, and sugar), we first estimate a seven dimension VAR system. We use the AIC and the Schwarz information criterion (SIC) to select the optimal lag order for the VAR system, while for the GARCH representation, we run univariate GARCH models for each of the seven return series to which we apply the AIC and SIC information criteria to select the lag order. The information criteria identifies VAR(1) and GARCH(1,1) as the optimal specification.

The top panel of the Table 2.2 represents the estimation results for the conditional mean return equation. It indicates that one-lagged returns estimates are not statistically significant (5 percent level) in predicting current price returns in the case of wheat, coffee, cocoa, and sugar. In contrast, maize, soybeans, and cotton respond to own autoregressive parameters, implying short-term predictability. The results also highlight few cases of mostly unidirectional cross-market mean spillovers (e.g. maize to coffee, soybeans to sugar, and wheat to maize). A bidirectional mean transmission is found between soybeans and wheat markets, underlining the strong substitution linkages between the two crops. In the cases of significant cross-market effects, the estimated coefficients are larger for the staples than cash crops, suggesting that information transmission flows mostly from staple food to cash crop markets.

Table 2.2: Copula-DCC-GARCH model estimation

	Maize	Wheat	*Soybeans*	Coffee	*Cocoa*	Sugar	*Cotton*
Conditional mean equation							
Const_mean	0.000036	-0.000013	0.000077	0.000085	0.000173	0.000053	-0.000005
	(0.862965)	(0.956263)	(0.682785)	(0.772745)	(0.457230)	(0.839375)	(0.981342)
Maize_L1	0.054839	0.028982	-0.019502	0.010552	0.037099	0.013944	0.008409
	(0.000727)	(0.110465)	(0.179806)	(0.640860)	(0.038869)	(0.492750)	(0.622101)
Wheat_L1	-0.020439	-0.023362	-0.033290	0.023505	-0.009255	-0.018694	0.000699
	(0.119870)	(0.112242)	(0.004715)	(0.199614)	(0.524647)	(0.256296)	(0.959649)
Soybeans_L1	-0.018980	-0.043603	0.038522	0.016390	0.006931	0.057231	-0.006917
	(0.247528)	(0.017648)	(0.008843)	(0.473924)	(0.702872)	(0.005408)	(0.688665)
Coffee_L1	0.025981	0.000375	0.008741	-0.018511	0.011093	0.020645	-0.004715
	(0.003680)	(0.970115)	(0.275458)	(0.137730)	(0.262554)	(0.065490)	(0.616199)
Cocoa_L1	-0.001075	0.000537	-0.008615	0.004119	-0.019684	-0.020378	-0.000758
	(0.923794)	(0.965951)	(0.392328)	(0.792658)	(0.113608)	(0.147893)	(0.948866)
Sugar_L1	-0.000030	0.012280	0.000164	-0.013488	0.023385	-0.016079	-0.000576
	(0.997593)	(0.270272)	(0.985366)	(0.331059)	(0.033806)	(0.197296)	(0.956135)

Cotton_L1	0.012654	0.000537	0.035887	0.032746	0.039903	0.001428	0.061007
	(0.288298)	(0.965951)	(0.000783)	(0.048803)	(0.002497)	(0.923807)	(0.000001)
Conditional variance-covariance equation							
Const_variance	0.000004	0.000004	0.000003	0.000010	0.000001	0.000002	0.000003
	(0.180312)	(0.000037)	(0.554334)	(0.000000)	(0.002192)	(0.000145)	(0.011884)
ARCH_L1	0.082725	0.036575	0.062549	0.042277	0.024828	0.034967	0.038806
	(0.000029)	(0.000000)	(0.054793)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
GARCH_L1	0.909160	0.951332	0.927097	0.941378	0.971951	0.961981	0.951759
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
DCC estimation of scalers α and β							
DCCα	0.004440						
	(0.000000)						
DCCβ	0.991278						
	(0.000000)						
Ljunk-Box test for autocorrelation (Null hypothesis: no autocorrelation in squared standardized residuals)							
LB(6)	7.427	9.036	7.608	11.38	7.6863	18.177	6.15
	(0.2831)	(0.1715)	(0.2683)	(0.077)	(0.262)	(0.0058)	(0.406)

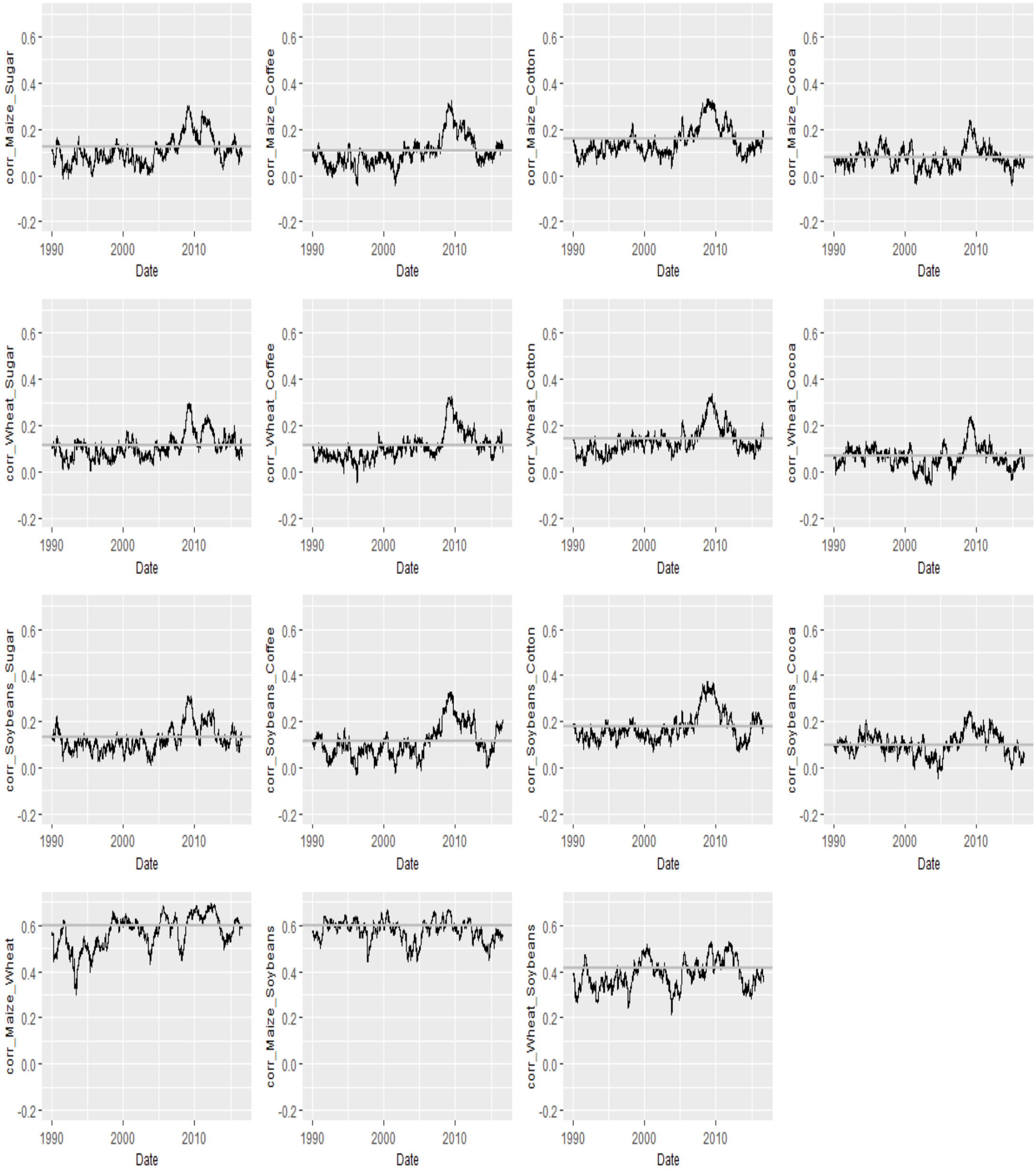
LB(14)	16.046	16.822	20.479	15.801	25.231	34.093	9.747
	(0.3106)	(0.2658)	(0.1158)	(0.3257)	(0.03236)	(0.00199)	(0.78)
Lagrange multiplier (LM) test for presence of ARCH (Null hypothesis: no ARCH effects in standardized residuals)							
LM(6)	1.9581	29.821	3.9264	21.349	15.457	18.221	0.6873
	(0.9235)	(0.0000465)	(0.6866)	(0.00158)	(0.01698)	(0.0057)	(0.9948)
LM(14)	4.956	32.407	14.848	32.557	18.044	20.843	2.4267
	(0.9864)	(0.0035)	(0.3886)	(0.0033)	(0.2048)	(0.1057)	(0.9997)
Hosking Multivariate Portmanteau test for cross-correlation (Null hypothesis: no cross-correlation in standardized squared residuals)							
HM(6)	283.9648						
	(0.652127)						
HM(14)	718.935						
	(0.185862)						
X^2 tests: Rt=R	16.27						
	(0.00000)						

Note: The information criteria AIC and SIC are used to select the optimal lag orders. DCC-GARCH estimation assumes Student-t copula. P-values reported in parentheses. One period lag is shown by L1.

Table 2.2 also shows result of the conditional variance estimations obtained by running univariate GARCH models. ARCH_L1 represents the past error terms of one of the food staples or cash crops. GARCH_L1, on the other hand, represents the past conditional volatility terms of one of the food staples or cash crops. In general, estimation results show some common patterns associated with the ARCH and GARCH coefficients. First, these estimated coefficients are highly significant for most of the univariate GARCH equations. Second, the ARCH estimates are generally lower than those obtained for GARCH, indicating that lagged shocks do not influence current conditional variance as much as lagged values of volatility for these markets. These results are in line with the volatility clustering feature that characterizes commodity prices (Deaton and Laroque 1992) in addition to supporting the use of GARCH(1,1) in modelling volatility persistence.

The estimated adjustment parameters α and β are significant at the 5 percent level, a result confirmed by the Wald test, which rejects the null hypothesis that the adjustment parameters are jointly equal to zero. Also, the sum of α and β is fairly close to 1, indicating high persistence in the conditional variances. Evidence against the assumption of a constant conditional correlation is further provided by the Engle and Sheppard Test of Dynamic Correlation (2001), which tests $R_t = R$. The test rejects the null hypothesis of constant conditional correlation. Table 2 displays some diagnostic statistics for the standardized residuals of the estimated DCC model. These confirm the adequacy of using a MGARCH. The Ljung-Box (LB), Lagrange Multiplier (LM), and Hosking Multivariate Portmanteau (HM) test statistics for up to 6 and 14 lags show no evidence of autocorrelation, ARCH effects, and cross-correlation, respectively.

Figure 2.3: Dynamic conditional correlations between staple foods and cash crops



Note: The solid grey line represents the estimated constant conditional correlation as developed by Bollerslev (1990).

As illustrated by Figure 2.3, the correlation between cash crops and staple foods goes through varying correlation regimes but remains for the most part positive. The initial increase of the correlation values, which begins in 2004, coincides with the rise in world demand for commodities, mostly driven by a robust economic growth in the emerging markets. It also coincides with the surge in international food futures prices to historical levels in 2007-2008. The subsequent fall in correlations observed in 2009 concurs with the period of the global financial crisis, when asset prices collapsed across the board. On the other hand, the 2011 spike displayed by the correlation pairs corresponds to the upturn in international cereal prices. The hike in these quotations was on the back of reduced supply availabilities in major producing countries, notably in the Russian Federation, the EU, and the United States, following severe droughts (e.g. United States) that affected crop yields. In addition, the Russian Federation imposed export restrictions on cereals to contain domestic price inflation.

While the results display some common patterns across crop markets, they also present some specific characteristics. We begin by looking at the evolution of the conditional correlations between maize and the cash crops. As shown in Figure 3, the correlations are highly volatile and fluctuate within a relatively large band. The correlations have mostly low values, with cotton on average displaying the largest correlation followed by sugar. The highest value for the 2009 peak is recorded by cotton (0.31) followed by sugar, while the lowest is found for cocoa (0.23). The correlations reaches a peak in 2011, when the largest value is recorded for sugar (0.26) followed by cotton (0.25), before declining to values similar to those of pre-2004 levels. Note that the conditional correlations present positive values for most of our sample period, with occasional negative values in the case of sugar (1990s), coffee, and cotton.

The level of interdependence between wheat and each of the cash crops shares resembling characteristics with that of maize. First, the dynamic correlations are quite volatile, with the exception of wheat and coffee which seems to fluctuate broadly around a narrower band. Also, the correlations are positive throughout the sample period, with only coffee presenting a negative correlation value with wheat in the mid-1990s. In the case of sugar, cotton, and to a lesser extent coffee and cocoa, a short-lived spike occurs in 2011. In 2009, the highest correlation value is estimated for wheat-cotton (0.32) followed by wheat-sugar (0.28), while in the 2011 peak the highest correlation value is recorded for cotton (0.25) ahead of sugar (0.22). Similarly, the estimated conditional correlations for the pairs of soybeans-cash crops display high volatility, with a rising relationship starting in 2004. There is also a marked surge in the correlation in 2011, in line with what is found for maize and wheat.

For comparison purposes, we also estimate conditional correlations for the pairs of staple foods. The conditional correlations are positive, volatile, and relatively elevated. For the maize-wheat pair, the estimated conditional correlation is found relatively elevated (0.6), reflecting substitutability, particularly in the feed market. There is a marked shift in the correlation level at beginning of 2000, when the level of the relationship increases to a new plateau. This coincides with the first expansion of the maize-based ethanol production in the United States.

After 2009, and excluding the 2011 peak, the estimated correlations fall steadily across the staple-cash crop pairs but remain positive. The declines in staple food futures are not matched with equivalent declines in cash crop futures which results in lower correlation values. In fact, cocoa futures remain relatively stable in the sample period following 2009, while coffee futures prices decline at a slower pace, when compared to staples. This asymmetry in the conditional correlation may reflect investors' choice to shift away from less liquid assets during period of market risks and uncertainty. It could also reflect a return of market fundamentals in shaping price movements.

2.5.2 *Results of the volatility spillover index approach*

While the DCC-GARCH approach evaluates the time-varying interaction between cash crop and staple foods, its specification does not allow an examination of the volatility transmission or spillover effects. For that, spillover indices are constructed based on the GFEV decompositions, as proposed by Diebold and Yilmaz (2012). Figure 2.4 illustrates the resulting net pairwise volatility spillovers expressed using equation (2.9). These spillovers are obtained based on a 10-day-ahead volatility forecast errors, as in Diebold and Yilmaz (2012), who also show that spillover indices are not sensitive to forecast horizons varying between 4 and 10. We also use 252-day rolling samples in the estimation of volatility spillovers. Overall, the net spillovers are generally negative, suggesting that the volatility runs from the staple food to the cash markets. The spillovers are found broadly larger during the recent period of the soaring commodity prices and the global financial crisis (2007-2012).

In the case of maize, the spillovers are largely negative in comparison to cash crops, suggesting volatility transmission runs from maize to cash crops. This is particularly marked for cocoa, coffee, and cotton. Despite being a net receiver of volatility from maize, particularly during the period of soaring commodity prices, sugar does transmit some shocks to the maize market more so than the other cash crops, reflecting the linkage with the energy sub-sector through the biofuel complex. Volatility transmission from maize is also significant during the financial crisis. Similar observations can be made for both soybeans and wheat, which are found to be net transmitters of shocks to cash crop futures prices, particularly during 2007-2012.

Table 2.3 and 2.4 illustrate the average results summarized in terms of volatility spillover matrix for the full sample and a restricted sample, respectively. The restricted sample covering 2007-2012, corresponds to the period when conditional correlation values are positive and increasing. The total (non-directional) volatility spillover for the full sample, appearing in the lower right corner of Table 2.3, amounts to about 20 percent. This means that 20 percent of the volatility forecast error variance of the VMA system is due to volatility spillover among the seven markets. The bulk of the forecast error variance for each of the variables is due to their own innovations. Results also show 18 percent of the forecast error variance of cash crop markets is explained by spillover effects from the staple food markets (directional spillover), while 12.8 percent of the forecast error variance of the staple food is explained by innovations in cash crop markets.

Table 2.3: Volatility spillover matrix full sample (1990-2016)

	maize	wheat	soybeans	coffee	cocoa	cotton	sugar	spillover
maize	0.6029	0.1814	0.1783	0.0065	0.0055	0.0160	0.0095	*0.3971*
wheat	0.2017	0.6697	0.0902	0.0072	0.0040	0.0160	0.0112	*0.3303*
soybeans	0.1961	0.0895	0.6621	0.0077	0.0077	0.0242	0.0125	*0.3379*
coffee	0.0093	0.0107	0.0112	0.9260	0.0216	0.0061	0.0152	*0.0740*
cocoa	0.0099	0.0059	0.0117	0.0220	0.9273	0.0110	0.0122	*0.0727*
cotton	0.0236	0.0212	0.0315	0.0052	0.0088	0.8981	0.0117	*0.1019*
sugar	0.0148	0.0152	0.0187	0.0154	0.0111	0.0119	0.9130	*0.0870*
						Total spillover %:		*20.014*

Note: The ijth entry of the volatility spillover matrix corresponds to the contribution to the forecast error variance of crop i coming from shocks to crop j. The diagonal elements are the own contributions.

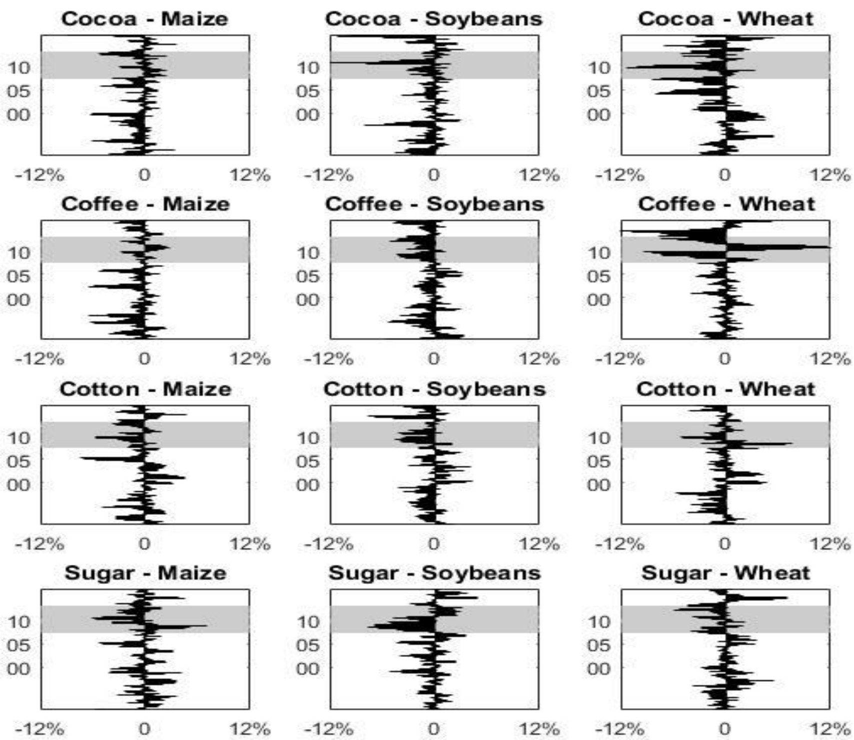
Table 2.4: Volatility spillover matrix (2007-2012)

	maize	wheat	soybeans	coffee	cocoa	cotton	sugar	spillover
maize	0.4745	0.2118	0.1820	0.0371	0.0174	0.0408	0.0364	*0.5255*
wheat	0.2291	0.5121	0.1317	0.0397	0.0166	0.0396	0.0313	*0.4879*
soybeans	0.1935	0.1299	0.5056	0.0483	0.0281	0.0558	0.0388	*0.4944*
coffee	0.0527	0.0534	0.0647	0.6626	0.0500	0.0501	0.0665	*0.3374*
cocoa	0.0341	0.0275	0.0449	0.0601	0.7634	0.0363	0.0339	*0.2366*
cotton	0.0583	0.0522	0.0746	0.0501	0.0266	0.6942	0.0441	*0.3058*
sugar	0.0533	0.0436	0.0548	0.0707	0.0304	0.0449	0.7023	*0.2977*
						Total spillover %:		38.362

Note: The ijth entry of the volatility spillover matrix corresponds to the contribution to the forecast error variance of crop i coming from shocks to crop j. The diagonal elements are the own contributions.

When we restrict the sample to 2007-2012 (Table 2.4), the bulk of the contribution to the variance of the forecast errors is still due to own innovations, but the size of those contributions are lower in comparison to the estimation with the full sample (Table 2.3). Lower own shocks are now balanced with higher spillover effects. Total (non-directional) volatility spillover, appearing in the lower right corner, show that 38 percent of the forecast error variance of the seven-dimensional VMA system is due to volatility spillovers among the selected variables. The contribution of volatility spillovers to the forecast error variance is almost double its size under the full sample estimation, suggesting higher volatility interdependence.

Figure 2.4: Net pairwise volatility spillovers staple foods and cash crops.



Note: The grey bar refers to the period of food price spikes, 07/07-12/12.

Overall, the spillover index analysis unveils evidence of volatility linkages between staple food and cash crop markets throughout the sample period, with information running from the staple food to the cash crop market, given the resulting larger spillover effects. Results also show that volatility transmission between both markets is relatively greater during the recent period of high commodity prices and financial turmoil. These findings can be related to those obtained for the conditional correlation estimations. Higher volatility, due to greater spillover effects, leads to larger standardized errors (u_t), and hence, larger conditional correlation estimates (see equation (2.4)). As a matter of illustration, the interaction between the estimated DCC conditional correlations and the net spillover indices for the maize-sugar pair in normalized form is presented in Figure A2.2. The upward trend in the conditional correlation from about 2004 to 2011 is influenced by shocks originating from both markets, with a marked net-volatility transmission from sugar to maize in 2008 (positive peak), while maize transmitting large shocks for most of the period with a pronounced peak in mid-2010 (negative peak). Figure A2.3 shows the evolution of the estimated conditional variances of maize and sugar, highlighting the large peak of volatility in maize in mid-2010, which far outweigh the conditional volatility in sugar.

2.6 Conclusion and implication

The analysis in this paper examines the interdependence and the dynamics underlying staple food and cash crop international futures prices. We use a multivariate Copula-DCC-GARCH framework and a FEVDs-based spillover index approach to explore the international price dynamics. While the unconditional correlation between staples and cash crop markets is relatively low (see Table A2.1), results from the estimation highlight the volatile nature of the conditional correlations across markets, with the estimated values being generally positive. Given the inelastic nature of cash crop and staple food markets, positive conditional correlation estimates means that, for NFIDCs, export earnings are a good hedge against rises in import bills. Governments can assess more accurately their financial requirements, as they deal with current account imbalances due to rising import bills, by taking into account that cash crop export earnings can limit, or offset, funding needs and borrowing costs.

Results also show that the conditional correlation values are stronger during 2007-2012, a period corresponding to high commodity prices and financial market stress, indicating the influence of broader financial markets on cash crop and staple food world quotations. Increasingly, commodities are considered as investment assets, very much like equity and bond holdings, a situation that may explain the synchronized price behaviour between seemingly unrelated futures price series such as wheat and cocoa. There is generally little substitution in supply and demand between cash crops and staple foods in the physical market, so the substitution principle is unlikely to explain the price co-movement in the short run. In the long run, aside from macroeconomic factors, changes in factor input costs could be responsible for some level of co-movement.

The volatility spillover analysis based on rolling generalized FEVDs indicates that transmission is generally asymmetric running mostly from food staple futures to cash crop futures prices. A similar outcome is found, when examining results from the conditional mean estimation. This means that NFIDCs can use information emanating from staple food markets to help predict and anticipate changes in cash crop export earnings. For instance, staple food price prospects can be useful in support of national cash crop price projections and sectoral planning.

The welfare cost of volatility has been examined quite extensively since the work of Lucas (2003), who developed a model for measuring the foregone consumption resulting from volatility. He argued for the necessity to take into account the potential gains from addressing market volatility in the design of policies. Similarly, Bidarkota and Crucini (2004) show that the welfare cost of terms-of-trade volatility is significant and could amount to two thirds, on average, of consumption. Consequently, volatility in international cash crop prices can undermine a government's fiscal revenue, ultimately lowering public and private investment, with long lasting negative effects on growth. Anticipating cash crop price volatility can help commodity-dependent developing countries build realistic budgets, especially for countries that depend on taxes levied on cash crop exports. This is particularly critical for countries with limited access to capital market (Eichengreen et al. 2003).

Future research should proceed on several fronts. First, there is a necessity for more research into the theoretical and empirical estimation of higher dimension MGARCH models that estimate spillover parameters. Most studies use a general form of BEKK-GARCH specification for that purpose. Generally, these models do not exceed a trivariate specification, given the prevailing convergence issues, especially when exogenous variables are added in the mean and/or variance equations. As opposed to a DCC-GARCH specification, a BEKK model enables the full use of information contained in the dynamic interaction among a system of variables, as it is the case with high dimension VAR systems. In addition to the convergence issues, there is considerable knowledge gap regarding the statistical and asymptotic properties of higher dimension BEKK-MGARCH. Second, further research is needed to explore the theoretical linkages between the own and volatility spillover GARCH-based estimates and those obtained from volatility indices based on the forecast error variance decompositions. As we see in this paper, there is scope for some complementarity between both methods. Finally, since our study on the interaction effects between cash crop and staple food futures prices is conducted at a global level, the next natural step is to verify whether the integration holds also at the country level.

2.7 References

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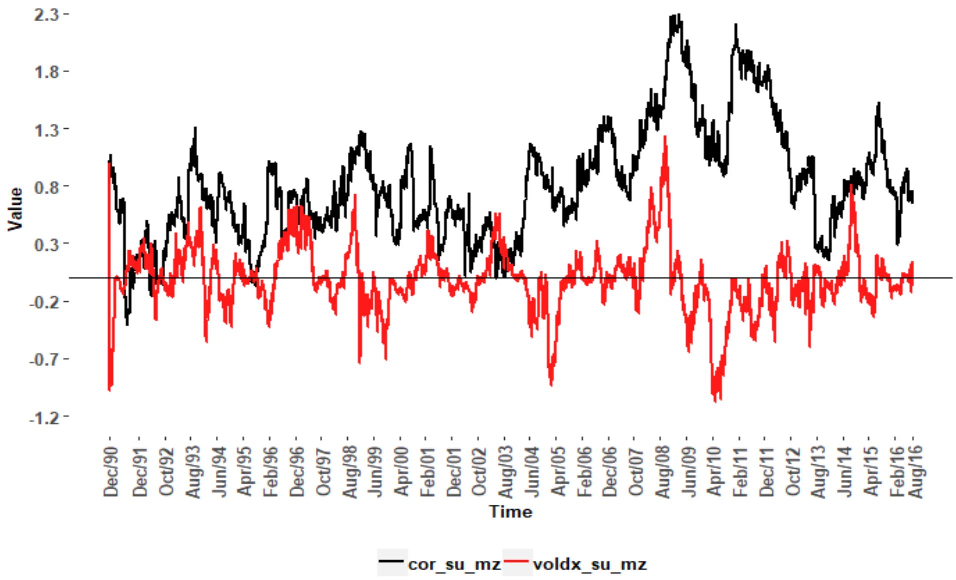
2.8 Annex

Table A2.1: Unconditional correlation between cash and staple foods

	Maize	Wheat	Soybeans	Coffee	Cotton	Cocoa	Sugar
Maize	1	0,548485	0,542463	0,096827	0,162436	0,097355	0,126245
Wheat	0,548485	1	0,365902	0,103355	0,154329	0,077876	0,127676
Soybeans	0,542463	0,365902	1	0,107259	0,188592	0,108983	0,138948
Coffee	0,096827	0,103355	0,107259	1	0,077756	0,153544	0,128315
Cotton	0,162436	0,154329	0,188592	0,077756	1	0,101417	0,114111
Cocoa	0,097355	0,077876	0,108983	0,153544	0,101417	1	0,109738
Sugar	0,126245	0,127676	0,138948	0,128315	0,114111	0,109738	1

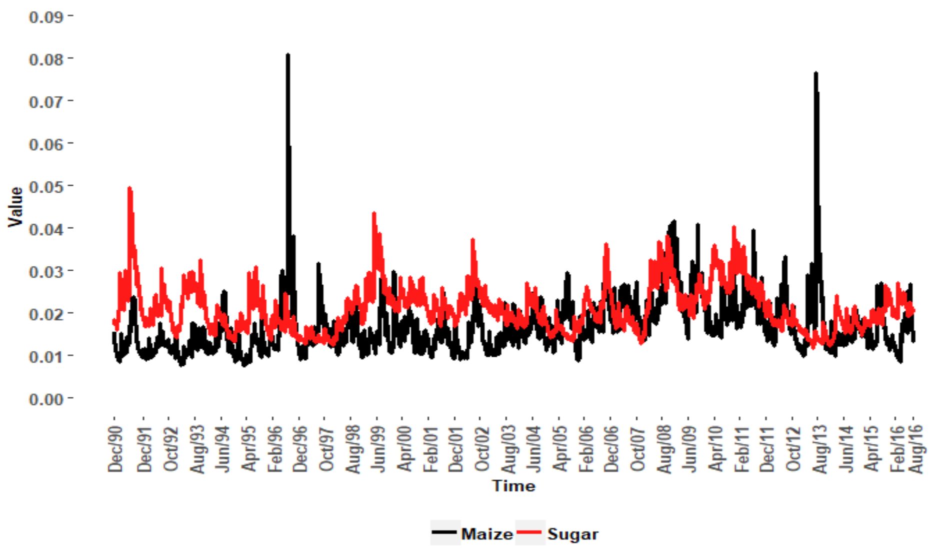
Note: All values are significant at 5 percent level

Figure A2.1: Net pairwise volatility spillovers and estimated conditional correlation between maize and sugar



Note: cor_su_mz stands for dynamic conditional correlation between maize and sugar, while voldx_su_mz is the derived net pairwise spillover between maize and sugar. Negative net spillover means that volatility runs mostly from maize to sugar.

Figure A2.2: Evolution of maize and sugar conditional variances



Note: The conditional variances are derived by estimating a Copula-DCC-GARCH model.

Chapter 3
International interdependence between cash crop and staple food futures prices indices: A dynamic assessment[1]

Abstract

This study examines the price level and volatility interaction between international staple food and cash crop futures price indices. Understanding the relationship between these commodities bears significant implication for low income food deficit countries that depend on cash crops to finance food import bills. We use a wavelet analysis to decompose the price indices, and then apply a BEKK-MGARCH approach to analyze the relationship across time scales. Results indicate the level of correlation and volatility linkages are strongest at lower frequencies (longer run) than at higher time scales (short run), with information running from staple food to cash crop markets.

Keywords: Cash crops; MGARCH; staple food crops; volatility spillover; wavelet

JEL classification : Q13, C13, G11, G01

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3.1 **Introduction**

For many low income food deficit countries (LIFDCs)[2], swings in staple food prices are an important source of macroeconomic instability. Theory suggests that in the face of instable current accounts, due to relatively volatile export earnings and/or import bills, agents should seek to enhance savings, a move that enables smoothing consumption over time (Ghosh and Ostry, 1994). Still, the ability to increase the level of savings is rather limited in many poor net food importing developing countries, mainly due to weak domestic financial systems. Countries can also try to borrow funds from international markets to finance import requirements, thus balancing a current account deficit with higher capital inflows. This is possible provided countries still have the ability to sustain additional borrowings without prompting a rise in default risks.

In this context of limited access to savings and borrowings, cash crop export earnings can act as an automatic consumption smoothing mechanism for LIFDCs. This is because international demand for agricultural commodities (including cash crops) is generally inelastic, implying that movements in prices outweigh those of quantities (Food and Agriculture Organization of the United Nations [FAO], 2004). Hence, rising cash crop and staple food prices translate into increasing export earnings and import bills. A casual review of price data series shows that staple food and cash crop quotations tend to display synchronized behavior. For example, during the recent commodity price surge episode, wheat and rice prices went up by 17 percent and 65 percent, between 2006 and 2009, respectively, while international prices for coffee, tea, and sugar, grew by 26 percent, 45 percent and 23 percent, over the same period, respectively[3]. Overall, between 2002 and 2008, the World Bank agricultural sub-index increased by 102.9 percent.

[2] A list of the LFIDCs is available at http://www.fao.org/countryprofiles/lifdc/en/. Criteria for inclusion are also provided.

[3] World Bank's pink sheet at: http://www.worldbank.org/en/research/commodity-markets.

The rise in cash crop prices, together with staple food prices, means that export revenues from the commodities that many LIFDCs rely on could act as a good hedge against surges in food import bills, and contribute to reducing current account instability[4].

This study looks at one particular aspect of current account instability that relates to the extent to which changes in cash crop prices can dampen the effect of higher food prices[5]. We explore the price relationship by examining co-movements and dynamics in terms of price level and volatility. While movements in quantities together with prices determine the direction and magnitude of export earnings, the focus in this paper is exclusively on the price component of the equation given its relative importance. Volatility is important to study because it helps shed some light on the transmission of information/uncertainty from one market to another. Research also indicates that the prevalence of high volatility hinders investment and planning.

In order to gain further insights into the staple food-cash crops price relationship, we apply a wavelet analysis to decompose the series into three time scale levels corresponding to the short, medium, and long run. That is because policy implications differ depending on the nature of the price linkages at each time horizon. For instance, if the price dynamics is stronger in the long run, as opposed to the short run, cash crop earnings could potentially limit, or offset, rises in international food prices, while in the short run, measures may be required to address current account imbalances.

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[4] In 2013, for instance, export of tropical beverage crops, fruits, and sugar as a percentage of total agricultural products was estimated at 77 percent, 74 percent, and 71 percent for Burundi, Mauritius, and Swaziland, respectively. Also in that year, these products accounted for 43 percent, 27 percent, and 24 percent of total merchandise export for Burundi, Uganda, and Kenya, respectively (FAO, 2016).

[5] International prices, such as those for coffee, cocoa and wheat, are generally assumed to refer to futures prices like those negotiated at the Intercontinental Exchange (ICE) and the Chicago Board of Trade (CBOT). Futures prices are relevant because they influence border prices, and hence, the value of import bills and export earnings (Chen et al., 2010).

Further, the application of wavelet analysis enables the detection of breaks or any sudden changes in the dynamics that may characterize the series.

After decomposing the series, a multivariate Baba, Engle, Kraft and Kroner (BEKK)-Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework (Engle and Kroner, 1995) is applied to explore the dynamics of the volatility interaction and conditional correlation at various frequency levels. The advantage of using the BEKK framework is that it ensures a symmetric and positive definite conditional variance-covariance matrix. In addition, the model produces fewer parameter estimates compared to other multivariate GARCH (MGARCH) models when evaluating volatility transmission across markets (Gardebroek and Hernandez, 2013). To minimize the effect of model convergence issues that are often associated with BEKK-GARCH parameterization, we construct two price indices that we use for the estimation exercise. The first price index captures daily futures price changes for sugar, cotton, cocoa, and coffee and is referred to as the cash crop price index. The second index depicts daily futures price changes for wheat, maize, and soybeans, and represents the staple food crop price index. Both price indices are volume weighted, with data on daily volumes obtained from the futures markets where the commodity is traded[6]. The idea of weighting by volume is to give prominence to the commodities in the price index that are traded the most[7]. Note that the data shows a jump in the assigned weights as the contract expiry date nears. Nonetheless, these changes do not alter the relative importance of specific commodities in the index. That is, sugar and maize remain the most traded contracts regardless of the changes in weights due to the effect of expiring contracts. Scaling the estimated conditional covariances by the estimated conditional variances yields a series of conditional correlations, which permit the examination of conditional correlation patterns between the cash crop and staple food indices at different time scales.

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[6] Sugar, cotton, cocoa, and coffee daily futures prices and volumes are taken from the ICE, New York, while those for wheat, maize, and soybeans are taken from the CBOT, Chicago.

[7] For the food index, maize has an average weight of 52 percent over the sample period, while for the cash crop index, sugar represents an average of about 64 percent of the index.

In addition to easing model convergence, undertaking the analysis at the aggregate level offers some insights into the relationship between cash crop and staple food international prices, before deciding on whether it is “worth” exploring further the analysis at the country level, given the challenges associated with the data. Indeed, data series on cash crop and staple food prices for developing countries are often short, contain missing values, and are generally available at low frequency only, which makes it difficult to obtain robust results using a BEKK-GARCH approach.

Our research contributes to the literature in four aspects. First, as opposed to the bulk of the existing studies on the relationship between staple foods and cash crops, we examine the price level and volatility interaction from a global perspective. Hence, we contribute to providing evidence-based analysis of the potential contribution of cash crop export earnings to food import bills, particularly during periods when food prices are relatively high and volatile. Second, we use wavelet transforms to decompose the price series into different time scales, enabling an assessment of volatility dynamics otherwise hidden in the original series. Third, we estimate conditional correlations between cash crops and staple food indices at difference time frequency domains. This way, we evaluate the potential dampening effect of cash crop export earnings on current account variability due to rising food import prices. Finally, the literature on the linkages between balance of payments and commodity export/import is quite substantive, with marked contributions from international organizations, including the FAO (FAO, 2016), the International Monetary Fund (IMF, 2008), and the United Nations Conference on Trade and Development (UNCTAD and FAO, 2017). Often the case, member countries of these organizations (notably through the Group of 77, an intergovernmental group of developing countries) request that normative work be carried out on this topic, given its practical relevance. This article adds to that research stream.

We should note that the observed synchronized movement between cash and staple food international prices cannot be explained by market fundamentals only, at least in the short term. That is because the substitution possibility in consumption and production between cash crops and staples in the physical market is limited and, hence, cannot explain the extent of price correlation. On the other hand, macroeconomic shocks, weather impacts affecting major producers of both commodity groups, changes in energy prices, and the potential influence of institutional investors, could cause futures prices to co-move. The influence of institutional investors on commodity markets still remains ambiguous (Irwin and Sanders, 2011; Fattouh et al., 2012; Hamilton and Wu, 2015). A causal attribution analysis is beyond the scope of this study. Figure A3.2 describes the main linkages between cash crop and staple food markets, and some of the possible factors underlying the relationship.

The rest of the paper is organized as follows: the next section covers a short review of relevant studies on cash crops and staples and the use of the GARCH methodology. We then present a discussion on the methodology and data used in the analysis, followed by a discussion about the main empirical results and observations. Finally, a summary of the main conclusions and implications are provided in the last section.

3.2 Literature review

The literature on the relationship between international staple food and cash crop prices is mostly concerned with farm resource allocation, and precisely whether cash crop production and export compete for resources with food crop production. The concern is that a focus on cash crop production may create some risks for smallholder farm households notably in terms of food security. One school of thought argues that cash crop production is detrimental to food security (Maxwell and Fernando, 1989; Mittal, 2009), while others contend that a cash crop strategy improves farm welfare because proceeds from cash crop provide the means to buy food in the local market (i.e. the access dimension of food security) (Timmer, 1997; Von Braun and Kennedy, 1986; Weber et al., 1988). Recent papers in this field claim that staple foods and cash crops should be viewed as complementary rather than competitive. By participating in cash crop schemes, smallholders can have access to productivity enhancing inputs such as credits, management training, fertilizers, and other factor inputs which would not have been available without the participation in cash crop programs (Govereh and Jayne, 2003; Theriault and Tschirley, 2014).

While many studies provide some interesting insights into the mechanisms that explain the allocation of farm resources to the production of cash crops by smallholders in developing countries (Norton and Hazell, 1986), they seldom address the interaction of cash crop and staple food prices at the international market level. The dynamics at the international level is relevant because it often determines movements in domestic prices. For example, coffee prices received by farmers in Ghana are associated with futures prices negotiated at the Intercontinental Exchange (ICE) market in New York. Similarly, wheat imports prices paid by Egypt, the world's largest wheat importer, are linked with wheat futures prices such as those negotiated at the Chicago Board of trade (CBOT) or EURONEXT/MATIF in Paris (Janzen and Adjemian, 2017). Hence, the benefit of specializing in cash crop production, and the use of revenues to import food, hinges on the interaction of cash crop and staple food futures prices. High exports revenues can help alleviate partially, or fully, the burden associated with food import bills during periods of high international food prices. The extent of the contribution depends on several factors which include, the contribution of cash crop earnings to total export revenues, the price elasticities of international demand and supply for cash crops, and currency movements.

Whereas the available research into the volatility dynamics between cash crop and staple food international prices is relatively limited, studies using GARCH methodology to assess the interdependence among markets, including agriculture, are quite prolific. For example, Vivian and Wohar (2012) use a GARCH approach to examine the volatility interaction among a sample of 28 commodities and found significant volatility linkages and volatility persistence even after taking structural breaks into account. Using a BEKK and a dynamic conditional correlation (DCC) trivariate GARCH approach, Gardebroek and Hernandez (2013) find evidence of unidirectional volatility spillover running from maize to ethanol, but weak evidence of transmission from crude oil to maize market in the United States. An MGARCH with structural breaks is applied by Teterin et al. (2016) to explore the volatility dynamics between crude oil and maize future prices. Their results show that the volatility between crude oil and maize is less persistent when accounting for structural breaks in the mean and volatility. In a recent study, Al-Maadid et al. (2017) conclude that there is significant volatility spillover effects between energy and food markets, with the interaction greater during the 2006 food crisis and the 2008 financial crisis. Other studies using a GARCH method to examine price volatility among various commodities include Chang and Su (2010), Ji and Fan (2012), Harri and Hudson (2009), Nicola et al. (2016), and Trujillo-Barrera et al. (2012).

A growing number of studies looking at agricultural price volatility have been using wavelet-based techniques. While these techniques are common in the fields of physics, medicine, and mathematics, the expansion of their application to economics and finance is a quite recent phenomenon. The advantage of this approach is that it allows a decomposition of the main components of a price series to gain additional insights into the underlying factors shaping their movements (Percival et al., 2004). For example, Filip et al. (2016) apply a wavelet analysis to study the linkages between the price of feedstocks and ethanol in both Brazil and the United States. Their results show that feedstock prices lead those of ethanol. Kristoufek et al. (2016) report similar results using a wavelet coherence approach. Mensi et al. (2017) combine wavelet and copula method to examine the interaction between implied volatility indices for oil, wheat and maize and find evidence of asymmetric tail dependence among the selected commodities. Also, using a wavelet approach to disentangle the interaction between commodity and credit markets in sub-Saharan Africa, Ftiti et al. (2016) find a strong relationship over long time scales, confirming that the credit market is affected by persistent commodity shocks. Power and Turvey (2010) use a wavelet method to study the volatility interaction among 14 commodities, while Pal and Mitra (2017) using a wavelet-based methodology find that world food prices co-move with crude oil prices, with the latter leading world food quotations.

With increasing evidence linking the market performance of equities to changes in commodity prices, several studies analyze the interaction between the financial market and commodities, including agriculture. These studies provide empirical evidence explaining the co-movement between financial markets and commodities. The use of GARCH-based techniques in these studies is very common. For example, Mensi et al. (2013) examine the volatility integration between energy, food, gold, and beverages price indices, and the United States' S&P 500 index. Their results show significant return and volatility transmission across markets. Gao and Liu (2014) use a bivariate GARCH model to investigate the volatility interdependence between the S&P 500 index and a sample of commodities, while Nazlioglu et al. (2013) look at the volatility transmission between crude oil and agricultural commodity markets, evidencing significant mean return and volatility integration. Other studies examining the linkages between financial markets and commodities include Olson et al. (2014), Park and Ratti (2008), Awartani and Maghyereh (2013), El Hedi Arouri et al. (2011), Malik and Ewing (2009), Diebold and Yilmaz (2012), Amatov and Dorfman, (2017), and Grosche and Heckelei (2016).

3.3 **Methodology and data**

3.3.1 *Wavelet analysis*

Wavelet analysis is used to decompose a signal into its main components, enabling the possibility to focus on specific frequencies (Percival et al., 2004). In contrast to the Fourier transform, wavelet transform combines information on both time and frequency domains, allowing to track timewise particular frequencies (Mensi et al., 2017). A wavelet transform is based on the mathematical operation of convolution, which specifies that the integral of the product of two functions, one of which is reversed and shifted, produces a third function which has similar features as the shifted and reversed function (Torrence and Compo, 1998). The wavelet transform is based on two specific functions: 1) the father wavelet $\Phi(\mathrm{t})$, and 2) the mother wavelet $\Psi(t)$. A series of wavelets called daughter wavelets $\Psi_{u,s}(t)$ can be built by simply scaling and translating (shifting) $\Psi(t)$:

$$\Psi_{u,s}(t) = \frac{1}{\sqrt{s}}\Psi(\frac{t-u}{s}), \tag{3.1}$$

where $1/\sqrt{s}$ is a normalization factor ensuring unit variance of the wavelet, i.e. $||\Psi_{u,s}(t)||^2 = 1$, and u and s are the location and scaling parameters, respectively (Crowley, 2005). The scaling parameter controls for the length of the wavelet and is related to the frequency of the input signal such that a larger (lower) value implies the wavelet will correlate with the low (high) frequencies contained in the time series. The term u determines the location of the wavelet in the time domain. A number of wavelets have been developed to capture specific frequency characteristics of time series, and these include the Daubechies, Haar, Morlet, and Mexican hat. There are two types of wavelet transforms that are widely used in the literature: 1) the discrete wavelet transform (DWT) and 2) the continuous wavelet transform (CWT) (Crowley, 2005). The DWT is suitable for data compression and noise reduction, while the CWT is useful for smooth extraction of frequencies. Mother wavelets have to satisfy two main conditions: 1) zero mean, that is $\int_{-\infty}^{\infty} \Psi(t)dt = 0$, and 2) unit energy (localized in time or space), i.e.$\int_{-\infty}^{\infty} \Psi^2(t)dt = 1$. In addition, wavelets have to satisfy the admissibility condition, which guarantees a reconstruction of the original time series from its wavelet transform using the inverse transform (Shalini and Prasanna, 2016). For this paper, we use the DWT, given the flexibility it offers in denoising time series (Crowley, 2005), but also because it produces a minimum number of coefficients necessary to reconstruct a series. Given its parsimonious nature, the DWT has wide applications (Moya-Martínez et al., 2015). To minimize the boundary effects at the extremities of time series when applying the DWT, we use the periodic decomposition often done in similar studies. Based on the DWT, any time series can be described as a linear combination of father and mother wavelets (Mensi et al., 2017):

$$\mathrm{X}(t) = \sum_k s_{j,k}\Phi_{j,k}(t) + \sum_k d_{j,k}\Psi_{j,k}(t) + \cdots + \sum_k d_{1,k}\Psi_{1,k}(t), \qquad (3.2)$$

where j represents the multiresolution, or scale level, and k depicts the number of coefficients at each scale level. Further $s_{j,k}$ and $d_{j,k}$ are the scaling (or smooth) and detail (or wavelet) coefficients, respectively, and can be expressed as

$$s_{j,k} = \int X(t)\Phi_{j,k}(t)dt, \text{ and} \tag{3.3}$$

$$d_{j,k} = \int X(t)\Psi_{j,k}(t)dt, \qquad \text{for j=1,2,…,j.} \tag{3.4}$$

The detail coefficient $d_{j,k}$ captures the high frequencies contained in the input signal, or time series, while the scale coefficient $s_{j,k}$ captures the smooth part, or the long term trend, of the input function (Moya-Martínez et al., 2015). The original input function X(t) can be reconstructed as a linear combination of the calculated coefficients (Mensi et al., 2017):

$$\mathrm{X}(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \cdots + D_1(t), \tag{3.5}$$

with the smooth, or approximation, components of the time series represented by $S_j = \sum_k s_{j,k}\Phi_{j,k}(t)$ and the details components of the series specified as $D_j = \sum_k d_{j,k}\Psi_{j,k}(t)$. In practice, a wavelet with some desired properties is chosen and convoluted with a time series to extract the various frequencies that are contained in the series. It is then possible to rebuild the series by excluding, for example, certain frequencies. The reconstruction of a time series using the DWT approach most often relies on Mallat's pyramid algorithm (Mallat, 1989), which consists of applying a series of low-pass and high-pass filters. Explicitly, a time series X(t) is convolved with high-pass and low-pass filters to extract the detail $\mathrm{D_1(t)}$ and approximation $\mathrm{S_1(t)}$ components of the series. Then $\mathrm{S_1(t)}$ becomes the input for the subsequent iteration phase to derive $\mathrm{D_2(t)}$ and $\mathrm{S_2(t)}$. This iterative process is repeated until the desired decomposition level j is achieved (Crowley, 2005).

Denoising a series is one of the most common applications of wavelet analysis and involves selecting a threshold value λ, which is then used to filter the derived wavelet coefficients. There are two types of thresholding: 1) hard thresholding, where wavelet coefficients with the absolute value less than the threshold are set to zero, and 2) soft thresholding, where the absolute values of the wavelet coefficients above λ are shrunk (Haven et al 2012). We define λ according to Donoho (1995) such that $\lambda = \sqrt{2\sigma^2}\log(N)$, where N represents the length of the signal, and σ stands for the variance of the noise, which is estimated by computing the variance of the wavelet coefficients derived from the first decomposition level[8]. Therefore, the threshold level increases with the volatility of the time series. The denoised time series is then constructed by substituting the detailed wavelet coefficients derived through the DWT with the 'thresholded' wavelet coefficients.

In this paper, we use the Daubechies' "extremal phase wavelets" (Daubechies, 1992), as previous studies have shown that the Daubechies extremal phase wavelets are appropriate for financial data, and implement the DWT to denoise the cash and staple food index series. Typically, denoising the price indices implies removing those wavelet coefficients which do not contribute significantly to the signal. In terms of our index series, noise may represent short term speculative behavior, scalping, herd behavior, outliers, or irrational price movements (Gardebroek and Hernandez, 2013). Daily observations such as futures prices typically contain a lot of noise which do not necessarily contribute to the underlying movement in prices.

3.3.2 *GARCH approach*

As highlighted in the literature review, the multivariate GARCH model is widely applied in the analysis of integration between markets. In this paper, we study the volatility spillover between cash crop futures price index and staple food futures price index at an international level. The basis for constructing the indices is discussed later in the data section. Our approach assumes that the variance-covariance matrix follows a BEKK-GARCH specification. The bivariate BEKK-GARCH model is expressed as

$$A(L)r_t = \varepsilon_t \ , \tag{3.6}$$

and

$$\varepsilon_t | \omega_{t-1} \sim N(0, H_t)$$

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[8] The Donoho approach is also referred to as the universal thresholding. Other thresholding methods include visu shrink, sure shrink, and Bayes shrink.

where $A(L)$ is a polynomial matrix in the lag operator L, r_t is a 2 x 1 daily return vector at time t, and ε_t is a 2 x 1vector of random errors representing the shocks, or innovations, at time t. H_t is a 2 x 2 conditional variance-covariance matrix, given market information ω_{t-1} available at time t-1. Equation (3.6) represents the mean conditional equation, and describes the impact of own and lagged shocks as well as lagged innovations in other markets on the conditional mean of a variable at time t. The order of the system can be selected on the basis of a standard information criterion (e.g. Akaike information criterion (AIC), Schwarz information criterion (SIC)).

With respect to the form that H_t can take, it generally depends on the number of variables and the objective of the research. Often, when the number of variables is large, a less flexible multivariate GARCH specification is chosen. This is because model convergence during the estimation process is difficult to achieve if the number of variables is larger than three, and, in particular, when exogenous variables are included (El Hedi Arouri et al., 2015). Convergence issues with higher model dimension can be limited by restrictive specifications such as the diagonal BEKK-GARCH and the scalar BEKK-GARCH models. These parsimonious specifications reduce the computational complexity and facilitate model solution. The list of more flexible GARCH specifications is fairly exhaustive, and we only mention here the most commonly used models which comprise the full BEKK-GARCH model, introduced by Engle and Kroner (1995), the constant conditional correlation (CCC)-GARCH model, specified by Bollerslev (1990), the dynamic conditional correlation (DCC)-GARCH model of Engle (2002), and the vector autoregressive (VAR)-GARCH introduced by Ling and McAleer (2003).

Based on the model proposed by Engle and Kroner (1995), the conditional variance-covariance matrix of the BEKK-GARCH specification can be expressed as

$$H_t = C_0'C_0 + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + G_{11}'H_{t-1}G_{11}, \qquad (3.7)$$

or in matrix form as

$$H_t = C_0'C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1,}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1,}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}, \quad (3.8)$$

where $C_0'C_0$ represents the decomposition of the intercept matrix, with C_0 restricted to be a lower triangular matrix. The unrestricted n x n matrices A and G contain the own ARCH and cross-market ARCH effects and the own GARCH and cross-market GARCH effects, respectively. With this specification, it is possible to trace the effect of innovations and volatility in one market and how they transmit to other markets. These estimates are contained in matrices A and G. Expanding equation (3.8) yields the variance-covariance equations:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2h_{22,t-1}, \quad (3.9)$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + g_{11}g_{12}h_{11,t-1} + (g_{21}g_{12} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1}, \quad (3.10)$$

$$h_{22,t} = c_{21}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + g_{12}^2h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2h_{22,t-1} \quad (3.11)$$

With the assumption that error terms follow a multivariate standard normal distribution, the BEKK-GARCH models are estimated by maximizing the log likelihood function using the Berndt, Hall, Hall and Hausman (BHHH) algorithm. The conditional log likelihood function L for a sample of T observations is

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta), \text{ with} \quad (3.12)$$

$$l(\theta) = -log2\pi - \frac{1}{2}\log|H_t(\theta)| - \frac{1}{2}\varepsilon_t'(\theta)H_t^{-1}(\theta)\varepsilon_t(\theta),$$

where θ represents the vector of all the parameters to be estimated

3.4 **Data**

Two price indices are produced to capture movements in cash crop and staple futures prices. The cash crop futures index is constructed by taking a weighted average of the daily closing futures prices realized at the Intercontinental Exchange (ICE) for sugar (raw sugar) No. 11 (SB) futures, cocoa (CC) futures, coffee “C” (KC) futures, and cotton No.2 (CT) futures. We first normalize the prices and use the daily traded volumes (number of contracts traded) as weights to derive the daily futures price index. We follow a similar procedure for the staple food futures prices, where we use the daily closing futures prices realized at the Chicago Board of Trade (CBOT) for corn (C1) futures, soybeans (SB1) futures and wheat (W1) futures, and use the respective traded volumes as weights. For both indices, daily futures prices and volume data are sourced from Bloomberg and cover the period of 3 January 1990 to 30 August 2016. All futures prices are historical first generic price series, and expiring active futures contracts are rolled to the next deferred contract after the last trading day of the front month[9].

The choice of the commodities included in the two indices is based on a pre-analysis that involves identifying the top exported cash crops and the top imported staple foods by the LIFDCs group[10]. We then select those crops for which an international futures contract exists. On this basis, coffee, cocoa, cotton, and sugar futures prices are selected to represent the group of cash crops, while wheat, corn, and soybeans futures prices are selected to characterize the staple food group. As with similar studies, the analysis is undertaken using the returns of the index series by taking the differences in the logarithm of two consecutive price indices. The choice of transforming

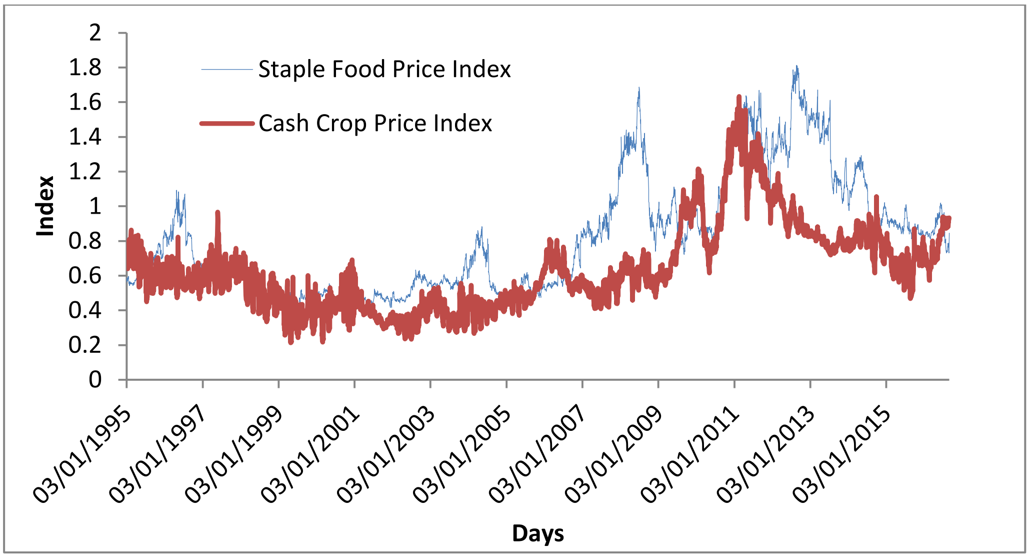
[9] Carchano and Pardo (2009) apply five different methodologies for rolling futures contracts, including the one we use in our paper. They found that the choice of the rollover date does not induce significant differences between series. That is, the series preserve their general statistical characteristics regardless of the rollover selection criteria

[10] The analysis uses FAOSTAT database: http://www.fao.org/faostat/en/#data.

the index series is determined by the fact that the cash crop and staple food indices are integrated at different orders. Both, the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests fail to reject the presence of unit root for the staple food index, while both tests reject the null hypothesis of non-stationarity for the cash crop index. Given that the indices are integrated at different orders, that is staples being I(1) and cash crops I(0), a Vector Error Correction Model (VECM) framework is not suitable in our case. Hence, a VAR is specified in returns in order to get consistent estimates. Figure 3.1 shows the daily movements of both cash and staple food price indices. The graph highlights the extent of the volatility that underpins both markets[11].

[11] One critique of transforming a VAR in first differences is that it may lead to overdifferencing, and thus induce non-invertibility in some series. As such, a VAR with differenced variables may be misspecified. We take the other view expressed in the literature, which shows that the cost of overdifferencing is not large, particularly when consideration is given to the properties of the model disturbances, within a stationary multivariate framework (see Marcet, 2005; Maddala and Kim, 1998; Plosser and Schwert, 1977; Damane, 2018). Hence, we use a VAR-BEKK-MGARCH in first differences with appropriate lag length and error structure.

Figure 3.1: Daily movements of staple food and cash crop price indices (2010 = 1)



3.5 Descriptive statistics and results

3.5.1 *Descriptive statistics*

The descriptive statistics of the price index return series are reported in Table 3.1. The statistics show that the food price index has the largest daily return and the lowest standard deviation, in comparison to the cash crop index. Overall, the series are asymmetric, with a small positive skewness, and have large kurtosis coefficients. The Jarque-Bera test statistics rejects the null hypothesis of normality for both price return indices. The ARCH test for heteroscedasticity points to the presence of ARCH effect in both index series. Also, the Ljung-Box test for autocorrelation evidences the presence of autocorrelation. These results corroborate the use of a multivariate GARCH model in assessing the volatility integration between cash crop and staple food markets. They are also in line with the underlying characteristics of commodity price movements, notably volatility clustering, as described in Deaton and Laroque (1992). With respect to the stationarity of the series, the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) tests reject the null hypothesis of non-stationarity at the 1 percent level of significance. The unconditional correlation between cash and staple food price index using the Pearson coefficient is estimated to be 0.74 at the 5 percent level of significance.

Table 3.1: Descriptive statistics of the price index returns

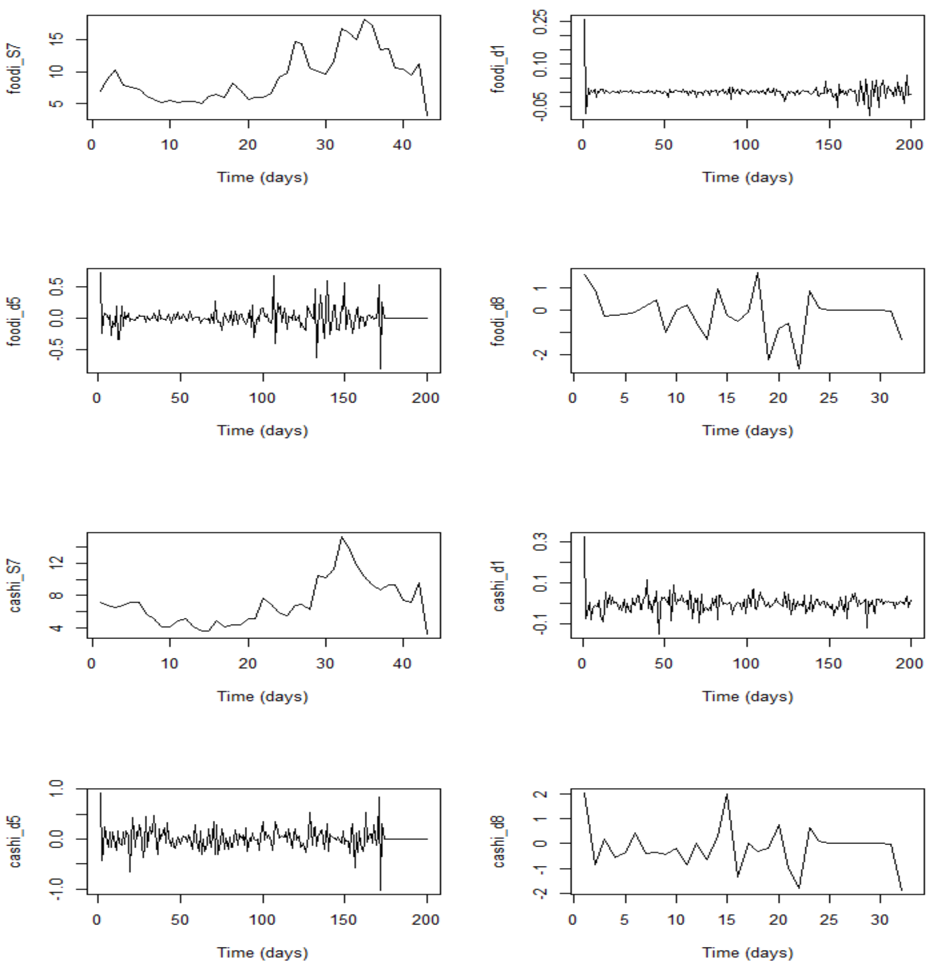
	Staple food index return	Cash crop index return
Mean (%)	0.0075	0.0053
Median (%)	-0.0247	-0.0117
Maximum	22.3032	71.1149
Minimum	-19.4870	-59.6080
Standard deviation (%)	2.3153	6.9209
Skewness	0.1380	0.6922
Kurtosis	8.6483	14.8098
Jarque-Bera	17081	50470
P-value	0.0000	0.0000
Q(14)	153.5700	467.8300
P-value	0.0000	0.0000
ARCH(14)	175	1176
P-value	0.0000	0.0000
ADF	-59.0660	-66.0250
P-value	0.0100	0.0100
PP	-86.0580	-104.3500
P-value	0.0100	0.0100

Note: Q(14) refers to the Ljung-Box test for autocorrelation of order 14. ARCH(14) is the Engle (1982) test for conditional heteroscedasticity of order 14, while the Jarque-Bera test is used to test for normality. The Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) methods are used to test for non-stationarity of the index series.

3.5.2 *Results of the wavelet analysis*

As discussed in the methodology section, we use the Daubechies' "extremal phase wavelets" to decompose the series into approximated and detailed series. The Daubechies family of wavelets are used in finance and economics because of their desirable properties of ortho-normality, asymmetry, and higher number of vanishing moments (Daubechies, 1992). Figure 3.2 illustrates the decomposition exercise based on a multiresolution analysis (MRA) at various scales for both food and cash crop price indices. A maximum scale level j of 12 is selected, which is standard in the literature, since previous studies have shown that moderate filters are appropriate for financial data (Gençay et al., 2001; Gençay et al., 2005; In and Kim, 2013). Note that, according to Nyquist's rule, half of the sample can be eliminated at each successive scale level. For illustrative purposes we present 3 detailed series and 1 approximation series derived from the calculated values of the wavelet transform coefficients. A wavelet coefficient can be interpreted as the difference between two adjacent averages for a certain scale (Percival et al., 2004). Practically, it shows how the average of a particular series changes when considering various scales (e.g. 2 days, 20 days, or 360 days). Analyzing the change in the average of price series at different scales helps detect any possible trends, discontinuities, or abrupt changes in the series. In Figure 3.2, the highest scale level (frequency) component d1 corresponds to time-scale (frequency) of 2^1=2 days (daily effects), while d5 accounts for variations in a time-scale (frequency) of 2^5=32 days. The coarser, or smoother, part of the series (S7) captures the trend.

Figure 3.2: Wavelet decomposition results at selected scales for cash and staple food series



Note: foodi stands for food price index, while cashi represents the cash crop price index.

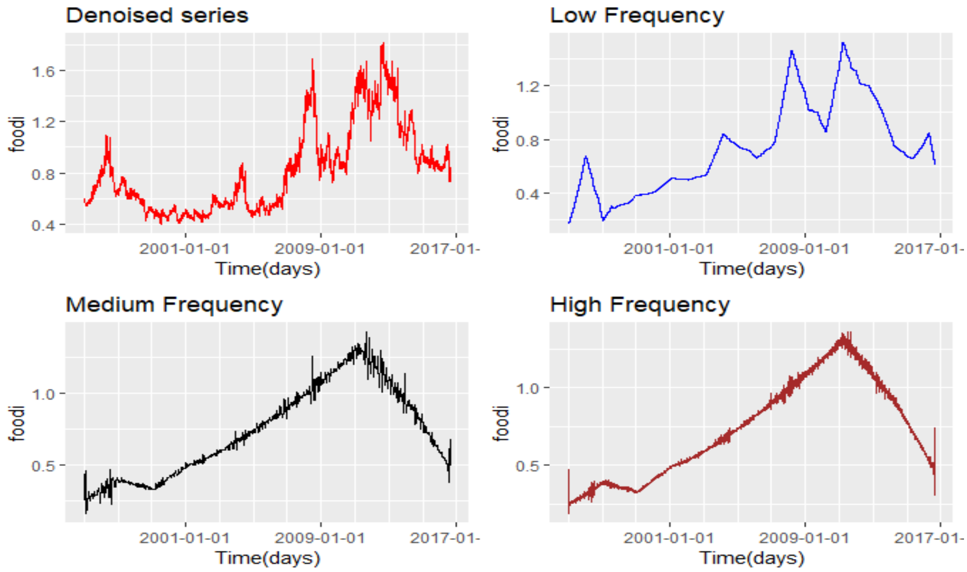
The MRA in Figure 3.2 suggests that the variations in the series are relatively heterogeneous across scales and time, with high fluctuations evidenced at finer scale resolutions for both cash and staple food series. Some localized features are interesting to point out. For example, a stretch of high volatility towards the end of the sample is revealed for the staple food index, while there are marked variances at the start and towards the end of the sample for the cash crop price index, underpinned by large fluctuations in the value of the wavelet coefficients. The smooth series for the cash and staple food series (S7 in Figure 3.2) highlight the upward trend underlining both series up to their respective peak. Hence, the MRA suggests that the fluctuations in the decomposed series are heterogeneous across time and scales, implying that we can gain additional insights into the dynamics of the indices by considering their relationship at various scale levels. After obtaining the wavelet transform values, we proceed by denoising the series, as described in the methodology section. Then, the series are reconstructed by adding to the trend, selected frequencies, or detail series, as described in equation (3.5). The selected scales (frequencies) are: 1) low frequency (d=9), 2) medium frequency (d=5), and 3) high frequency (d=1)[12], as illustrated in Figure 3.3 and 3.4.

It is also possible to quantify how much each scale contributes to the overall variability of the index series through scale-based variance decomposition, as in Percival et al. (2004). The wavelet variance decomposition indicates that the largest contribution to the sample variance is accounted for by variations at the largest scale (long run fluctuations) for both the cash crop and staple food indices. Hence, long run variations have more weights on the series than short run fluctuations.

In general, the results of the wavelet analysis show that the index series have common trends and volatility patterns, although differences in volatility prevail at specific scales. This suggests that the level of interdependence and the dynamics of volatility between cash crop and staple food price indices may vary depending on the considered time scale. As a result, we apply a GARCH-BEKK model using the denoised series at various time-frequency domain to account for the heterogeneity in the variance dynamics. This is described in the next section.

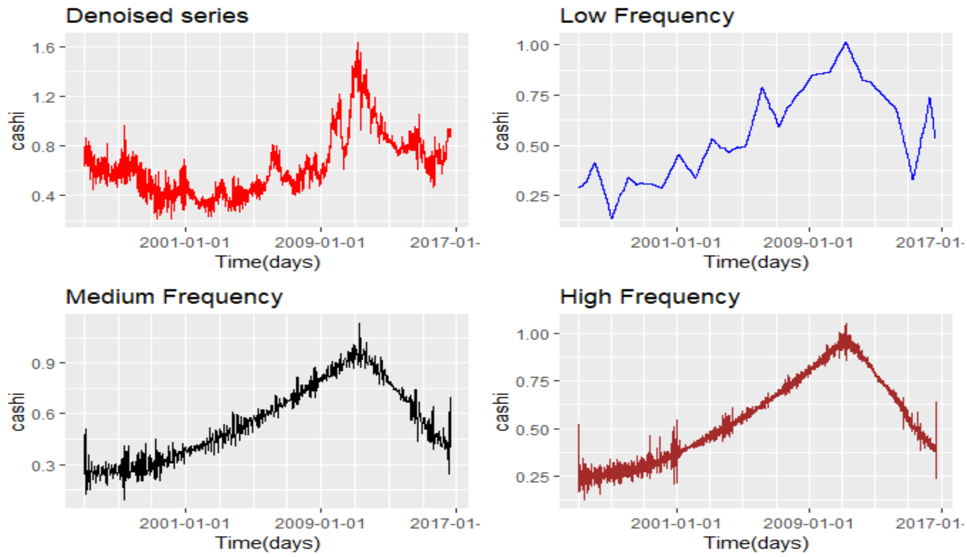
[12] In the discrete wavelet transform (DWT) the number of observations needs to be dyadic, that is an integer power of two. We use business days, so that d=9 corresponds to 2^9= 512 days. We chose three scales, corresponding to short, medium, and longer term, for the sake of clarity and to simplify reference to the results in the context of the study.

Figure 3.3: Reconstructed staple food price series at selected scales



Note: foodi stands for food price index.

Figure 3.4: Reconstructed cash crop price series at selected scales



Note: cashi represents the cash crop price index.

3.5.3 *GARCH model*

Using the staple food and the cash crop return indices, we estimate 4 bivariate VAR-BEKK-GARCH models. The first model uses the original series, while the other 3 models are applied to the denoised series but for different scale frequencies: low frequency (model 2), medium frequency (model 3), and high frequency (model 4). The VAR specification describes the conditional mean of the model, while the GARCH component explores the volatility interactions. We apply the AIC and SIC information criteria to identify the optimal lag order of the VAR system and run univariate GARCH for both index series to which we apply the same information criteria to examine the lag order for the GARCH component. The information criteria selects VAR(3) and GARCH(1,1) as the optimal specification. A comparative estimation of the log-likelihood values derived from other alternative lag specifications confirms the data is best characterized by a GARCH(1,1) specification.

The estimation results are reported in Table 3.2. The ARCH terms (a_{1i}, a_{2i}) indicate whether the conditional volatility is driven by lagged innovations, while the GARCH estimates (g_{1i}, g_{2i}) show if the current conditional volatility is influenced by its lagged values, reflecting volatility persistence. In general, estimation results for the 4 pair-wise bivariate VAR(3)-BEKK-GARCH(1,1) models reveal some similar patterns with respect to the estimated ARCH and GARCH coefficients. First, the coefficients are found to be statistically significant for most of the pair-wise estimations. Second, the estimated values for the ARCH coefficients are generally lower than the GARCH estimates, implying that lagged shocks do not impact current conditional variance as much as lagged volatility values. The diagnostic tests carried out on the standardized residuals and squared standardized residuals show a significant reduction in ARCH effects and autocorrelation depicted in the return series (see Table 3.1), indicating that the estimated models are sufficiently flexible to describe the volatility dynamics between staples and crop returns.

Table 3.2 also reports estimations for the mean price return equations. Results indicate that, generally, the own autoregressive parameters for both staple food and cash crop return indices are found to be statistically significant, implying short term predictability. Results also show that some cross-market returns parameters are found positive and statistically significant, but their number is much less than in the case of own mean spillover estimates. Also, we note that the information transmission flows mostly from the staple food to the cash markets, as shown by the number of significant coefficients capturing the effect of changes in staple food crop returns on cash crop returns. This result may in fact reflect the relatively greater liquidity in the staple food futures markets relative to cash crop futures markets.

Table 3.2: Estimates of VAR(3)-GARCH(1,1) for staple food and cash crop price indices at various time-frequency domains

	Model 1		Model 2		Model 3		Model 4	
	Food (i = 1)	Cash (i = 2)	Food (i = 1)	Cash (i = 2)	Food (i = 1)	Cash (i = 2)	Food (i = 1)	Cash (i = 2)
Conditional mean								
Constant	0.0000	0.0000	0.0000	0.0000	0.00001	0.0000	0.0004	0.0003
	(0.7989)	(0.9604)	(0.8992)	(0.8217)	(0.8997)	(0.9849)	(0.0570)	(0.6238)
Food(-1)	-0.1576	0.1314	1.1701	0.0011	1.0698	-0.0024	-1.2659	0.1042
	(0.0000)	(0.0008)	(0.0000)	(0.9573)	(0.0000)	(0.9374)	(0.0000)	(0.0037)
Cash(-1)	0.0104	-0.3118	0.0122	1.1818	-0.0076	1.0526	-0.0012	-1.3202
	(0.0263)	(0.0000)	(0.5105)	(0.0000)	(0.2730)	(0.0000)	(0.7634)	(0.0000)

Food(-2)	-0.0554	0.0195	-0.3225	0.0047	-0.2752	0.0018	-1.0645	0.0798
	(0.0000)	(0.6230)	(0.0000)	(0.8806)	(0.0000)	(0.9658)	(0.0000)	(0.0613)
Cash(-2)	0.0021	-0.1367	-0.0070	-0.3321	0.0011	-0.2792	-0.0015	-1.1122
	(0.6672)	(0.0000)	(0.8017)	(0.0000)	(0.9092)	(0.0000)	(0.7777)	(0.0000)
Food(-3)	0.0144	0.0216	0.1415	-0.0071	0.0559	-0.0021	-0.4570	0.0715
	(0.2880)	(0.5826)	(0.0000)	(0.7330)	(0.0001)	(0.9450)	(0.0000)	(0.0281)
Cash(-3)	0.0069	-0.0719	-0.0067	0.1373	0.0042	0.0649	-0.0065	-0.5151
	(0.1394)	(0.0000)	(0.7156)	(0.0000)	(0.5446)	(0.0000)	(0.1118)	(0.0000)
Conditional variance-covariance								
c_{i1}	-0.0062		0.0000		-0.0010		-0.0008	
	(0.0000)		(0.0005)		(0.0000)		(0.0000)	

c_{i2}		-0.0002		0.0000		-0.0006		0.0028
		(0.7099)		(0.0269)		(0.0000)		(0.0000)
a_{1i}	-0.3569	0.0046	0.6107	0.1825	1.6485	0.0678	-0.2557	-0.6631
	(0.0000)	(0.7483)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
a_{2i}	-0.0077	-0.2607	0.2019	1.9197	0.0134	1.5411	-0.0147	0.4915
	(0.0380)	(0.0000)	(0.0000)	(0.0000)	(0.0089)	(0.0000)	(0.0000)	(0.0000)
g_{1i}	0.8997	0.1050	0.0303	0.3049	0.4068	-0.0102	-0.9685	0.0603
	(0.0000)	(0.0174)	(0.0010)	(0.0000)	(0.0000)	(0.5044)	(0.0000)	(0.0000)
g_{2i}	0.0017	-0.9681	0.8198	0.4907	-0.0909	-0.5653	-0.0059	-0.8627
	(0.8324)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Dignostic tests								
AIC	-21799.5600		-75342.1200		-47452.4000		-28805.3100	
LB	26.9200	97.3560*	1104.4000*	720.1400*	5249.7000*	3748*	1332*	1554.9000*
LB2	28.6570	36.3710	14.5900	5.5227	1163.3000*	1076.1000*	79.6930	5157.8000*
LM (ARCH)	24.9390	36.6620	13.6070	4.9566	1000.8000*	775.3000*	430.5400*	1729.9000*
Market correlation	1	0.0200	1	0.6300	1	0.3400	1	0.1200
	0.0200	1	0.6300	1	0.3400	1	0.1200	1

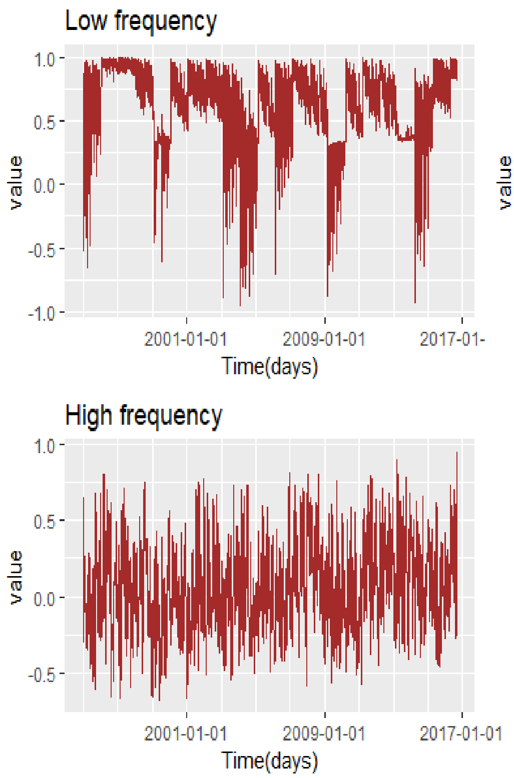
Note: A bivariate model VAR(3)-Full-Bekk-GARCH(1,1) model is estimated for each model from January 2, 1990 to August 28, 2016. The information criteria AIC and SIC were used to select the optimal lag order for the VAR model and the GARCH specification. Model 1: Original series; model 2: Low frequency; model 3: medium frequency; model 4: high frequency. LB and LB^2 is the Ljung-Box Q-statistic for standardized and standardized square residuals. P-values reported in parentheses. * stands for significant at the standard 5 percent level. Stationarity condition tests show that the estimated full BEKK-GARCH model is stationary. The estimates of matrix A (ARCH effects) and G (GARCH effects) shown in the Table are reported as expressed in equation (3.8). Note that we only show results for conditional variances. Estimated results for the conditional correlations are presents in Figure 3.5.

The diagonal elements of matrix A (see equation (3.7)), which captures own shocks, and the diagonal elements of matrix G, associated with own GARCH effect, are significant for most of the estimated models. That is, own news and past volatility movements affect the current conditional variance values. Also, a general assessment shows that the off-diagonal elements of matrix A and G are for most cases significant, but with some degree of variations, reflecting asymmetries in the dynamics. In terms of model 1 (i.e. original series), results are generally in line with those obtained with the other models. For the staple food and cash crop equations, own ARCH and own GARCH terms are highly significant. In absolute terms, estimates of the ARCH coefficients are generally found much smaller than those obtained for the GARCH component, implying larger effects of past conditional variances than lagged innovations on current conditional variances.

For the low frequency model (i.e. long run), results indicate that the current conditional variance for cash crop return indices depend on their own ARCH and own GARCH terms, meaning that market volatility of cash crops can generally be predicted on the basis of past shocks and past variance. However, in contrast to model 1, the own ARCH effect is found larger than the own GARCH effect, suggesting that unexpected shocks play a much more important role in driving variability of staple returns at low frequencies. Likewise, the own ARCH estimate for staples and cash crop equations are found greater than the own GARCH effects for the medium frequency model. In the case of the high frequency model, the own GARCH effect is larger than the own ARCH effect for both the staple food and cash crop equations, in line with the outcome obtained with model 1. That is, at high frequencies, the conditional variances of cash crop and staple food returns are influenced by their respective past variances more so than unexpected news.

We now turn our attention to volatility transmission between staple food and cash crops, which is captured by the cross-estimates of ARCH and GARCH terms. Overall, there is significant volatility transmission between staple foods and cash crops as evidenced by the number of significant cross effects terms estimated for the various pair-wise systems. We note that the cross-market GARCH estimates are generally much larger than those of the cross-market ARCH effects. This is an indication that the conditional volatility of cash crop (staple food) markets is largely influenced by periods of volatility in the staple food (cash crop) markets rather than by the effects of lagged price return innovations in the staple food (cash crop) markets. Specifically, the GARCH cross-market effects are all statistically significant, with the exception of model 1, where past volatility in the cash market is statistically insignificant in the staple food market, and the medium frequency model, where the past volatility in the food market is statistically insignificant in the cash market. On the other hand, the cross-market ARCH effects are all statistically significant, with the exception of model 1, where past innovations in the staples market do not show a statistically significant influence on the volatility of cash crop returns. Overall, the results show that the absolute values of the estimated cross-market GARCH and ARCH estimates are generally higher and statistically significant in the low frequency case than for the other frequency models, suggesting that the level of volatility interdependence between cash crop and staple returns is much stronger at lower frequencies. Further, the low frequency model yields the largest Pearson correlation estimates, reflecting a tighter interdependence in the long run. The fact that the conditional correlations are larger at lower frequencies may suggest that external factors common to both markets, such as macroeconomic variables and world energy prices, explain the larger correlation in the long run. In the short run, commodity-specific factors (e.g. supply shocks impacting sugar crops) dominate movements in prices, a feature that underlines the lower conditional correlation between staples and cash crops. These results are also corroborated by the estimated conditional correlations, which indicate that the correlation at lower frequency is mostly positive, and increasing in periods of high commodity prices (see Figure 3.5). Figure 3.5 also shows that as the frequency increases from low to high, the conditional correlation between staple and cash crop markets weakens. As mentioned, weaker volatility integration may be attributed to the influence of commodity-specific factors rather than common factors across staples and cash crops.

Figure 3.5: Estimated conditional correlation between the cash crop price index and the staple food price index at various time-frequency domains



Estimation results also show that the cross-market values associated with the staple foods are generally larger than those relevant to cash crops. This means that information coming from the food markets influences cash crop markets to a larger extent than in the opposite direction, which could reflect the effect of greater liquidity underlying the staple food futures. The implication for LIFDCs is that market information relevant to staple foods affects ultimately the variability of cash crop earnings. Despite the bidirectional nature of the relationship, both the own GARCH and own ARCH effects are found mostly larger in magnitude than the cross effects, highlighting the dominant role of intrinsic market factors.

Figure 3.5 shows the estimated conditional correlations between staple food and cash crop return series at various time scales calculated following equation (3.10). The estimated values exhibit high volatility throughout the sample period, with values ranging between -0.5 and 0.5, notably for the medium and high frequency scales. In the case of the low frequency model, conditional correlations fluctuate between 0.5 and 1, with occasional and abrupt changes mostly towards the negative values and periods of upward or downward trends.

Relatively high conditional correlation values associated with low frequency scale implies that cash crop sales are a good hedge against increases in staple food import bills, and can contribute to limiting current account instability in the long run, more so than in the short term. The extent to which export earnings offset current account deficits due to import bills depends on the elasticity of cash crop markets. The smaller the elasticity, the larger the increase in export earnings resulting from higher prices. What do these results mean for a country like Burundi, which relies on cash crop exports and imports of staple foods? Strong and positive conditional correlation between cash crop and staple food markets means that the Government can evaluate more accurately its financial needs in the face of current account imbalances due to import bills by taking into consideration the fact that revenues from cash crop exports can reduce funding requirements, and hence borrowing costs. Second, the Government can also use price information relevant to international staple foods in the design and planning of investment strategies for the cash crop sub-sector, given the linkages between both commodity sub-sectors. For example, information on staple food price prospects can be utilized to strengthen the robustness of national cash crop price projections.

3.6 Conclusions and implications

The analysis carried out in this paper examines the volatility interaction between staple food and cash crop futures prices returns. The dynamics between these commodity groups is relevant for developing countries that depend on cash crop export earnings to address current account imbalances and sustain food imports. We apply a BEEK-GARCH framework supplemented by a wavelet analysis to locate precisely marked periods of volatility and changes in the dynamics at different time horizons.

Estimation results show that the GARCH and ARCH elements associated with the staple foods exhibit, for the most cases, larger absolute values than their corresponding elements related to cash crops. This implies that the information transmission takes place mostly from staple foods to the cash crop markets at the international level. When the GARCH framework is applied at different time scales, based on the wavelet transform analysis, the outcome reveals that the relationship between cash crop and staple foods is the strongest at the lower frequency scale. The estimated conditional correlations for the lower frequency model are mostly positive, with marked periods of upward and downward trends. Several studies attribute this synchronized behavior to the financialization of commodity markets, as investors seek to diversify market risks (Basak and Pavlova, 2016; Grosche and Heckelei, 2016). In the long run, however, co-movement between staple food and cash crop markets can reflect changes in factor input costs, notably labor costs.

Results of our analysis convey some implications from both an investment and policy making perspective. Because the correlation is found relatively higher in the long run, with significant cross market effects, investors cannot use cash crop assets as a hedging strategy against holding staple food assets. However, the significance of the cross-market effects means that they can take into account information contained in staple food futures when predicting cash crop returns. From a policy perspective, results imply that cash crop exports are a good hedge against rises in staple food import bills in the long run, and can contribute to reducing current account instability. This is because higher cash crop prices imply higher export earnings, given the inelastic nature of international cash crop markets.

These results highlight the importance of the cash crop sub-sector as an automatic consumption smoother, in the face of increases in import bills. It is often argued, however, that developing countries should diversify away from commodity production and export. The reasoning is based on the observation that real commodity prices have been on a declining trend relative to the price of manufactures. The Prebisch-Singer hypothesis provides the theoretical background behind the decline in relative prices, which translates into deteriorating terms of trade for the developing countries (UNCTAD/FAO, 2017). Often, the recommended solution is to move away from the production and export of commodities, such as cash crops, and into more value added products and services. The problem with this argument is that it is highly sensitive to the metrics used to derive real prices, in addition to the various issues related to trend estimation. Perhaps, the conclusion on whether to move away from commodity production and export should be looked at from several perspectives. As an example, results of this paper indicate that when comparing a cash crop price index relative to a staple food index, there is no obvious downward trend; in fact the relationship between the indices seems to remain relatively steady in the long run, with prevailing short-lived peaks (see Figure A3.1). Hence, when considering the movements of cash crop prices relative to staple foods, it appears that cash crop sales have a role to play in limiting the impact of higher staple food prices and the resulting current account instability. Perhaps a better policy advice to cash crop producing developing countries would be to argue for more investment in the cash crop sub-sector so that it is more resilient and efficient, while at the same time, expanding the mix of exported products, particularly into more value added products.

A number of conceptual and methodological aspects still require further investigation. First, while we apply a discrete wavelet transform (DWT) to reconstruct the series into various time scales, the use of a continuous wavelet transform (CWT) approach does not require the arbitrary selection of time scales and accounts endogenously for the presence of structural breaks. A CWT framework enables the measurement of the correlation between staples and cash crop returns in a continuous time-frequency domain. Future research could examine the interaction between cash crop and staples returns using CWT and compare the results with those obtained using a DWT method. Second, additional efforts are needed towards understanding the theoretical and empirical estimation of higher dimension MGARCH models. Many of the statistical results still lack theoretical background to be generalized. Still, joint estimation of higher dimension MGARCH model remains very interesting from a research aspect as it makes full use of the dynamics characterizing a system of variables. Finally, for these results to be translated at country level, an assessment of the transmission of futures prices to export prices and import prices is warranted. This will help anticipate the extent to which a country’s cash crop export earnings can cover for food import bills given the volatile nature of international agricultural commodity markets.

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3.8 **Annex**

Figure A3.1: Cash crop price index vs staple food price index

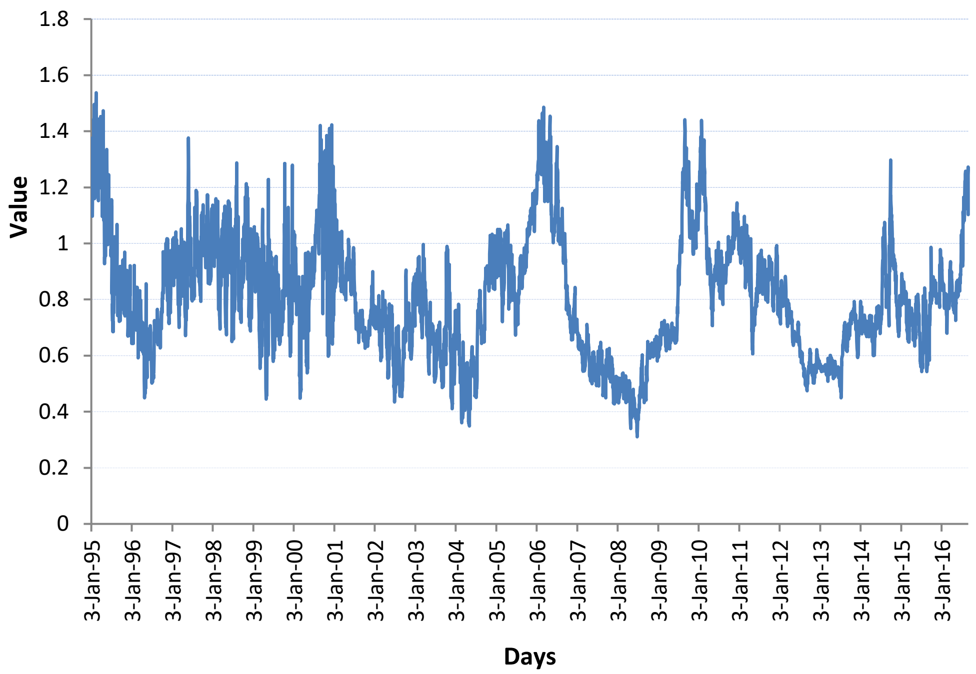
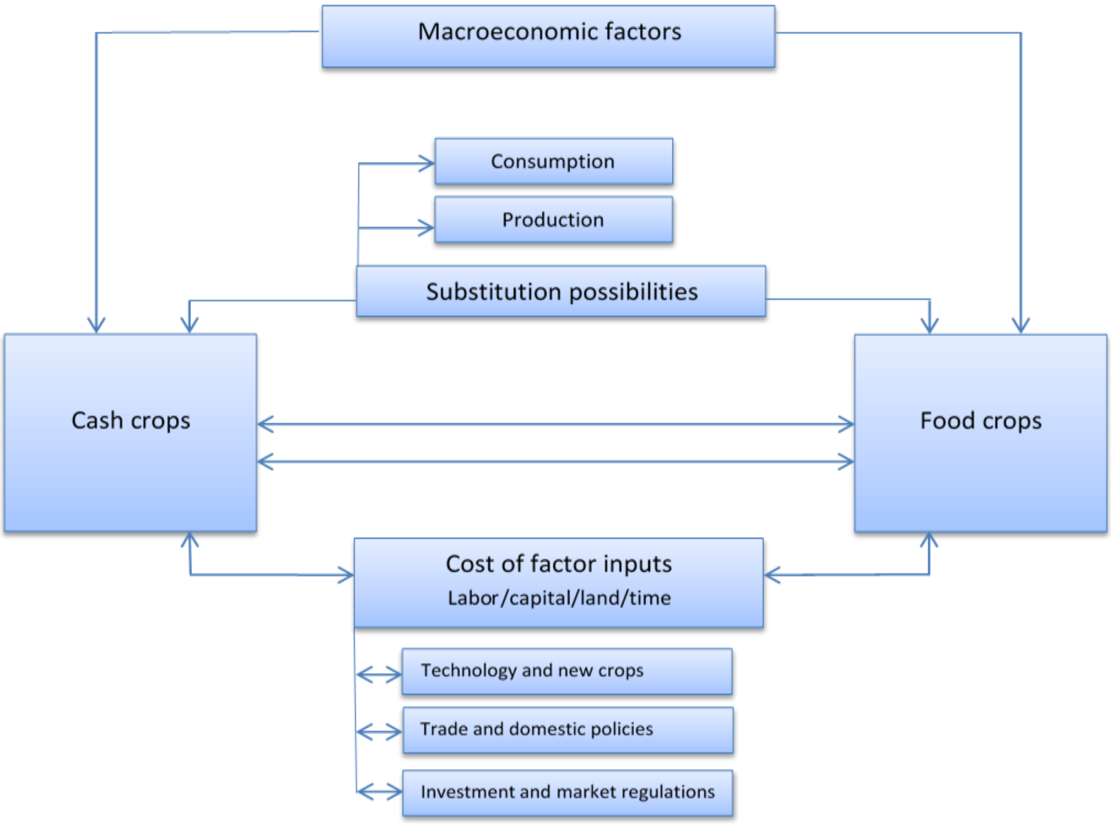


Figure A3.2: Interaction between cash crop and staple food prices: a conceptual framework



Note: Aside from macroeconomic drivers, other underlying factors can cause cash crops and staple foods to correlate. These include factors related to: 1) changes in the cost of labor and other factors of production, 2) technological improvements and the introduction of a new farming activity that bids factor input costs, 3) trade and domestic policies, and 4) commodity investment and market regulations. Substitution possibilities in consumption and production between cash crops and staple foods in the physical market are rather limited and, hence, cannot explain the full extent of the price correlation.

Chapter 4
Forecasting international sugar prices: A Bayesian Model Averaging Analysis[1]

Abstract:

This paper examines the relative importance of key variables for the prediction of international sugar prices. Understanding movements in world sugar prices helps policy-makers and participants in the sugar value chain to formulate effective investment strategies and forecast the effects of market shocks more accurately. We combine a Bayesian Model Averaging (BMA) technique to address specification uncertainty with an out-of-sample analysis to evaluate price predictability. Results show that world sugar quotations are mostly influenced by their own dynamics, changes in international staple food prices, sugar production costs, and macroeconomic variables. The predictability of the BMA is found to be generally high, compared with a sample of benchmark time series approaches.

Keywords: Sugar prices, Bayesian Model Averaging (BMA), forecast, parameter priors, model priors

JEL classification: Q13, C13, G11, G01

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[1] A shorter version of this chapter is published in *Sugar Tech* as Amrouk, E.M., and T. Heckelei (2020): Forecasting international sugar prices: A Bayesian Model Averaging Analysis. *Sugar Tech.* https://doi.org/10.1007/s12355-020-00815-0.

4.1 **Introduction**

International sugar prices are commonly recognized for being highly volatile (FAO, 2016). This volatility stems from the economic and physical characteristics of the sugar market. On the supply side, sugar production is inelastic as a result of the perennial nature of sugarcane, the dominant sugar crop[2] (Elobeid and Beghin, 2006; Gemraill, 1978; Hammig et al., 1982). This means that a price decline is not likely to trigger a large supply response, at least in the short run. Likewise, sugar demand is relatively irresponsive to price changes in the short run. The net effect of inelastic supply and demand is the dominance of relatively volatile sugar prices[3] (see Figure 4.1).

The volatile nature of the sugar market is further exacerbated by the effects of various support measures that benefit the sub-sector (Mensbrugghe et al., 2003). Sugar is known for being one of the most protected commodities, as governments seek to safeguard producers from low prices through the implementation of various policy instruments such as border measures, minimum price level, and subsidies (FAO, 2016). Often, policy objectives include measures to protect both consumers and producers (e.g. India). For years, however, there have been calls to reduce, or eliminate, the level of these interventions, particularly those that are market distortive. Dispute cases over sugar subsidies were brought before the World Trade Organization (WTO) in several instances (Burrell et al., 2014; WTO, 2019). A number of major sugar producers, noticeably the European Union (EU), have introduced important legislative changes to their domestic sugar market, with the objective of reducing the level of public support (OECD/FAO, 2017).

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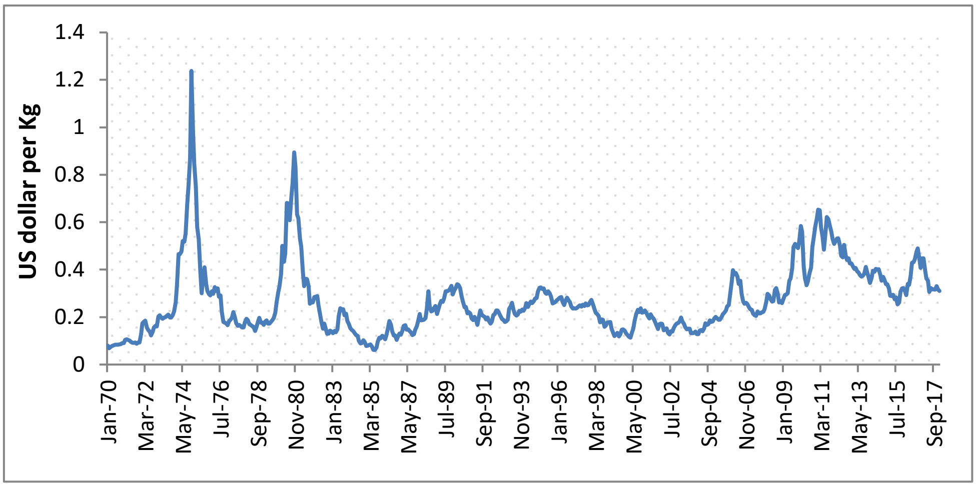
[2] Sugarcane represents 80 percent of the world sugar output compared to 20 percent from sugar beet.

[3] The world reference quotation for sugar is the International Sugar Agreement (ISA) Daily Prices, which is based on the first three futures positions of the New York ICE, Contract No. 11.

Figure 4.1: Monthly international sugar prices



The literature on modelling international sugar markets and projecting their prices tends to use structural specifications, such as general equilibrium models (e.g. Mensbrugghe et al., 2003) or partial equilibrium models (e.g. OECD/FAO, 2017; Adenäuer et al., 2004; Nolte et al., 2010). These are generally recursive models that provide yearly market equilibriums for production, consumption, trade, and world sugar prices over a projection period. The strength of these trade models is their ability to incorporate a wide range of policy variables, and thus measure the effect of specific policies on international sugar market. The other approach to sugar price analysis relies on time series techniques as in Stephen (2013), Stephen (2015), Chang et al. (2018), RaboBank, (2018), World Bank (2018), and Rumánková et al. (2019) . With time series, policy simulation possibilities are relatively narrow, but the technique allows the use of data at a much higher frequency level (e.g. daily) than partial or general equilibrium models, enabling to take advantage of more information.

Often the case, a lot of the sugar prediction work is available from the private sector, particularly investment banks, and is, therefore, not accessible to the general public. That research is either used internally or sold to clients. For many governments, price projections are needed for sectoral planning, investment at both farm and factory level, and adequate market interventions for the many countries that support their domestic sugar market. Academic research can help produce publicly available forecasts, which can be used by government agencies, commodity market analysts, and interested users at large.

In this paper, we identify key drivers of international sugar market and examine their relative importance for short term predictions of world sugar prices. We use a Bayesian Model Averaging (BMA) approach to address model uncertainty stemming from the many possible combinations between explanatory variables, followed by an out-of-sample prediction analysis to assess price predictability. Since its development by Leamer (1978), the BMA method has been used extensively in statistics and econometrics. The BMA framework allows pooling information from different models in a consistent manner. For example, in a forecasting exercise, the BMA can pool various forecasts by assigning weights based on the posterior model probability (PMP) derived for each model. The BMA is one of the many possible methods for pooling information. Stock and Watson (2003) note that a simple weighted average of various forecasts has superior predictive power than the forecasts of any single model. Equal weighting works especially well when model forecast errors have relatively similar variance and are not correlated (Bunn, 1985). Hendry and Clements (2004) argue that it is difficult to do better than equal-weighted forecasts because weight estimation introduces errors that may bias the results. The key question for these simple weighted average forecasts relates to the choice of the weights. The BMA tackles the question by applying the Bayesian methodology of estimating posterior model probabilities, which are then used as the building block for the weights.

The use of BMA covers a wide range of topics, including economic development (Koop and Potter, 2003), cross-country growth comparison (Fernández et al., 2001a; Sala-I-Martin et al., 2004; Man, 2015), inflation rate forecasting (Wright, 2009), portfolio analysis (Cremers, 2002; Maltritz and Molchanov, 2013), and energy forecasting (Zhang and Yang, 2015; Drachal, 2016). In a recent study using BMA, Arin and Braunfels (2018) examine the impact of oil rents on economic growth in the medium and long run using panel data and 54 growth determinants. They found no evidence of resource curse but, instead, some positive effects of oil rent on growth in the long run. Likewise, Drachal (2016) applies dynamic model averaging (DMA) to allow for time-varying coefficients in the analysis of crude oil spot prices. The study finds that the DMA does not consistently outperform other alternative models such as ARIMA specifications. The DMA approach in their study reveals that the 2008 oil price shock was driven by changes in exchange rates and stock markets, while the fundamentals of supply and demand played minor roles. Zhang and Yang (2015), on the other hand, study natural gas consumption in China using BMA and found that it has a better prediction ability than alternative models, including Gray prediction model and artificial neural networks. Application of BMA to agricultural commodity markets remains limited. One study by Crespo et al. (2016) combines BMA and key explanatory variables to decompose price movements of coffee, wheat, and soybeans. Their results show that macroeconomic indicators and market fundamentals explain most of price changes, while financial developments play a much weaker role.

The use of BMA is quite prolific in the study of economic development. For example, Eriș and Ulașan (2013) investigate the relationship between trade openness and economic growth utilizing a BMA approach. Trade openness is measured by several indicators, including non-tariff barriers and tariff rates. The results suggest that economic institutions and macroeconomics uncertainty contribute to economic growth more so than trade openness. Man (2015), on the other hand, investigates the contribution of economic and political competition to economic growth. The BMA-based analysis indicates that economic growth is positively influenced by the level of competiveness in the financial sector. Likewise, Horvath (2011) looks at the effect of research and development (R&D) on growth using BMA and finds positive effect on long run growth, with the results being robust to alternative definition of R&D.

Other analyses address theoretical issues related to BMA. For instance, Ley and Steel (2009) investigates the effects of prior assumptions on BMA results and recommend priors for use, with an application to cross-country growth regressions. On the other hand, Eicher et al. (2011) compare 12 parameter priors and two model priors in the specification of a BMA framework. They find that unit information prior (UIP) and uniform model prior yield better predictive performance than other considered priors. Along the same vein, Ley and Steel (2012) explore the effect of prior selection on BMA results, assigning a hyperprior to the shrinkage parameter g. They propose a benchmark Beta prior with fixed g, which renders model selection more consistent.

Our analysis contributes to the existing studies in several aspects. First, a lot of the work on short term sugar price forecasts is not freely accessible to the general public. We contribute to filling this gap by characterizing the drivers of international sugar prices, measuring their relative importance and providing a framework for short term forecasts that can be used by policy-makers. Second, the analysis covers the period from 1990 to 2016, which allows taking into consideration the effect of the last decade surge in food prices in 2007/2008 and 2011, as well as the implication of the global financial crisis of 2007/2008. We also take into account the period of end-1990 and beginning 2000 when several agricultural commodity prices recorded historical lows in real terms (e.g. sugar). Third, we combine a Bayesian model averaging method to address specification uncertainty with an out-of-sample analysis to evaluate price predictability against a sample of time series models. The remainder of the paper is structured as follows: the next section discusses the main drivers of international sugar prices, followed by a review of the methodology and data employed in the empirical section. We then outline and discuss the main results. The final section gives a summary of the main conclusions and some suggestions for future research.

4.2 The determinants of sugar price dynamics

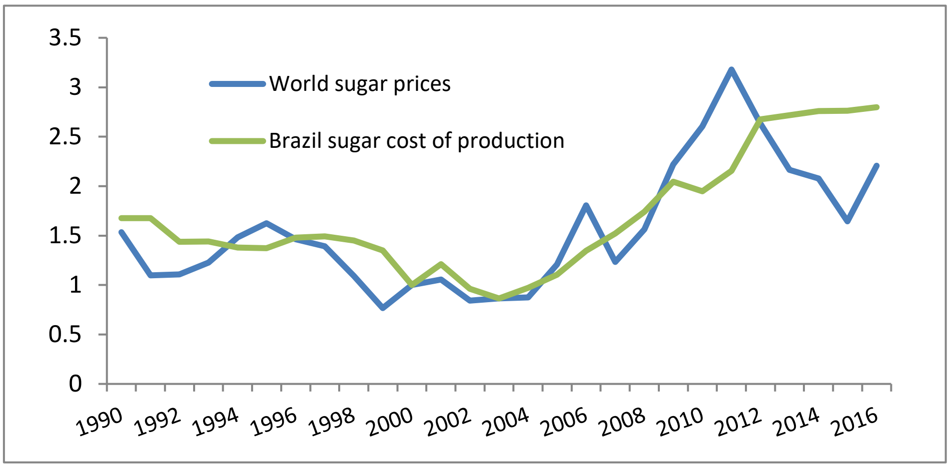
4.2.1 *World sugar production surplus/deficit and stock-to-use ratio*

World sugar production has been for most of the last decades in excess of global sugar consumption. For example, there were five consecutive production surpluses between 2010/11 and 2014/15, resulting in large stock buildups and a downward pressure on sugar prices. Production surpluses were quite sizeable in 2012/13, 2013/14, and 2017/18 with production exceeding consumption by 8.2 million tons, 8.8 million tons, and 7.2 million tons, respectively (ISO, 2018). On the other hand, when consumption outpaces production, stock-out occurs and prices tend to surge (Stephen, 2013). Another related driver of sugar prices is the stock-to-use ratio. Often, it is the interaction between the world production surplus/deficit and the level of the stock-to-use ratio that determines the extent of a price movement (Elobeid and Beghin, 2006). For instance, an expected production deficit, combined with a low stock-to-use ratio, tends to cause prices to surge more than a situation where the stock-to-use ratio is relatively elevated. Hence, the stock-to-use ratio tends to amplify, or dampen, the effect of a production surplus/deficit market situation. Note that the price effect of sugar substitutes is relatively limited at the global level. However, there are instances where domestic sugar quotations can be influenced by other sweeteners, as in the case of high fructose corn syrup (HFCS) in the United States.

4.2.2 *Sugar cost of production in Brazil*

The global sugar market is dominated by Brazil, the world's largest sugar producer and exporter. Between 2010 and 2014, Brazil accounted for 26 percent of world sugar production, up from 16.3 percent in 2000-2004. The expansion in sugar production was driven by a number of factors, including government supports, increasing demand for ethanol-based sugarcane production, and vast and suitable natural resources (OECD/FAO, 2017). Also, between 2010 and 2014, Brazil accounted for about 58 percent of the world's raw sugar export, while it was responsible for 23 percent of the world's total export of refined sugar (FAO, 2015). The dominant position of Brazil means that supply shocks in that country have significant impacts on international sugar prices and trade flows. It also implies that world sugar prices tend to follow changes in marginal cost of production in Brazil (Stephen, 2013). That is because Brazilian sugar producers need to cover their marginal cost if import demand is to be fulfilled. The relationship between Brazil production sugar cost of production and international sugar prices is shown in Figure 4.2.

Figure 4.2: World sugar prices vs Brazil sugar cost of production (2000=1)

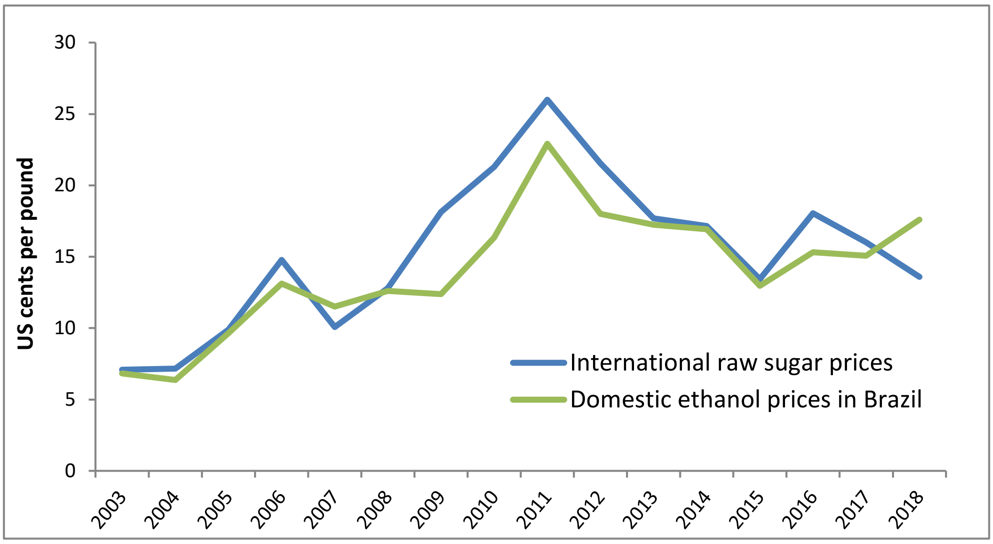


Source: Authors' calculations and FAO

4.2.3 *Energy prices*

Sugarcane and sugar beet can also be used as feedstocks for the production of ethanol. However, it is in Brazil where the interaction between sugar and ethanol is most evident with both products competing for sugarcane (see Figure 4.3). The higher the sugar/ethanol price ratio the larger the share of sugarcane going into sugar. Sugar mills in Brazil generally have the infrastructure to switch between both products depending on the relative price returns. Given the dominant position of Brazil in the world sugar market, the relative profitability of sugar vs ethanol has a direct effect on Brazil's sugar export availability and consequently on international sugar prices (Stephen, 2015). Given that ethanol competes with gasoline in the fuel transportation sub-sector, changes in the ratio of gasoline to ethanol, on an equivalent energy content, determines demand for ethanol, and consequently the demand for sugarcane. However, the relationship between ethanol and gasoline prices is not linear because of tax policies and various subsidy programs that support the Brazilian biofuel sub-sector. For example, the mandatory blending ratio between gasoline and anhydrous ethanol is set by the government and often varies between 20 percent and 25 percent (FAO, 2016). Also, States in Brazil have the liberty to set their own tax regime that applies to the energy sector. These policies often hamper the full transmission of price changes in the energy market.

Figure 4.3: International sugar prices vs domestic ethanol prices in Brazil, in raw sugar equivalent



Source: Authors' calculations

4.2.4 *Macroeconomic and financial factors*

The main macroeconomic variables that have an influence on the sugar market are population growth and per capita GDP growth, with their effects running through various channels (Mitchell, 2004; Carman, 1982; ISO, 2010). Their impact is particularly visible through changes on the demand side of the market. In the case of GDP, during recession periods, for example, demand for beverages and food manufacturing tend to fall, exerting downward pressure on sugar quotations. This is because the bulk of demand for sugar stems from the beverages and food manufacturing sectors, with both sectors highly influenced by the overall economic performance (ISO, 2016). The influence of population growth is mostly important in developing countries, as increases in population continue to remain relatively important. On the supply side, changes in GDP, labor market, and inflation rates, affect investment decisions at the farm and sugar processing level.

Another set of variables driving international sugar prices relates to financial markets. Most important is the movement in the value of the Brazilian currency (Real) with respect to the value of the United States Dollar (USD) (Stephen, 2013). This has two main effects. First, a depreciation of the Real against the US dollar tends to lower dollar denominated sugar production costs in Brazil, which boosts sugar exports and affect world sugar prices, ceteris paribus. Also, because world sugar prices are denominated in US dollar, a depreciation of the Real incentivizes sugar exporters in Brazil to ship greater volumes in order to lock in higher return in local currency. Second, an appreciation of the Brazilian Real raises US dollar denominated costs of production and, as a consequence, limits export supplies from Brazil. In addition to the important role played by the Brazilian currency, changes in the currency of major sugar importers can influence world sugar prices. Currency depreciation against the US dollar can hamper the ability of an importing country to maintain the same level of purchases, as international sugar prices are measured in US dollar. Likewise, an appreciation in the currency value of a sugar importing country can render imports relatively cheaper, encouraging greater imports.

4.3 **Empirical approach**

As mentioned earlier, the empirical method adopted for this analysis relies on the Bayesian model averaging approach to analyze the effect of key explanatory variables on world sugar prices. This section describes the underlying aspects of the methodology and goes on to discuss model selection and data.

4.3.1 *Bayesian model averaging*

Given the large number of variables that can potentially explain changes in sugar prices, as illustrated in the previous discussion, the question becomes which variables should then be included in a model. Making inferences by selecting one particular model specification over a number of possible alternatives can lead to biased estimates, as discussed in Eicher et al. (2011). Also including many variables in a model can result in losing degrees of freedom, particularly when the number of observations is limited. One alternative to address specification uncertainty is to estimate a model for each possible variable combination and to use these models as weights for any statistics, say a parameter of a specific model. This is in essence what the BMA approach does. The weights are the posterior model probabilities associated with each of the model specifications, assuming that among all the possible specifications, there is one true model (Chua et al., 2013). Specifically, assume there are n possible models, $M_1, \ldots\ldots M_n$, that depict the behavior of international sugar prices, with the *i*th model indexed by a vector of parameters Θ_i, the BMA posterior distribution of any statistic Δ can be expressed as

$$\mathrm{P}(\Delta|D) = \sum_{k=1}^{K} p(\Delta|D, M_i)\, p(M_i|D) \;, \tag{4.1}$$

while the posterior model probability that model *i* is the true model can be elaborated following Wright (2009) as

$$\mathrm{P}(M_i|D) = \frac{P(D|M_i)P(M_i)}{\sum_{j=1}^{n} P\big(D|M_j\big)P\big(M_j\big)}, \tag{4.2}$$

where D represents data, $P(M_i)$, the prior for model *i*, $P(D|M_i)$, the marginal likelihood, or integrated likelihood, for model *i*. Because the denominator of the equation (4.2) is constant over all models, PMP becomes proportional to the marginal likelihood times the model prior. The marginal likelihood can be described as

$$P(D|M_i) = \int P(D|\,\Theta_i, M_i)P(\theta_i|M_i)d\theta_i \;, \tag{4.3}$$

where $P(D|\theta_i, M_i)$ is the joint likelihood of model M_i and its parameters θ_i and $P(\theta_i|M_i)$ is the prior density of the parameter vector associated with model M_i. A typically used point estimate of a model coefficient is an average of the coefficient posterior means across alternative model specifications weighted by the posterior model probabilities. Generally, PMPs are not tractable in closed form, and therefore need to be approximated. One popular application is to use sampling techniques, such as the Markov Chain Monte Carlo (MCMC), to simulate random draws from the probability distributions (Baldwin and Larson, 2017). We assume that the various models describing world sugar prices follow a linear regression. Following Wright (2009), the *i*th model can be described as

$$y = \alpha_i + X_i\beta_i + \epsilon_i, \tag{4.4}$$

where y is a vector representing observations of international sugar prices, α_i is the constant vector, X_i stands for the matrix of explanatory variables, β_i is the parameter vector, and ε_t represents a vector of normally distributed random shocks, assuming that shocks are i.i.d with mean 0 and variance σ^2. As it is done in similar studies, we assume improper priors for the constant and the error variance, that is $P(\alpha_i) \propto 1$ and $P(\sigma) \propto \sigma^{-1}$. The key prior is on the regression coefficients β_i. We derive the priors based on Zellner's g (Zellner, 1971), so that the priors are assumed to be normally distributed with mean zero and a variance structure expressed as $(g\sigma^2(X_l'X_l)^{-1})$. This structure implies that the variance of the coefficients depends on the variance–covariance emanating from the data. The hyperparameter g captures how confident the research is about the value assumed for the prior mean. The larger the value of g, the less certain the researcher is about the assumed prior. This prior framework results in a posterior distribution for the coefficients that follows a t-distribution, with an expected value equal to $(g/(g+1))\ \beta_i^{ols}$, with β_i^{ols} representing the OLS estimate of β_i. Note that as g tends to infinity, the coefficient estimator approaches OLS estimator. The use of a g-prior structure of β_i leads to an analytically tractable marginal likelihood $P(D|M_i)$ that is linked to R-squared and includes a size penalty parameter associated with model size k_i, as illustrated in Zeugner and Feldkircher (2015):

$$P(D|M_i) \propto (y-\bar{y})'(y-\bar{y})^{-\frac{N-1}{2}}(1+g)^{-\frac{k_i}{2}}(1-\frac{g}{1+g})^{-\frac{N-1}{2}} \quad (4.5)$$

Given the often large number of explanatory variables involved in the BMA analysis, elicitation of posterior distributions becomes a tedious exercise. To reduce the computational efforts, MCMC samplers are often used to approximate posterior distributions as closely as possible. Often, the technique relies on the Metropolis-Hastings algorithm (Tierney, 1994; Chib and Greenberg, 1995). The algorithm requires a decision to be made on whether to accept or reject a certain drawn model proposal. In the end, the number of times a proposal is selected will eventually converge to the posterior model probability $P(M_i|D)$.

A key decision that has a critical importance on the posterior distributions is the value of the hyperparameter g. Standard literature often assumes unit information prior (UIP), that is g=N for all models, literally assigning to the prior the same information that is available in one observation (Zeugner and Feldkircher, 2015). Another possibility is to assign a large value to reduce the effect of the prior on the posterior distribution. Fernández et al., (2001b) recommend the use of a large g-prior, while others recommend intermediate values (Eicher et al., (2011)). Another popular alternative is the use of model-specific g-priors, which can be implemented via several approaches. For example, the empirical Bayes g-local (EBL) involves using the information contained in the data and assigning g priors to specific models, while the hyper-g prior (Hyper), assigns a beta prior to the hyperparameter g (Ley and Steel, 2009).

With respect to model priors, the standard procedure is to assume a uniform prior across models, implying that the researcher believes that each of the models are likely to be the true model. Other popular model prior specifications include the binomial prior and the beta-binomial prior. The latter results in a distribution that is less tight around the prior expected model size (Ley and Steel, 2009).

4.3.2 *Data and model selection*

From the discussion on the determinants of sugar prices, a total of 18 potential explanatory variables are selected. These can be grouped into three broad categories: 1) fundamental variables (e.g. world sugar stock-to-use ratio, world sugar production), 2) economic variables (e.g. sugar cost of production, index of manufacture production in the United States), and 3) financial variables (e.g. Brazil exchange rate, trade weighted US dollar index). The impact of some of these variables may take some time to reach the producers, however, the effects on sugar futures prices can be immediate as market participants adjust their price expectations. See Table 4.1 for a description of the variable series. The data are monthly series spanning from January 1990 to December 2016, with a pseudo out-of-sample period running from January 2017 to December 2017.

Considering the number of regressors included in this study, a total of 262144 models (that is 2^{18}) are evaluated by the BMA approach. An MCMC method with the Metropolis-Hastings algorithm is implemented to approximate posterior model distributions in view of the relatively large number of predictors. The pseudo out-of-sample prediction is used to assess the performance of the BMA against alternative methods. We also use sensitivity analysis on key parameters of the BMA to evaluate its predictive power. We use the R package BMS (Zeugner and Feldkircher, 2015) to implement and estimate the BMA models, supplemented by our own R scripts for simulation analysis and forecasting.

4.4 **Results**

4.4.1 *BMA estimation*

Table 4.2 shows the outcome of the BMA analysis resulting from assuming uniform model priors and the hyperparameter g set to UIP, which we subsequently refer to as the baseline BMA model. The first column shows the various explanatory variables ranked by their relative importance. The ranking is based on the posterior inclusion probability (PIP) shown in the second column. The PIP is the sum of PMPs for each model where the explanatory variable is present. The higher the value the more weight a variable carries in explaining movements in sugar prices. The first five predictors with the largest PIPs are: world sugar prices lagged one year, the food price index, Brazil sugar cost of production, Brazil exchange rate, and world sugar production lagged one year. Results also show that the posterior

Table 4.1: Data sources

Variables	Sources
World raw sugar prices (ICE No.11)	Pink sheet, World Bank Database
Food price index	FAO; Food Price Index, excluding sugar series
Brazil sugar cost of production	Authors; FAO
Brazil / US Foreign Exchange Rate	US Federal Reserve Economic Data, FRED database
World sugar production	US Department of Agriculture, USDA database
US ethanol prices	US Department of Agriculture, USDA database
World crude oil prices (WTI)	Pink sheet, World Bank Database
India sugar net-export	US Department of Agriculture, USDA database
World sugar stock-to-use ratio	US Department of Agriculture, USDA database
US HFCS prices	US Department of Agriculture, USDA database
Number of licensed new cars in Brazil	Associação Nacional dos Fabricantes dos Veiculos Automotores
Trade weighted US Dollar index: Major Currencies	US Federal Reserve Economic Data, FRED database
EU sugar net-export	US Department of Agriculture, USDA database
World sugar export	US Department of Agriculture, USDA database
World sugar surplus	US Department of Agriculture, USDA database
World sugar production	US Department of Agriculture, USDA database
US Manufacturing production	US Federal Reserve Economic Data, FRED database

model mass is mostly concentrated around models that include the lagged sugar price as a variable. With a PIP of 100 percent, the lagged sugar price variable is included in all possible combinations of models, highlighting the importance of dynamics in sugar price movements. Likewise, the world food price index has a PIP of 82 percent, a result in line with previous research, which singles out the influence of staple food prices on cash crop prices, and sugar in particular (see Amrouk et al., (2019)). The third column of the Table shows the resulting posterior means, while the fourth column lists the posterior standard deviations. Finally, the last column represents the sign certainty statistics and illustrates how likely it is for the posterior mean of an explanatory variable to be positive.

Overall, the posterior means of the parameters have the expected signs. In particular, parameters on the lagged sugar prices, the world food price index, and Brazil sugar cost of production all have positive signs. An increase in the value of sugar in the previous period is positively associated with a rise in sugar quotation in the current period, a result that tends to illustrate the dynamics typically characterizing commodity markets. Likewise, the estimated parameter that captures the effect of Brazil sugar cost of production is found positive. As discussed in section 4.2, because Brazil is the world's largest sugar exporter, world sugar prices are influenced by changes in the marginal cost of sugar production in Brazil. An increase in marginal cost will shift the cost curves upward and drive world sugar values higher. The impact of an increase in marginal cost on sugar futures prices can be instantaneous through changes in price expectations.

Similarly, the positive sign of the coefficient capturing the food price index illustrates the relationship between overall price movements in food and sugar markets. A general rise in staple food world prices tends to be associated with an increase in sugar quotations. This co-movement may reflect common macroeconomic, financial, and fundamental factors at play, but could also illustrates the financialization of commodity markets in general and cash crops and staple foods in particularly (Basak and Pavlova, 2016; Grosche and Heckelei, 2016). As expected, the estimated coefficient associated with the Real/USD exchange is negative, meaning that a depreciation of the currency against the United States Dollar lowers international sugar prices. The PIP for the world ethanol prices is estimated at 9.5 percent, with relatively smaller posterior mean. Likewise, world oil prices and the variable capturing net sugar exports for India, the world's second largest sugar producers, have PIPs estimated at 9.2 and 9.1 percent, respectively. Their relatively weak influence is due to smaller marginal likelihood values, as their inclusion in various models does not have as much effect on sugar prices over the sample period.

Table 4.2: Bayesian model averaging coefficient results

Variables	**PIP**	**Post Mean**	**Post Standard Deviation**	**Sign certainty**
Lagged world sugar prices	1.000	0.283	0.053	1.000
Food price index	0.829	0.371	0.216	1.000
Brazil sugar cost of production	0.214	0.042	0.096	1.000
Brazil / US Foreign Exchange Rate	0.146	-0.003	0.009	0.000
Lagged world sugar production	0.130	-0.050	0.163	0.000
US ethanol prices	0.095	0.005	0.021	1.000
World crude oil prices (WTI)	0.092	0.005	0.021	0.000
India sugar net-export	0.091	0.000	0.000	0.000
World sugar stock-to-use ratio	0.091	-0.011	0.050	1.000
US HFCS prices	0.065	0.006	0.043	1.000
Number of licensed new cars in Brazil	0.064	0.001	0.006	1.000
Trade weighted US Dollar index	0.063	-0.008	0.075	0.005
EU sugar net-export	0.062	0.000	0.000	0.000
EU 2006 sugar regime reform	0.058	0.000	0.001	0.406
World sugar export	0.057	0.001	0.009	0.180
World sugar surplus	0.055	0.000	0.000	0.937
World sugar production	0.055	-0.002	0.075	0.981
US Manufacturing production	0.052	-0.001	0.144	0.293
Mean number of regressors:	3.318			
Correlation PMP	0.990			
g-Prior	UIP			
Model Prior	uniform			
Burnins	50000			

The bottom part of the Table 4.2 shows some statistics concerning the estimation process. The estimated mean number of regressors per model is found to be 3.31, a much lower value than the prior expected model size of 9 variables, given the assumed uniform model priors. The difference is due to the fact that following the update with the sample data, more weight is given to models with fewer predictors in the posterior model size distribution. The bottom panel of Table 4.2 also indicates that the correlation PMP is 0.99, meaning that the PMPs distribution derived analytically and those obtained via the MCMC sampler method converge at 99 percent for the best models.

4.4.2 *Predictive performance of the estimated BMA*

In addition to using the BMA approach to conduct inferences on the parameters, the method can also be used for forecasting purposes. We should note that a model that performs well in explaining the data may not necessary do well in forecasting. This is because inferences on parameters require certain assumptions that may not be met in a model used for predictions. In our case, the focus is on the forecasting capacity of the BMA.

The ability of the BMA to produce good predictive performances can be evaluate by looking at out-of-sample forecasts. In this section, we look at the performance of the estimated BMA model by considering pseudo out-of-sample forecasting of international sugar quotations and compare the results with a selection of benchmark forecasting models. Root square prediction errors (RSPEs) and root mean square prediction errors (RMSPEs) are then used as loss measures to assess the performance of the BMA model.

Alternative forecasts based on a selection of benchmark models are also developed and their respective loss measures computed and compared with those obtained with the BMA. The selected benchmark models include: 1) vector autoregression (VAR) process, 2) autoregressive (AR) process, 3) random walk (RW), 4) ordinary least squares (OLS), 5) FAO-OECD price forecasts made in 2016 for the year 2017 based on Aglink-COSIMO model, 6) Food and Agricultural Policy Research Institute (FAPRI) price forecasts made in 2016 for the year 2017, and 7) the World Bank price forecasts made in 2016 for the year 2017. We consider ARIMA-based auxiliary equations to construct the iterated multistep forecasts for the explanatory variables. For the lag structure of the autoregressive processes, the use of the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) selects AR(1) and VAR(2) as the most appropriate specification.

Table A4.1 shows the RSPEs at different horizons up to 12 months and for each of the selected models. RMSPE values are also shown in the bottom panel. We refer in the text to the longer horizon, as a period spanning from 6 to 12 months, while a shorter horizon corresponds to a period between 1 and 5 months.

Over the 12-month period, results indicate that, among the time series-based methods, both the BMA and the AR(1) approaches have the lowest root mean square prediction error, followed by values for OLS, VAR(2), and RW. In contrast, RMSPEs for the FAO-OECD, FAPRI, and the World Bank approaches are comparatively lower. However, the BMA and the other time series benchmarks do well at shorter horizons than at longer horizons, relative to the forecasts provided by the three institutions (FAO-OECD, FAPRI, and the World Bank). For the time series models, AR(1) and BMA have comparable performances and have consistently superior predictive power than the RW, OLS, and VAR(2), both at shorter and longer horizons. For instance, using BMA instead of an OLS model enables an average reduction in the RSPE of about 5 percent. Forecasts produced by FAO-OECD, FAPRI, and the World Bank outperform those generated by the time series approach mostly at longer horizons.

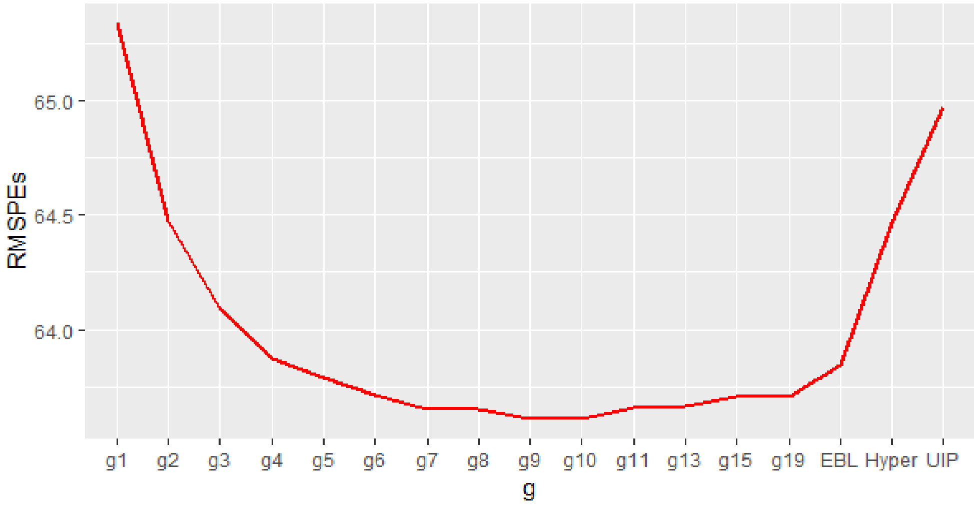
Results derived by the BMA approach can be sensitive to the assumptions on the shrinkage parameter as well as model priors. A large g-prior value indicates the researcher willingness to accept that the density of the prior is less tight around zero, giving more weights to the information contained in the data. To assess the sensitivity of the results to the value taken by the g-prior, a series of simulations are carried out. These consist of assigning specific values to the hyperparameter g and computing the resulting RSPEs and RMSPEs. As can be seen in Figure 4.4, when the shrinkage value increases, the predictive performance of the BMA model improves, as RMSPE declines consistently, but only up to a certain point where it starts to rise again. The increase in RMSPEs reflects a stronger size penalty imposed by selecting large g values (Wright, 2009). This is because as g increases, more weights are given to the likelihood than the prior, and as shown in the methodology, the marginal likelihood contains a size penalty parameter that controls for overfitting. The results show that the lowest

RMSPE is obtained by considering a shrinkage value equal to 10, which yields a 2 percent average reduction in prediction errors over the 12-month pseudo out-of-sample period, in comparison to the case where g is assumed to equal the unit information prior. Relative to other forecasting approaches, the BMA performs better than the AR(1), VAR(2), OLS, RW, but does not outperform FAO-OECD, FAPRI, and the World Bank.

These differences between RMSPEs can be tested statistically using bootstrapping technique. Bootstrapping method is useful when dealing with small samples. In this case, each forecasting model produces a sample of 12 RSPEs, corresponding to one observation per month, and hence 1 RMSPE per model. To be able to test statistically the mean difference between the RMSPEs, more observations are required. Considering that each of these sample represents a possible realization, we bootstrap, or resample, 1000 times each dataset and calculate for each sample the ratio of the RMSPE for the BMA relative to the RMSPEs of benchmark models. A ratio below one indicates that the BMA has superior predictive power. Since the bootstrap distribution of the ratio is asymmetrically distributed, we cannot use the standard t-distribution to make inferences about the ratio. Hence, a bootstrap t-Distribution is constructed using the bias-corrected and accelerated (BCa) boostrap method, which corrects for the prevailing asymmetry (DiCiccio and Efron, 1996). The generated distribution is then used to test whether the RMSPEs of the BMA relative to the RMSPEs of benchmark models is equal to 1, against the alternative that it is less than 1.

For example, the test rejects the null hypothesis that the ratio of RMSPE for the baseline BMA (UIP g-prior and uniform model prior) relative to RMSPEs of other methods/assumptions is equal to 1, in favor of the alternative hypothesis that it is less than one, in the case of VAR(2), RW, and OLS. This result implies that the BMA has a higher forecasting ability. The hypothesis is not rejected for AR(1). Likewise, when g =10, corresponding to a tighter density around the prior zero mean, the null hypothesis is rejected in the case of VAR(2), RW, and OLS, while it is not rejected for the other forecasting approaches. The BMA for g=10 performs particularly well in the longer horizon, when compared with the results under the assumption that g follows a unit information prior. Setting the prior for *g* equal to EBL and Hyper does not alter significantly the pattern of the overall results. In both cases, the null hypothesis using the bootstrapped t-Distribution is rejected for VAR(2), RW, and OLS, while the test fails to reject the null in the case of the other benchmark models, implying that these models have better predictive power.

Figure 4.4: Root mean square prediction errors (RMSPEs) for various g-prior values



Note: EBL refers to empirical Bayes local prior, while Hyper and UIP represent hyper-g prior and unit information prior, respectively.

One of the key assumptions made for the baseline BMA model is that of uniform model priors. Two simulations are carried out to evaluate the effect of relaxing this assumption. First, it is assumed that model priors follow a binomial distribution, where the prior of a model of specific size is the product of the inclusion and exclusion probabilities assigned to each potential explanatory variable. It is shown that within this framework, selecting a prior expected model size comes down to choosing to put more, or less, emphasis on large models (Ley and Steel, 2009). Running the model with g =UIP and with binomial model prior shows that the calculated RMSPE is below that obtained for the baseline BMA model. Based on the bootstrapped t-Distribution, hypothesis testing lead to the rejection of the null hypothesis that the RMSPE for the BMA with binomial prior relative to RMSPEs of benchmark models is equal to one, in favor of the alternative hypothesis that the ratio is less than 1, in the case of VAR(2), RW, and OLS. This indicates that the BMA has a superior predictive ability than these models. Note, however, that the variable capturing lagged sugar production is no longer among the top 6 regressors with the highest PIP, but is replaced by the variable capturing international oil price movements. Also, the mean number of regressors is now 1.63, in contrasts with 3.2 obtained for the baseline model, reflecting the fact that binomial model priors put more emphasis on parsimonious models. Given its emphasis on smaller models, many of the PIPs under the binomial model priors have become smaller. Results under the assumption of beta-binomial model priors are also similar to those of the binomial, although the estimated PIPs and the posterior means of the parameters display relatively smaller levels.

4.4.3 *Discussion on the various sensitivity analysis*

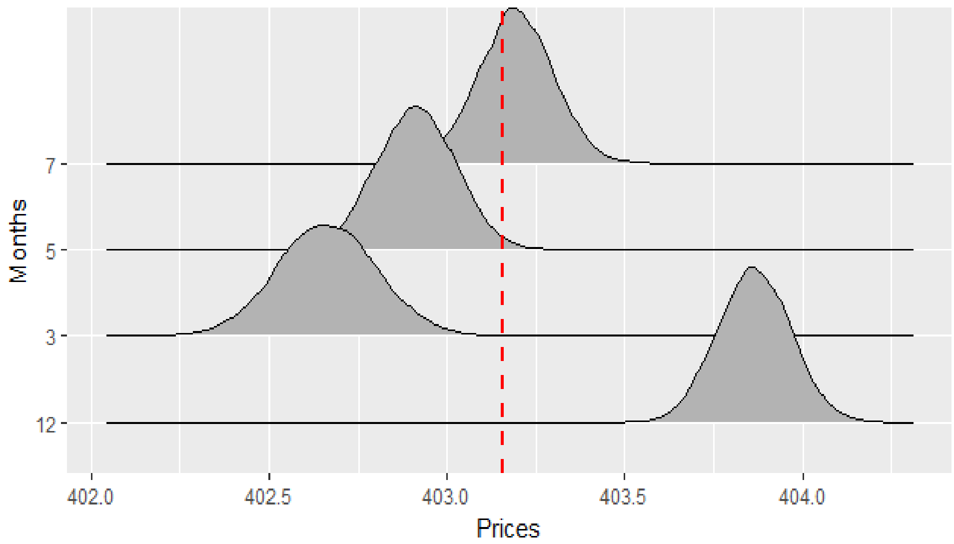
The various simulations carried out so far on the effects of the underlying assumptions of the baseline BMA suggest that the predictive power of the BMA model is influenced by the values of the shrinkage parameter and the shape of the model prior distribution. As the shrinkage parameter increases, the forecast performance of the BMA model seems to improve, but only up to a certain level when it starts to worsen. Also, changing the assumptions on model priors does seem to improve the forecasting accuracy of simulated models with respect to the baseline BMA model. To test statistically the significance of the differences in RMSPEs among the simulated models, we use the same bootstrapping approach, as discussed earlier, where 1000 bootstrapped samples are generated. Each sample represents a possible realization of the RMSPE values for each of the 18 simulated models. Using a constructed bootstrap t-Distribution, results of the tests suggest that the null hypothesis that the ratio of the RMSPE of the baseline model relative to the simulated models' RMSPEs is equal to unity is rejected, at the 5 percent level, in cases where g is less than 5, implying alternative forecasting approaches have better predictive power than the baseline BMA. For value greater or equal to 5, the predictive performance of the BMA improves up to g=10, after which it starts to decline.

The various simulations involving changing the value of the hyperparameter g and the assumptions on the model priors did not generally result in the selection of values for the PIPs that are fundamentally different from those generated under the baseline BMA model, and reported in Table A4.1. There are, however, some noticeable cases. First, when model priors are assumed to follow a binomial or a beta binomial distribution, the PIP of the variable capturing changes in crude oil prices increases, and is retained among the top six determinants of sugar price movements. As previously stated in section 4.2, oil prices can influence sugar prices through factor input costs, including transportation cost, and most importantly, through higher demand from the ethanol sub-sector. A rise in ethanol translates into higher demand for sugar crops-based ethanol. Likewise, the variable accounting for the net sugar exports of India, the world's second largest producer, gains in importance for certain values of the hyperparameter g, but its coefficient remains low, as in the baseline BMA model. The fact that India trades large volumes of sugar only occasionally explains its limited influence on prices. We note also that the PIP for the variable capturing the introduction of the 2006 sugar reforms in the EU increases from 6 percent to 43 percent, when the hyperparameter g is set to 1, albeit with a small coefficient value. The rise in the PIP is due to a less severe penalty size factor imposed by choosing a low shrinkage value. The weak coefficient means that, over the sample period, the 2006 reforms of the EU sugar sub-sector, which eventually turned the EU into a net sugar importer, did not affect world sugar prices significantly[4]. Recently, the EU introduced drastic modifications to its legislative sugar policy framework. A key element of the reform is the removal of domestic sugar production quotas and isoglucose production quotas as of the 2017/2018 marketing season. It is still to be seen to what extent these reforms will impact the world sugar prices,

[4] The 2006 EU sugar reforms included a cut in the sugar production quotas along with a 36 percent reduction in the guaranteed minimum price.

but the results of this analysis could serve as an indication of their potential effect. Finally, the covariate capturing changes in HFCS prices gains more importance when g is set between 1 and 8, although the coefficient remains small. HFCS is particularly important as a sugar substitute in the United States, still its share in the market has been declining in recent years.

Figure 4.5: Time-varying distributions of forecasted world sugar prices



Note: Forecasted world sugar prices are in US dollar per ton.

One of the advantages of a Bayesian approach to forecasting is that it produces a joint posterior distribution for the predictors. Using the joint posterior distribution of the top 6 explanatory variables generated by the baseline BMA model, we sample 10000 possible values from the marginal posterior distribution associated with the parameter of each predictor. These coefficient values, along with forecasted values of the regressors, are combined to yield a time-varying distribution of forecasted sugar prices[5]. For illustrative purposes, price distributions obtained for the months 3, 5, 7, and 12 of the pseudo out-of-sample are shown in Figure 4.5, with the forecasted sample mean portrayed with a vertical dashed line. Over the 12-

[5] The forecasts of the predictors are obtained with the assumption that they follow an ARIMA-based process.

month period, the BMA model forecasts international sugar prices to average USD 403.2 per ton, with a maximum possible value of USD 407 and a minimum of USD 400.2 per ton; while the actual average price during that period is USD 353 per ton. These price distributions can be quite useful, especially for sugar analysts and policy-makers, as they provide probabilistic information about price levels and variations not only for the whole forecasting period but also for specific times within that period.

4.5 Concluding comments

The main objectives of this paper are four folds: 1) to use the Bayesian model averaging approach to examine the relative importance of key variables for the short term prediction of international sugar prices, 2) to examine the sensitivity of the BMA results by altering key assumptions linked with the shrinkage parameter and model priors, 3) to compare the predictive ability of the BMA relative to other forecasting alternatives, and 4) to produce time-varying density forecasts based on the joint posterior distribution for the predictors. Results of this analysis show that changes in the lagged value of world sugar prices, the price of a basket of international food commodities, the cost of producing sugar in Brazil, movements in the value of the Brazilian currency (Real) against the United States dollar, lagged value of the world sugar production, and ethanol prices, influence the most sugar price movements at the global level.

These findings are in line with our prior expectations and the theory of the international sugar market, as described in the introductory section. Other variables such as sugar stock-to-use ratio, the price of the alternative sweeter HFCS, net sugar exports of India, the world's second largest sugar producer, do not have as much impact on sugar prices. Interestingly, the policy variable, which captures the introduction of a large set of reforms to the sugar sub-sector by the EU in 2006, does not seem to have an effect on prices over the estimation period. Overall, these results do not change much following a series of simulations where assumptions with respect to the shrinkage value and model priors are altered. The result emerging from these scenarios is that, for some instances, the variable associated with India's net exports of sugar gains importance in explaining sugar prices, with ethanol losing some of its significance, as its posterior inclusion probability falls. This is particularly the case when the value for the hyperparameter g increases and the model size penalty embedded in the marginal likelihood becomes relatively significant. The results are also relatively comparable when changing the assumptions on model priors from uniform priors to binomial and beta-binomial. One noticeable change is the importance, in terms of higher PIPs, given to changes in international crude oil prices, and a smaller PIP assigned to the value of lagged sugar production. The ethanol-sugar complex strongly links to crude oil through the energy market. Increasing crude oil prices raise demand for biofuels and, particularly, demand for sugar crops-based ethanol. In addition, the various simulations show that the predictive power of the BMA model is the highest when the shrinkage value g is set to 10, after which it starts to worsen. Overall, however, the BMA forecasts perform relatively well, especially for shorter horizons.

Generating robust projections for sugar can support sectoral planning, investment at both farm and factory level, and anticipate adequate market interventions for the many countries that support their domestic sugar market. As discussed in the introduction, several governments make use of various instruments to stabilize domestic sugar market. BMA-based projections can support policy-makers by providing good evidence-based assessment of the nature, level, and duration of market interventions, such as those that involve sugar stock purchases and open market sales. Also, results of this study suggest that staple food prices, as well as the evolution of broader macroeconomic drivers, can serve as good indicators for sugar price movements and should be taken into consideration in the design and implementation of policies aimed at strengthening the sugar sub-sector.

Future research could examine whether better BMA forecasts can be obtained by considering nonlinear models, in addition to the linear specifications explored in this paper. The inclusion of commodity forecasts made by the private sector (e.g. private banks), as well as known institutions such as the FAO-OECD, the World Bank, and research institutes, can improve the predicative ability of the BMA approach. How to incorporate these forecasts given their longer term focus can present some challenges. There is also a need to explore how the predictive power of the BMA can be improved when the forecasting period is relatively long. One option could be to enhance the BMA with a training ability, by splitting the sample or doing a cross validation, as it produces forecasts for a certain time horizon. Finally, the BMA offers an alternative approach to the more traditional framework that relies on partial or general equilibrium models for conducting commodity projections, particularly when these models are costly to operate and maintain because of data requirements.

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4.7 **Annex**

Table A4.1: Root square prediction errors (RSPEs) and root mean square prediction errors (RMSPEs) for different g-priors and model prior assumptions

Benchmark models								BMA models										
Months	VAR(2)	AR(1)	OLS	RW	FO	FP	WB	UIP	g=1	g=5	g=7	g=10	g=11	g=15	Hyper	EBL	Bbin	Bin
1	41.42	45.04	41.65	39.17	136.19	127.19	48.19	44.56	42.53	43.87	44.07	44.22	44.23	44.31	44.43	43.86	44.96	44.96
2	39.16	45.29	41.15	38.19	135.31	126.31	47.31	44.57	42.07	43.87	44.12	44.32	44.34	44.43	44.45	43.85	45.23	45.20
3	10.95	3.25	7.38	12.19	86.60	77.60	1.40	4.06	6.42	4.48	4.22	4.03	4.01	3.94	4.07	4.50	3.23	3.28
4	47.67	39.06	42.95	48.48	50.89	41.89	37.11	39.87	41.92	39.91	39.67	39.50	39.50	39.45	39.76	39.94	38.93	39.01
5	57.33	48.07	51.67	59.02	42.06	33.06	45.94	48.84	50.54	48.49	48.27	48.11	48.12	48.10	48.59	48.51	47.81	47.91
6	105.51	95.89	99.19	108.97	5.56	14.56	93.56	96.60	97.96	95.85	95.65	95.53	95.54	95.55	96.22	95.89	95.50	95.61
7	89.87	80.23	83.24	93.88	10.31	1.31	77.69	80.87	81.90	79.74	79.56	79.45	79.48	79.52	80.36	79.77	79.70	79.83

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Table A4.1 continued

	Benchmark models							BMA models										
Months	VAR(2)	AR(1)	OLS	RW	FO	FP	WB	UIP	g=1	g=5	g=7	g=10	g=11	g=15	Hyper	EBL	Bbin	Bin
8	95.64	85.95	88.68	99.32	4.80	4.20	83.20	86.51	87.22	85.01	84.85	84.76	84.81	84.87	85.88	85.05	85.27	85.42
9	95.54	85.72	88.19	98.53	5.24	3.76	82.76	86.21	86.60	84.34	84.20	84.14	84.19	84.28	85.46	84.38	84.90	85.07
10	96.99	87.03	89.25	101.47	4.14	4.86	83.86	87.44	87.52	85.22	85.10	85.06	85.12	85.24	86.57	85.27	86.07	86.25
11	83.06	72.91	74.89	86.57	18.47	9.47	69.53	73.24	73.02	70.68	70.58	70.55	70.62	70.77	72.26	70.73	71.81	72.00
12	96.97	86.57	88.33	100.36	5.02	3.98	82.98	86.82	86.30	83.93	83.84	83.83	83.91	84.08	85.72	83.98	85.32	85.53
Mean (1 to12)	71.68	64.58	66.38	73.84	42.05	37.35	62.79	64.97	65.33	63.78	63.68	63.62	63.66	63.71	64.48	63.81	64.06	64.17
p-value	0.02	0.80	0.05	0.01	0.99	0.98	0.86		0.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99

Note: BMA: Bayesian Model Averaging; VAR: Vector autoregressive; AR: autoregressive model; OLS: ordinary least square; RW: random walk; FO: FAO/OECD Outlook; FP: Food and Agricultural Policy Research Institute Outlook; WB: World Bank Outlook. Hyper: Hyper-g prior; EBL: Empirical Bayes local prior; Bbin: Beta-binomial model prior; Bin: Binomial model prior. Figures in the table represent the calculated RSPEs based on forecasts produced by the BMA, VAR, AR, OLS, and RW models. Forecasts generated by the FO, FP, and the WB are taken from their respective medium-term Outlook reports published in 2016. Monthly RSPEs are computed for the pseudo out-of-sample running from January 2017 to December 2017. The computed p-values, using the bootstrapping technique (see section 4.4.1), is for the null that the ratio of RMSPEs for the baseline BMA relative to RMSPEs of alternative methods/assumptions is equal to 1, against the alternative that the ratio is less than 1 (see section 4.4.2 for details).