# Sugar with your Coffee?

## *Fundamentals, Financials, and Softs Price Uncertainty*

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## Abstract

We investigate empirically the factors related to price uncertainty in the markets for two key Central American commodities: coffee and sugar (“softs”). Specifically, we analyze the predictive power of physical market fundamentals and financial variables with respect to (i) market expectations of future price volatility in the markets for both commodities and (ii) the extent to which these markets co-move with equity markets. We capture commodity market uncertainty through option-implied volatilities. Variables considered on the physical side include global macroeconomic conditions (driving current consumption demand); precautionary and speculative demand (through commodity-specific inventory conditions, as implied by the commodity futures price slope); and idiosyncratic supply shocks (including extreme weather episodes and disease epidemics). The two main variables on the financial side are a proxy for investor “sentiment” or overall uncertainty in financial markets and a measure of the intensity of financial speculation in commodity futures markets. We find that physical market fundamentals (inventories, weather events, diseases) matter. Beyond fundamentals, our results highlight the crucial role of financial market sentiment in understanding cross market linkages and the magnitude of softs market uncertainty. Similarly, increases in financial speculation help predict increases in softs uncertainty. We find qualitatively similar results for cattle, another important Central American export commodity.



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*"(The) economic consequences of booms and slumps in (commodity) prices (are) one of the most challenging issues facing policymakers in commodity-exporting (...) countries"*
(Cashin, McDermott and Scott, 2002).

*"What commodity prices lack in trend, they make up for in variance."*
Deaton (1999, p. 27)

## 1. Introduction

The large swings in commodity price of the past two decades have translated into big movements of poor and emerging countries' terms of trade (Schmitt-Grohé and Uribe, 2015). It has long been argued that such terms-of-trade shocks are a major source of economic instability for those countries (Serven, 1999). Indeed, calibrated business-cycle models show that terms of trade shocks constitute a major source of business cycles in small open economies whose exports are dominated by primary commodities, including Central American countries (Mendoza,1995; Kose, 2002). Insofar as the welfare costs of business cycles in those countries are much higher than in advanced economies (Pallage and Robe, 2003), commodity prices fluctuations are thus very costly to producer countries. Costs extend further as export income volatility also forces governments "to hold precautionary reserves" and curtails their "ability to borrow against future export income" (Borensztein, Jeanne, and Sandri, 2013 p. 105).

In this paper, we investigate empirically market participants' *expectations* of future price volatility. That is, we seek to understand the factors related to *forward-looking* uncertainty regarding commodity prices. We focus on two "soft" commodities, coffee and sugar, that are major sources of export revenues for many Latin American countries. To that effect, we construct a weekly dataset of physical and financial variables between 1995 and 2015, and then use an econometric model that considers the relation between those two sets of variables and (i) forward-looking softs price volatility and (ii) the extent to which softs markets co-move with financial markets.

We measure uncertainty in softs markets through option-implied return volatilities (IVol). Intuitively, as trading financial options allows market participants to bet on (or to hedge against) future volatility, option prices reveal these participants' forward-looking views on price uncertainty. We capture the strength of cross-market linkages *via* correlations between the returns on passive positions in equity and coffee or sugar markets.

On the physical side, the factors we consider include global macroeconomic conditions (which drive current consumption demand); precautionary and speculative demand (through commodity-specific inventory conditions, as proxied by the slope of the relevant term structures of commodity futures prices); and supply shocks (e.g., disease outbreaks such as coffee rust epidemics, drought in a commodity's largest producing country, etc.). Our two main variables on the financial side are option–implied volatility in financial markets (captured by the equity VIX) and the intensity of speculative activity in the relevant commodity futures markets.

We find that the VIX, the state of commodity inventories, and market-specific supply shocks are statistically and economically significantly related to near- and longer-term forward-looking volatility in sugar and coffee markets as well as to the intensity of cross-market linkages. A weekly index of global economic activity is negatively correlated to volatility expectations and to the strength of softs-equity return linkages;[2] that index, however, has insignificant statistical power beyond that of the VIX.

Documenting the importance of the VIX for softs IVols and for softs-equity co-movements is novel, yet our findings are intuitive. Bekaert, Hoerova, and Lo Duca (2013) show that elevated VIX levels capture heightened uncertainty about macroeconomic conditions and increased levels of risk aversion among investors. One reason why the VIX should matter for softs IVols, then, is the linkage between equity and softs markets that stems from changes in the level of uncertainty regarding the global demand for goods (including soft commodities) and services. A second reason is that changes in investors risk-bearing desire or capacity are likely to permeate all asset markets. He, Kelly and Manela (2016) empirically show that an intermediary capital factor prices many classes of assets, including commodities. Constraints to financial market risk bearing brings about changes in the same direction for the VIX, softs IVols, and the strength of cross-market linkages.

We also show that storage dislocations (i.e., overfull or depleted inventories) and supply shocks are a harbinger of increased forward-looking volatility but are associated with lower return correlations between softs and equity markets. The impact of extreme weather in the largest commodity-producing countries is statistically significant in the case of coffee IVol (frosts and droughts in Brazil) but not in the case of sugar (likely reflecting the lower level of geographic concentration of sugar production beyond the two main producers, Brazil and India).

[2] The negative signs of the regression coefficient are intuitive as commodity-market uncertainty and cross-market linkages go up during recessions – see, e.g., Gorton and Rouwenhorst (2006) and Büyükşahin and Robe (2014).

Finally, we find that a proxy for the relative magnitude of financial institutions' positions in softs futures markets has some explanatory power for the strength of return linkages between softs and financial markets. Furthermore, we show that changes in the intensity of financial speculation help predict forward-looking softs market volatility. Precisely, Tuesday-to-Tuesday weekly changes in the intensity of financial speculation in coffee and sugar futures markets predict changes in the same direction of forward-looking volatility measured the following Wednesday. To the best of our knowledge, this result is new.

The remainder of the paper proceeds as follows. Section 2 discusses our contribution to the literature. Section 3 presents evidence on softs IVols and softs-equity linkages during the 1995–2015 period. Section 4 and 5 link forward-looking volatility and market cross-correlations to fundamentals, financial speculation, financial market stress, and their interactions. Section 6 concludes and outlines avenues for future research. An Appendix documents qualitatively similar empirical results for cattle, the source of another important Latin American export.

## 2. Related Literature

A long line of research seeks to understand the price dynamics of commodities in general and softs in particular – see, e.g., Mehta and Chavas (2008) and Igami (2015) in the case of coffee and see Cafiero, Bobenrieth, Bobenrieth, and Wright (2015) in the case of sugar. The present paper is, to our knowledge, the first to systematically investigate the factors related to market *expectations* of softs price volatility expectations.[3]

Although numerous articles study the information content of option-implied volatilities,[4] only more recently have researchers asked what drives implied volatilities themselves. In the equity space, Mixon (2002), Guo, Han, and Zhao (2014), and Andreou and Ghysels (2014) link the implied volatility surface for the S&P 500 index to macroeconomic variables. In the energy space, Robe and Wallen (2016) show that the (equity-market) VIX and physical-market fundamentals both affect crude oil implied volatilities. In a contemporaneous working paper, Adjemian, Bruno, Robe and Wallen (2016) carry out a structural analysis of what drives

[3] There also exists a large parallel literature on *realized* volatility in commodity markets. It consists mostly of GARCH modeling or forecasting studies of realized commodity price volatility – see Robe and Wallen (2016) for a review. Closer to our approach are studies by Ng and Pirrong (1994), Karali and Power (2013), and Watugala (2015) that seek to link price volatility in commodity markets to select macroeconomic factors, physical fundamentals, or financial market frictions; those three studies, however, look at *realized* volatility rather than volatility *expectations*.
[4] For agricultural markets see, e.g., Fackler and King (1990) and Egelkraut, Garcia, and Sherrick (2007).

forward-looking volatility in grains and livestock markets.[5] The present study builds on that extant work to understand what factors are related to volatility expectations in the softs space.

Similar to Robe and Wallen (2016), we show that financial market sentiment, the state of commodity inventories, and exogenous supply shocks are key to understanding commodity volatility expectations. Unlike for crude oil, however, we find for softs that the intensity of financial speculation in the U.S. futures markets where coffee or sugar price discovery takes place is a statistically significant predictor of forward-looking price uncertainty. One possible interpretation of this result is that traders' positions capture market-relevant information that is not explicitly accounted for in our model.

This result, and the methodology we implement to derive it, are both new. Using the same proxy for financial speculation as we do and the same source of information regarding trader positions in commodity markets – the U.S. Commodity Futures Trading Commission's (CFTC) Commitments of Traders Reports (COTs), but with a different empirical approach and a shorter (2006-2009) sample period, Irwin and Sanders (2010) also conclude that higher levels of speculation in grain, livestock, and softs markets are followed by amplified forward-looking volatility in those markets. The relation they identify, though consistently positive, is not statistically significant – ours is not only positive for both sugar and coffee but it is also significant. While it should be stressed that our methodology does not speak to the issue of causality (and of whether financial speculation is destabilizing), our finding of an information content in traders' positions is therefore noteworthy.[6,7]

As well, we find that financial speculation is positively related to return linkages between softs and financial markets. This finding connects our paper to another strand of literature, concerned with whether the "financialization" of commodity markets (i.e., the substantial increase in the relative magnitude of financial institutions' positions in those markets after 2003) has made the latter move more in sync with financial markets.[8] Several theoretical models

[5] The only other paper on what moves implied volatilities in agricultural markets is Isengildina-Massa, Irwin, Good, and Gomez's (2008) event study of the impact of WASDE reports on corn and soybean implied volatility.

[6] In a related setting, Büyükşahin and Robe (2014) also find that COTs contain information. Both their and our conclusions are consistent with Schwartz's (2012) finding of market-moving news in COT reports.

[7] In addition to Irwin and Sanders (2010), a number of papers including Brunetti, Büyükşahin, and Harris (2016) and Kim (2015) investigate empirically whether futures speculation induces increased *realized* (as opposed to forward looking) volatility. Their answer is negative – see Kim (2015) for a literature review.

[8] Irwin and Sanders (2011), Fattouh, Kilian, and Mahadeva (2013), and Cheng and Xiong (2014), among others, review the literature on the role of financial institutions in commodity markets. In this Section, we focus on the work most closely related to ours.

(Gromb and Vayanos, 2010; Başak and Pavlova, 2016; Ellwanger, 2015) predict such a development; a number of empirical studies (Büyükşahin and Robe, 2011, 2014; Cheng, Kirilenko and Xiong, 2015; Bruno, Büyükşahin, and Robe, 2016) provide, for different commodity markets, evidence consistent with the notion that increased commodity trading by financial institutions should impact commodity-equity correlation levels and patterns.

We extend that prior work. By focusing on coffee and sugar, we can account cleanly for physical fundamentals in each market. Indeed, an independent contribution of the present paper is the construction of a weekly dataset of fundamental variables for analyses of softs markets.

## 3. Volatility Expectations and Cross-Market Linkages, 1995-2015

We analyze forward-looking uncertainty (IVol) in softs markets and the co-movements between softs and equity markets. This Section describes how we quantify those variables. It also establishes some important empirical facts.

### 3.1 Prices, returns, and forward-looking volatility

We use data from the U.S. derivatives markets where price discovery takes place for coffee (Fortenberry and Zapata, 2004), sugar (Zapata, Fortenbery, and Armstrong, 2005) and, in the Appendix, live cattle (Mattos and Garcia, 2006). For coffee and sugar, we construct daily time series for the term structures of futures prices and IVols based on ICE (formerly, New York Board of Trade) settlement prices for futures and options on futures contracts for Sugar No. 11 and Coffee C. For cattle, we use CME Group (formerly, Chicago Mercantile Exchange) data.

Our sample period is January 1995 to mid-September 2015. We obtain from Bloomberg the daily futures prices and IVols computed from the prices of European options on those futures, plus volume and open interest for futures and option contracts. Our IVol series are based on the Wednesday closing prices of the most actively traded contracts, i.e., at-the-money options – see Cui (2012).[9] Mindful that low liquidity could affect option prices and artificially inflate

[9] We measure IVols and estimate correlations using Wednesday settlement prices because one of the variables we use to explain these variables is based on data regarding trader positions in commodity markets. As explained in the Appendix, the public position data come from the U.S. Commodity Futures Trading Commission's (CFTC) weekly Commitments of Traders Reports (COTs), which are based on Tuesday end-of-day futures and options positions. In order to avoid possible endogeneity issues, we therefore regress Wednesday IVols and correlations on Tuesday

IVols ahead of prompt-contract expiration dates, we use the preponderance of the futures open interest (rather than calendar dates) to select roll dates for futures and options on futures.

Figure 1 shows the evolution of our three commodities' nearby-futures settlement prices over time. For comparability, all prices in Figure 1 are scaled relative to their value on Wednesday, January 4th, 1995. The plot suggests that, while coffee and sugar experience similar long-term price cycles, the timing and the magnitudes of short-term deviations from that long-term trend differ markedly across these two commodities. Live cattle's price path stands apart from the softs, with lower volatility overall and an upward trend throughout the sample period.

Figure 2 plots, from January 1995 to September 2015, nearby and six-month-out implied volatilities for coffee (Panel A) and sugar (Panel B). For both commodities, near-dated IVols fluctuate much more than longer-dated (6-month out) IVols. These maturity-related differences in uncertainty levels generally become more muted in the second half of our sample period.

Han (2008) shows that investor sentiment is an important determinant of Standard and Poor's S&P 500 equity index option prices. Bekaert, Hoerova, and Lo Duca (2013) show that the VIX captures not only investors' uncertainty about the macro-economy but also their risk aversion. Thus, we use the forward-looking volatility implied by these prices ("VIX") as a proxy for global uncertainty and financial market sentiment. Table I compares summary statistics for softs IVols and the VIX. Figure 2 shows that, while softs and equity IVols all show increases in the months following the demise of Lehman's Brothers in September 2008, there are numerous commodity-specific IVol spikes that do not seem related to the behavior of the VIX.

## 3.2 Commodity-equity return correlations

We assess the strength of commodity-equity linkages by computing exponential-smoothing (ES) correlations between weekly returns on passive investments in investable commodity and stock market indices. For equities, we use returns on Standard and Poor's S&P 500 index. For commodities, we use the unlevered total returns on commodity-specific Standard and Poor's S&P GSCI indices. Each figure is a return on a "fully collateralized commodity futures investment that is rolled forward from the fifth to the ninth business day of each month."

position information. If a Wednesday is a market holiday, we use the Tuesday immediately prior to the holiday and adjust position data accordingly. If that Tuesday is also a holiday, then we select the Monday prior to the Tuesday.

In all markets, we obtain index data from Bloomberg and compute Wednesday-to-Wednesday weekly returns.[10] To estimate the ES correlations, we follow Büyükşahin, Haigh, and Robe (2010) and set the smoothing parameter $\lambda = 0.94$. Our estimation period for ES correlations is 1983–2015, a period long enough to eliminate any influence of initial conditions in the 1995–2015 sample that we use in the econometric analyses of Section 5.

Table I provides summary statistics for all of our ES commodity-equity return correlation estimates. Figure 3 plots them from January 3rd, 1995 to September 15th, 2015. It highlights three empirical facts.

First, Panel A of Figure 3 shows that the strength of the co-movements between equities and individual commodities varies substantially over time. After superimposing a plot of the return correlations between the S&P 500 equity index and the cross-commodity S&P GSCI (covering 24 commodities), a similar pattern emerges – suggesting the presence of a strong common component to individual cross-market linkages. This observation forms the basis of a key aspect of our econometric modeling strategy for cross-market linkages in Section 4.

Second, as first documented by Büyükşahin, Haigh, and Robe (2010), softs-equity return co-movements rose quickly and massively after Lehman Brothers' demise in September 2008. By 2013, however, they had fallen back to pre-crisis levels and even turned negative for both sugar and coffee. To paraphrase Bruno *et al.* (2016), "contrary to any notion that (agricultural) markets have entered a permanent 'market of one' era, return correlations dropped dramatically once the Great Recession and the concomitant financial crisis ended."

Third, Panel B of Figure 3 shows an inverse relationship between commodity-equity return correlations and the global business cycle (as captured by a weekly economic activity index, *REAL_95*, based on Kilian's (2009) methodology – see Section 4.1 below). The inverse relationship that Panels A and B of Figure 3 together depict in the case of softs is consistent with similar patterns documented for other kinds of commodities – see Gorton and Rouwenhorst (2006), Büyükşahin and Robe (2011), Bhardwaj and Dunsby (2013), and Bruno *et al.* (2016).

[10] Precisely, we measure the percentage rate of return on the $I^{th}$ investable index in period $t$ as $r^I_t = \text{Log}(P^I_t / P^I_{t-1})$, where $P^I_t$ is the value of index $I$ at time $t$.

## 4. Potential Drivers of Price Uncertainty and Cross-market Linkages

Our premise is that physical market fundamentals and derivatives (i.e., paper) market variables both contain information about market expectations of near- and longer-dated volatility and about the extent to which commodities move in sync with equities. This Section discusses the variables we use in the econometric models of Section 5: macroeconomic conditions (Section 4.1), softs physical-market fundamentals (4.2), and financial variables (5.3).

Our approach hews closely to two extant studies that thoroughly discuss the rationale for including each of the variables introduced in the present Section when seeking to predict either forward-looking volatility (Robe and Wallen, 2016) or the intensity of cross-market linkages (Bruno *et al*. 2016). For concision's sake, we therefore only summarize the arguments made by those authors regarding the inclusion of each variable we use, referring the reader to the relevant section of those two papers for more information. In this Section, we focus instead on how to measure the explanatory variables in the context of softs markets.

Table I and Table II provide summary statistics for our variables.

### *4.1. Macroeconomic Fundamentals: Consumption Demand*

*Ceteris paribus*, we expect both commodity market uncertainty (Robe and Wallen, 2016, Section 5.1) and the strength of cross-market linkages (Bruno *et al*., 2016, Section 5.1) to move counter to the world business cycle.

To measure world economic activity, we follow most of the recent literature and draw on Kilian's (2009) argument that "increases in freight (shipping) rates may be used as indicators of (demand shifts) in global industrial commodity markets." Kilian's measure is a monthly global index of single-voyage freight rates for bulk dry commodity cargoes. It accounts for "different fixed effects for different routes, commodities and ship sizes" (Kilian, 2009 p.1056). The measure is deflated with the U.S. consumer price index (CPI) and linearly detrended to remove the impact of a "secular decrease in the cost of shipping dry cargo" (*ibidem*).[11]

[11] Other studies of agricultural price dynamics that rely on Kilian's measure include Enders and Holt (2012, grains), Janzen, Smith, and Carter (2013, cotton), Janzen, Smith, Carter, and Adjemian (2014, wheat), Etienne, Irwin, and Garcia (2014b, grains), Bruno *et al*. (2015), Adjemian *et al*. (2016), etc. Alquist and Coibion (2014) use principal-component analysis to look at the impact of global economic fluctuations on cross-commodity price co-movements. Their analysis, which is quarterly, finds that the business cycle matters.

To construct a weekly series, denoted *REAL_95*, we follow Bruno *et al*. (2016) and adapt Kilian's (2009) methodology to Tuesday spot values of the Baltic Dry Index (BDI) for dry-bulk freight rates between 1995 and 2015. Panel B of Figure 3 depicts the resulting time series.

When seeking to explain cross-market linkages, we follow Büyükşahin and Robe (2011, 2014) and use the level of *REAL_95*. When seeking to explain commodity IVols, we follow Robe and Wallen (2016) and use the first difference of *REAL_95*. Given that we seek to explain IVols and cross-correlations sampled or estimated on Wednesdays, we use Tuesday values of the BDI to construct *REAL_95* in order to avoid possible endogeneity issues in the regressions.

### *4.2. Precautionary and Speculative Demand: Inventories*

A rich theoretical and empirical literature analyzes the role of inventories for commodity price dynamics.[12] "By increasing stocks when price is falling, storers reduce the dispersion of price and prevent steeper price slumps. (As long as stocks are available, stock d)isposal when supplies become scarcer reduces the severity of price spikes" (Wright, 2011, p. 39). In contrast, when storage facilities are either full to the brim or empty, markets should be more susceptible to supply shocks and thus commodity IVols should increase – especially in the near-term (Robe and Wallen, 2016, Section 5.2.4). For the same reason, depleted or overflowing inventories should decrease "the relative importance of pricing factors common to commodities and equities" – leading to a decrease in cross-market correlations (Bruno *et al*., 2016, Section 5.3).

Because there do not do exist global, high-frequency data on physical inventories of soft commodities, we follow the approach suggested by Working (1933, 1948, 1949) and Fama and French (1987, 1988) and use, as a proxy for the inventory conditions in each commodity market, the slope of the term structure of futures prices for that commodity.[13] This slope, expressed in percentage terms, measures the net cost of carry for that commodity and, as such, captures market participants' views of the state of inventories. We eliminate the influence of interest rate fluctuations on that cost of carry by subtracting, from the annualized percentage calendar spread, an appropriately scaled money factor based on the London Interbank Offered Rate (LIBOR). Given that the implied volatilities and cross-correlations that we seek to explain are sampled or

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[12] On the theory side see, e.g., Vercammen and Doroudian (2014), Cafiero *et al*. (2015), and references cited therein. On the empirical side see, e.g., see, e.g., Kilian and Murphy (2014) and Robe and Wallen (2016) for crude oil; Janzen, Smith, and Carter (2013) for cotton; Janzen, Smith, Carter and Adjemian (2014) for wheat; etc.

[13] Joseph, Garcia, and Irwin (2014) document the continued validity of this approach in agricultural markets.

estimated on Wednesday, we use Tuesday futures prices when computing *SLOPE* – sidestepping again possible endogeneity issues in the regression analyses of Section 5.

We denote the resulting variable, which measures the net calendar spread return or net cost of carry, *SLOPE*. In our regressions, we use the absolute value of *SLOPE*, so that high values of our variable capture extreme (either low or high) inventory levels.

When seeking to understand near-dated IVols and cross-correlations, we use "nearby" calendar spreads (first-deferred *vs*. nearby futures). To explain 6-month IVols, we use medium-term calendar spreads (i.e., nearby *vs*. 5– to 7–months out futures; we use a weight-averaging so as to effectively retain a constant 6-month contract maturity, similar to what we do in Section 3 to obtain constant-maturity 6-month IVols).

## *4.3. Output shocks*

Softs output is affected mostly by planting decisions, disease epidemics, and weather conditions (temperature and rain).[14] Unlike planting, which take place at *(very)* low frequency in the case of sugar *(coffee)*, diseases outbreaks and weather events are the sources of exogenous, high frequency shocks to softs markets. Intuitively, disease and extreme weather episodes should bring about sharp, commodity-specific price movements – resulting in increased uncertainty and a weakening of the connection between softs and equity markets.

We start from the Commodities Research Bureau's (CRB) *Commodity Yearbook*, an annual trade publication, to identify major events that impacted softs prices in our sample period. In addition, we also review periodic publications of the U.S. Department of Agriculture' Foreign Agricultural Service (USDA "World Markets and Trade") for both coffee and sugar. Finally, we use prior research and hand-collected information to precisely identify the actual supply shocks.

### *4.3.1 Diseases*

Between 1995 and 2015, neither the *CRB Yearbooks* nor the USDA's "World Markets and Trade" reports make any mention of disease outbreaks that would have substantially affected sugar production and price dynamics. The coffee market, in contrast, was deleteriously affected by several major episodes of coffee rust in that same time period. We draw from Avelino *et al.* (2015) to create weekly dummy variables for two severe outbreaks in Colombia (January 2008 to

[14] Beef supply is directly affected by cattle disease outbreaks and indirectly affected by weather events impacting the production of corn, due to the latter's use as animal feed. The Appendix discusses how we account for those shocks.

October 2011) and Central America (November 2012 to September 2014). We give each dummy the value 1 on disease weeks (from the outbreak to its eventual containement) and 0 otherwise.

#### *4.3.2 Weather*

Producing coffee or sugar requires suitable temperatures and adequate amounts of water. On the one hand, frosts and droughts in Brazil (by far the world's biggest producer) were the cause of about five major global coffee bean output deficits in the last two decades (Flury, 2015). On the other hand, a reading of the *CRB Yearbooks* and USDA reports suggests that extreme precipitations in Brazil or India (the two largest growers of cane) can substantially affect sugar price dynamics. We create several variables to take those realities into account.

Frosts, as they hurt or kill coffee trees, have a long-lasting impact on bean production. Substantial amounts of time may elapse, though, before uncertainty regarding a frost's impact on bean production is resolved (CRI, 2016). In an analysis of the impact on prices of the 1965–1989 International Coffee Agreement, a cartel, Igami (2015) proposes to take the impact of a severe ("white") frost into account by setting a dummy variable equal to 1 in the two years following the frost. We follow that approach to account for the two white frosts that hit Brazilian Arabica coffee-growing areas in 1994, on the nights of June 25-26 and July 9-10. With regard to market volatility, using a two-year dummy gives the inventory depletions that follow a frost-induced output drop the time to take place and to impact market fragility.

Next, we turn to the impact of precipitations. To capture that impact, we follow the orange juice market insight of Boudoukh, Richardson, Shen, and Whitelaw (2007) that only extreme weather fluctuations should materially affect production levels and, thus, have a market impact. In our setting, we incorporate this intuition by way of dummy variables for extreme precipitations in the dominant producer country (coffee) or countries (sugar).

We use two dummies to capture the impact of droughts in Brazilian coffee- and sugar-growing areas. Our first drought dummy takes the value 1 from August 1999 through July 2001, and from January through August in 2003, 2005, and 2014. Its value is designed to "roughly" reflect the information contained in trade and USDA publications. Our second drought dummy is based on monthly Brazilian precipitation data collected from individual weather stations located in the main coffee- and sugar-growing states. Its construction is described in Appendix 2.

In the case of sugar, we account for unusual precipitations not only in Brazil (as described in the previous paragraph) but also in India, the world's second largest producer country.[15] Recognizing that both drought in the growing season and excess rain at harvest time can negatively impact output, we create two dummy variables for "drought" and "rain" based on monthly precipitation data collected by the India Meteorological Department for the main sugar-growing states. Their construction is described in Appendix 2.

### *4.4. Global Uncertainty and Investor Sentiment in Financial Markets*

Insofar as commodity markets are not segmented from financial asset markets, higher levels of uncertainty or risk aversion in financial markets are likely to spill over into commodity markets. Spillovers in the opposite direction are unlikely to happen in the case of most commodities – especially not in the case of softs, which make up but a very small part of the world's asset markets.[16] In other words, we submit that investor sentiment or global uncertainty, which are jointly captured through the options-implied volatility in equity markets (the *VIX*), should help explain forward-looking volatility in softs markets.

We test this hypothesis, which was first proposed by Robe and Wallen (2016) for oil in the 2000–2014 period and is also investigated by Adjemian *et al*. (2016) in a contemporaneous piece on uncertainty in grains and livestock markets. Including the VIX allows us to straightforwardly take into account the possibly non-linear effects of changes in investor uncertainty or risk aversion on commodity IVols. Because directionality is not an issue in the case of softs, we use the same-day VIX values in all of our regression analyses.

In the same vein, we investigate the explanatory power of the VIX for cross-correlations. Empirical evidence shows that correlations between returns in different asset markets increase in periods of stress – see, e.g., Longin and Solnik (international equity markets, 2001), Straetmans and de Vries (bond *vs*. equity markets, 2004), and Büyükşahin, Haigh, and Robe (commodity *vs*. equity markets, 2010). We therefore expect a statistically significant and positive relation between the VIX and the strength of softs-equity co-movements.

Finally, we consider the possibility that co-movements between softs and equities echo, at least partly, the co-movements between equities and commodities as a whole. To test this possibility, we investigate the explanatory power of the contemporaneous return correlations

[15] For example, USDA reports indicate that unfavorable precipitations during the Indian monsoon were the main reason for poor crops in 2009 and 2013.
[16] Although sugar and coffee commodity prices are very important to many producer countries, commodities as an asset class are much smaller than bonds or equities. Among commodities, coffee and sugar together account for only about two percent of the S&P GSCI commodities index, in line with their share of world commodity trade.

between equities and a broad portfolio of commodities (the S&P GSCI commodity index). We denote this variable *GSCI_SP500*. Because coffee and sugar *together* account for a mere two percent or so of the well-diversified S&P GSCI index, endogeneity is not a concern: hence, we include the contemporaneous (Wednesday) value of *GSCI_SP500* in the regression equation.

### *4.5. Paper Markets*

In addition to physical market fundamentals, we investigate the possibility that activity in commodity futures markets helps further explain forward-looking volatility or softs-equity co-movements. As well, we introduce two variables to controls for the possible impact of low option market liquidity and time-to-maturity on softs IVols.

#### *4.5.1. Financial speculation in softs futures markets*

As pointed out by Robe and Wallen (2016, Section 5.3.1), "Commodity Index Traders' (CITs) arrival in oil markets has garnered a lot of attention (…). Although there is still a spirited debate regarding whether CIT activity impacts commodity price *levels*, there is agreement that CITs are essentially passive, long-only investors. Hence, their positions in WTI or Brent futures are unlikely to hold predictive power for oil price option-implied *volatility*. In contrast to "passive" market participants like CITs, intuition suggests that more active trading by speculators could help predict oil price disruptions and increases in (commodity IVols). In the spirit of Brunetti, Büyükşahin, and Harris (2016) and Büyükşahin and Robe (2011, 2014), we therefore include a proxy for hedge fund activity in our analysis." Likewise, there is little empirical evidence that CIT activity generally impacts commodity-equity co-movements but robust evidence that hedge fund activity does have an impact in energy (Büyükşahin and Robe, 2011) and grain markets (Bruno *et al*., 2016).

To capture the relative importance of the coffee and sugar futures positions held by financial institutions such as hedge funds, we also use Working's (1960) *T* index of speculative intensity. To compute the index, we use the data on end-of-Tuesday trader position published every Friday in our sample period by the U.S. Commodity Futures Trading Commission (CFTC). Appendix 3 provides details of the *T* index computation. Using (changes in) trader positions on Tuesdays for the analysis of Ivols or cross-correlations that are estimated on Wednesday avoids possible endogeneity issues between trader activity and the distribution of commodity returns.

Figure 4 plots, from January 3rd, 1995 to September 14th, 2015, the indices of speculative intensity (Working's *T* index minus 1) in coffee, sugar, and live cattle futures markets. Notably, the *T* index is quite volatile. Still, all series trend upward in the sample period. The weakest growth is seen in the coffee market, in contrast to stronger growth starting in 2003–2004 for sugar and in 2004–2005 for live cattle.

*4.5.2. Technical variables: Paper market liquidity and Time-to-maturity effects*

Intuitively, insofar as option prices include a liquidity premium, option prices (*IVols*) and market liquidity should be negatively (*positively*) related. Our regressions therefore include a variable to account for liquidity. To avoid possible endogeneity issues, we capture paper-market liquidity through Tuesday-to-Tuesday (i.e., one-day lagged) changes in coffee or sugar options-on-futures trading volumes.

Finally, we follow Robe and Wallen (2016, p. 332) and "include a variable (in our IVol regressions) that takes a value equal to the number of days left before the 'nearby' contract expires (where the 'nearby' is defined based on the preponderance of the futures open interest). Based on the Samuelson (1965) effect, we expect the sign of this variable's regression coefficient to be negative."[17]

# 5. Findings

We use macroeconomic, physical, and financial variables introduced in Section 4 with ordinary least squares (OLS) regressions to analyze sugar and coffee IVols or with auto-regressive distributed lag (ARDL) regressions to analyze the co-movements between each soft market and equity markets. Section 5.1 discusses econometric considerations. We summarize the regression results for IVols and cross-market linkages in Sections 5.2 and 5.3, respectively.

## *5.1. Modeling considerations*

As submitted in Section 4, we investigate softs IVols using levels for financial explanatory variables (*VIX*; inventory conditions as captured by the relevant futures term

[17] According to Samuelson (1965), futures price volatility should increase as the prompt contract nears maturity. See Bessembinder, Coughenour, Seguin and Monroe Smoller (1996) for a thorough discussion of the conditions under which this pattern should arise.

structure *SLOPES*) but changes for the world business cycle index (*REAL_95*) and for trading activity (*T* index of financial speculation intensity; aggregate option volume). Augmented Dickey Fuller (ADF) unit root tests show that, as we use them, all these variables are stationary (see Tables I and II). We therefore rely on OLS regressions for our IVol analyses. Still, because the sugar and coffee IVol time series are autocorrelated, we must also include a lagged value of the dependent variable as an independent variable.

Precisely, we regress nearby and 6-month sugar and coffee IVols, estimated using Wednesday option prices, on: the relevant one-week lagged IVol; financial market sentiment, as proxied by the same-day equity-market implied volatility (VIX); global macroeconomic conditions (proxied by the Tuesday-to-Tuesday change in the weekly *REAL_95* index of global economic activity); softs market fundamentals, as captured by our disease and weather variables and by the matching-maturity absolute net cost of carry (Tuesday nearby or six-month term structure *SLOPE*, minus an interest rate factor); the Tuesday-to-Tuesday change in the intensity of financial speculation in the relevant commodity futures market (*T*); the Tuesday-to-Tuesday change in the relevant options trading volume; and the nearby contract's time-to-expiration.

We use the same variables to study sugar-equity and coffee-equity return correlations, but follow Büyükşahin and Robe (2011, 2014) who argue that, in analyses of market co-movements, one should use the level of (rather than the change in) global macroeconomic conditions (*REAL_95*) and the intensity of financial speculation (Working's *T*). Hence, we use the ARDL (1,1) specification that they suggest after verifying the presence of a co-integrating vector. As discussed in Section 4.4, we also consider an alternative specification in which we replace the business cycle indicator, *REAL_95*, by a financial variable – the correlation between returns on equity *vs*. diversified commodity investments (*GSCI_SP500).*

As discussed in Section 4, we anticipate that the regression coefficients should have the following signs:

| **Variable** | **Predicted sign** ***(IVol)*** | **Predicted sign** ***(Softs-Equity Linkages)*** |
|---|---|---|
| Lagged dependent variable *(Previous-Wednesday IVol)* | + | *N-A* |
| Global business cycle *(REAL_95, Tuesday)* | – (*Change*, Section 4.1) | – (*Level*, Section 4.1) |
| Inventory Dislocations *(Tuesday futures term structure SLOPE)* | + (Section 4.2) | – (Section 4.2) |
| Extreme Weather and Disease Outbreaks | + (Section 4.3) | – (Section 4.3) |
| Global financial uncertainty (Wednesday *VIX*) | + (Section 4.4) | + (Section 4.4) |
| Equity-Commodity Return Correlation *(GSCI_SP500, Wednesday)* | *N-A* | + (Section 4.4) |
| Financial speculation (Tuesday *Working T* index) | + (*Change*, Section 4.5.1) | + (*Level*, Section 4.5.1) |
| Days to expiration (*TTM*) of nearby option contract | – (Section 4.5.2) | *N-A* |
| Softs *Options Volume (Tuesday-to-Tuesday change)* | + (Section 4.5.2) | *N-A* |

### *5.2. Softs Market Uncertainty*

The results of our *IVol* regressions are summarized in Table III. The technical variables (option market liquidity, nearby contract time-to-expiration) both have the expected signs and term structure patterns, so we can focus on the results that matter from an economic perspective.

Table III shows that, even after controlling for lagged IVols, the *VIX* index is positively associated with forward-looking volatility in each commodity market. The statistical significance of the VIX is strong at all maturities: the *p*-values are less than two percent for coffee and less than one percent for sugar (the same is true for live cattle, see Appendix 1 for a discussion). Interestingly, the economic significance of the regression coefficient is much smaller for coffee than for sugar, which itself is only half the magnitude of the regression coefficient documented by Robe and Wallen (2016) in the case of crude oil. Put differently, softs market uncertainty levels tend to move together with generalized financial uncertainty (or investor sentiment) – but less so for softs than for the key industrial commodity that is crude oil.

After controlling for the *VIX*, Table III shows that an index of global macro-economic conditions (*REAL_95*) is not statistically significant. Although our regressions are consistent with the notion that forward-looking volatility should increase when the world economy stutters (the regression coefficients of *REAL_95* are negative for both coffee and sugar, at near- as well as longer-dated horizons), the statistical significance of the business cycle variable is "soaked up" by the VIX.

Table III also demonstrates the importance of modeling physical market fundamentals. First, while none of our weather dummies are statistically significant in the case of sugar (the Indian excess rain variable is closest to being significant, with a *p*-value of 11%), droughts and frosts in Brazil bring about a significant increase in coffee forward-looking volatility. The impact of extreme weather events on uncertainty in the coffee market is, as intuition would suggest, statistically and economically stronger for short-term uncertainty.[18]

Second, our proxy for unusual inventory conditions is highly significant for both sugar and coffee. As discussed in Section 4.3, we use the *SLOPE* of the part of the futures term structure, net of interest costs, to measure costs-of-carry at the relevant horizon (first-deferred *vs*. nearby futures contracts for the nearby IVol, 6-month *vs*. nearby futures for the 6-month IVol) and capture dislocations in the commodity storage space. Table III shows that softs storage-market disruptions have significant effects on forward-looking price volatilities that extend beyond the short term, though of course the impact is statistically and economically stronger in the case of nearby volatility expectations.

Finally, we find statistical evidence of a relationship between the intensity of softs-market speculation and softs price forward-looking volatility. Namely, after taking into account macroeconomic and physical-market fundamentals, Table III shows that the Tuesday-to-Tuesday change in Working's (1960) *T* index of speculative intensity in the relevant commodity futures market contains significant levels of information regarding forward-looking volatility.[19] One possible interpretation of this result is that traders' positions capture market-relevant information that is not explicitly accounted for in our model.

[18] A puzzle is why the Central American epidemic of the disease is associated with a significant decrease in near-dated volatility expectations. Our time dummies for coffee rust, however, are generally not significant.

[19] We obtain qualitatively similar results for coffee and sugar in the near term; the importance of financial speculation further out the uncertainty term structure is higher for sugar than for coffee.

### *5.3. Softs-Equity Market Linkages*

Table IV shows the long-run coefficients of our ARDL regressions of softs-equity return correlations on the VIX, sugar or coffee inventory conditions, output shocks (disease outbreaks and extreme weather events in the main producer countries), financial speculation in sugar or coffee markets, and either a global business cycle index (*REAL_95*) or the correlation between two diversified portfolios of commodities and equities (*S&P_GSCI vs. S&P_500*).

In a nutshell, our cross-market linkages results reinforce our main findings for IVols. The *VIX* is statistically significant in all cases, with the highest statistically significance found in the *REAL_95* regressions. After controlling for the *VIX*, the index of global macro-economic conditions (*REAL_95*) is, as is the case for IVols, statistically insignificant. In contrast, a variable that captures return correlations between equities and a broad portfolio of commodities is highly significant both for sugar and for coffee, confirming our intuition that there is a strong common element to the co-movements between individual commodities and financial markets.

Similar to Büyükşahin and Robe's (2011) findings for energy-equity linkages and Bruno *et al*.'s (2016) findings for grain-equity co-movements, we find that Working's *T* index of financial speculation in softs markets is positively related to the strength of softs-equity linkages. One possible interpretation is that financial institutions such as hedge funds help integrate commodity markets with other asset markets.

Market fundamentals have less explanatory power for soft markets' linkages to financial than they do for softs IVols. First, the dummy meant to capture a possible impact of coffee rust on co-movements is either not or barely statistically significant, and in the latter case again does not have the expected sign. Second, extreme weather events have almost no significant explanatory power for ES correlations. Finally, storage conditions do not hold much explanatory power. This result is surprising, given our results for softs IVols in Table III – but it is consistent with Bruno *et al*.'s (2016) conclusions in the case of grains and livestock.

## 7. Conclusions

We identify empirically major factors related to price uncertainty in the markets for two key Central American commodities: coffee and sugar ("softs"). Specifically, we analyze the predictive power of physical market fundamentals and financial variables with respect to (i) market expectations of future price volatility in the markets for both commodities and (ii) the extent to which these markets co-move with equity markets. We capture commodity market uncertainty through option-implied return volatilities. Variables considered on the physical side include global macroeconomic conditions (driving current consumption demand); precautionary and speculative demand (through commodity-specific inventory conditions, as implied by the futures price slope); and idiosyncratic supply shocks (such as extreme weather episodes, disease epidemics, etc.). The two main variables on the financial side are a proxy for overall uncertainty and risk aversion (or "sentiment") in equity markets, and a measure of the intensity of financial speculation in commodity futures markets. We find that physical market fundamentals (inventories, weather events, diseases) matter. Beyond fundamentals, our results highlight the importance of financial market sentiment in understanding both the strength of linkages between softs and financial markets and the extent of forward-looking uncertainty in softs market. Finally we show that increases in financial speculation help predict increases in softs uncertainty. We get qualitatively similar results for cattle, another important Central American export commodity.

Our empirical findings suggest three venues for further research. First, further theoretical work seems necessary to explain why inventories matter for IVols but are generally statistically insignificant in the case of cross-market linkages could be statistically – despite the intuition that stock levels should in theory affect the intensity of co-movements between commodity and other markets (as they do affect other aspects of commodity price dynamics). Second, all of the relevant variables in the model can be sampled daily – suggesting the possibility of building a forecasting model for uncertainty in softs markets at a frequency high enough that it could be of use to policy makers. Third, our analysis deals with forward-looking uncertainty. A natural topic of study would be the extent to which the volatility expectations that we study translate into realized volatility. The answer would be of not only academic but also policy interest, as the answer may help inform the undersatnding of the linkages between commodity price volatility, terms of trade shocks, and countries ability to borrow against future commodity export revenues.

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## Table I: Summary Statistics – Net Costs of Carry, Option-implied Volatilities, and Commodity-Equity Correlations

| | Mean | Median | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | | ADF Level | | ADF Diff | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **KC_IV_N** | 39.51 | 38.27 | 115.26 | 19.03 | 9.94 | 1.51 | 8.68 | 1861.69 | *** | 0.00 | *** | 0.00 | *** |
| **ABS(KC_SLOPE_N_Tue)** | 0.13 | 0.10 | 0.86 | 0.00 | 0.10 | 2.63 | 13.43 | 6143.61 | *** | 0.01 | *** | 0.00 | *** |
| **Coffee_SP500** | 0.15 | 0.13 | 0.71 | -0.36 | 0.21 | 0.22 | 2.68 | 13.18 | *** | 0.00 | *** | 0.00 | *** |
| **SB_IV_N** | 32.19 | 31.72 | 77.97 | 13.82 | 10.16 | 0.59 | 3.26 | 65.74 | *** | 0.03 | ** | 0.00 | *** |
| **ABS(SB_SLOPE_N_Tue)** | 0.16 | 0.11 | 0.70 | 0.00 | 0.14 | 1.49 | 4.83 | 552.58 | *** | 0.00 | *** | 0.00 | *** |
| **Sugar_SP500** | 0.03 | 0.03 | 0.60 | -0.60 | 0.22 | 0.24 | 2.81 | 11.92 | *** | 0.00 | *** | 0.00 | *** |
| **LC_IV_N** | 14.88 | 14.37 | 50.59 | 7.16 | 3.93 | 1.70 | 11.63 | 3878.02 | *** | 0.00 | *** | 0.00 | *** |
| **ABS(LC_SLOPE_N_Tue)** | 0.13 | 0.13 | 0.45 | 0.00 | 0.09 | 1.18 | 4.79 | 397.22 | *** | 0.00 | *** | 0.00 | *** |
| **Livecattle_SP500** | 0.08 | 0.10 | 0.72 | -0.36 | 0.18 | 0.26 | 3.63 | 30.16 | *** | 0.00 | *** | 0.00 | *** |
| **ABS(C_SLOPE_N_Tue)** | 0.14 | 0.12 | 1.30 | 0.00 | 0.14 | 4.30 | 27.00 | 29276.25 | *** | 0.00 | *** | 0.00 | *** |
| **GSCI_SP500** | 0.15 | 0.09 | 0.78 | -0.43 | 0.30 | 0.37 | 2.11 | 60.81 | *** | 0.01 | ** | 0.00 | *** |
| **VIX** | 20.59 | 19.20 | 74.26 | 9.89 | 8.32 | 1.97 | 9.80 | 2777.89 | *** | 0.00 | *** | 0.00 | *** |

**Notes:** The commodity option-implied volatility (***IV***) variables are self-explanatory and expressed in annualized percentage points (Source: ICE for coffee (***KC***) and sugar (***SB***), CME Group for live cattle (***LC***), as reported in Bloomberg). ***VIX*** is the forward-looking return volatility (in annualized percentage points) implied by Standard and Poor's S&P500 equity index options (Source: CBOE). For the nearby coffee (***KC***), sugar (***SB***), live cattle (***LC***) and corn (C) futures, annualized percentage costs-of-carry are computed using the ***SLOPE*** of the futures term structure, net of the corresponding interest costs (capture by the relevant-maturity London Interbank Offered Rate, or LIBOR). The absolute value of the slope is employed, so that higher values of the variable capture episodes of substantial backwardation or contango (i.e., unusual inventory levels). The nearby futures contract that anchors each futures and options term structures is defined as the nearest-maturity futures contract with the highest open interest (Source: Bloomberg). We also compute "6-month-out" ***IV_6M*** and ***SLOPE_6M*** variables (see Figure 2), defined by weight-averaging variables for contracts bracketing the 180-day cutoff, so as to effectively retain a constant 6-month contract maturity. The three variable ending with the suffix ***_SP500*** are the exponential-smoothing (ES) correlation between the Wednesday-to-Wednesday returns on passive investments in (ii) Standard and Poor's S&P 500 equity index and (ii) either Standard and Poor's S&P GSCI Index (***GSCI***) or Standard and Poor's S&P GSCI single-commodity index for coffee (***Coffee***), sugar (***Sugar***), or live cattle (***Livecattle***). We estimate all correlations with a smoothing parameter set to $\lambda$ = 0.94. For the augmented Dickey-Fuller (ADF) tests, we provide p-values. Stars (*, **, ***) indicate the rejection of non-stationarity at standard levels of statistical significance (10%, 5% and 1%, respectively). The lag length is set equal to 4 for all series, using the SBIC criterion. Sample period for all summary statistics: Wednesdays from January 4th, 1995 to September 15th, 2015. ES correlations are estimated using weekly data for the period 1983-2015; Table I reports the ES summary statistics for our 1995-2015 sample period.

**Table II: Summary Statistics – Macroeconomic and Physical Market Fundamentals, and Paper Market Conditions**

| | Mean | Median | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | | ADF Level | | ADF Diff | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Real_1DLag** | 0.01 | -0.04 | 0.87 | -0.57 | 0.34 | 0.57 | 2.46 | 72.14 | *** | 0.10 | * | 0.00 | *** |
| **D(Real_1DLag)** | 0.00 | 0.00 | 0.27 | -0.23 | 0.04 | -0.01 | 9.67 | 2003.25 | *** | 0.00 | *** | 0.00 | *** |
| **Real_95_Tue** | 0.00 | -0.06 | 0.88 | -0.54 | 0.34 | 0.62 | 2.49 | 80.27 | *** | 0.09 | * | 0.00 | *** |
| **D(Working_T_KC)** | 0.00 | 0.00 | 0.13 | -0.15 | 0.03 | -0.30 | 6.30 | 506.59 | *** | 0.00 | *** | 0.00 | *** |
| **D(Working_T_T_SB)** | 0.00 | 0.00 | 0.09 | -0.19 | 0.02 | -0.67 | 13.94 | 5468.77 | *** | 0.00 | *** | 0.00 | *** |
| **D(Working_T_T_LC)** | 0.00 | 0.00 | 0.25 | -0.19 | 0.04 | -0.02 | 9.68 | 2007.46 | *** | 0.00 | *** | 0.00 | *** |
| **KC_Vol_Option_1m_Tue** | 4390.50 | 3530.00 | 19562.00 | 260.00 | 3079.79 | 1.60 | 6.10 | 893.25 | *** | 0.00 | *** | 0.00 | *** |
| **SB_Vol_Option_1m_Tue** | 8840.98 | 5753.00 | 128982.00 | 208.00 | 9274.63 | 3.80 | 34.70 | 47857.53 | *** | 0.00 | *** | 0.00 | *** |
| **LC_Vol_Option_1m_Tue** | 2161.33 | 1138.00 | 20153.00 | 100.00 | 2565.38 | 2.57 | 11.52 | 4458.50 | *** | 0.00 | *** | 0.00 | *** |
| **KC_TTM_N** | 77.98 | 76.00 | 138.00 | 36.00 | 23.90 | 0.35 | 2.26 | 46.16 | *** | 0.00 | *** | 0.00 | *** |
| **SB_TTM_N** | 71.43 | 64.00 | 181.00 | 14.00 | 38.52 | 0.80 | 2.85 | 115.34 | *** | 0.00 | *** | 0.00 | *** |
| **LC_TTM_N** | 63.98 | 54.00 | 115.00 | 36.00 | 20.05 | 0.85 | 2.46 | 144.28 | *** | 0.00 | *** | 0.00 | *** |
| **NBER** | 0.10 | 0.00 | 1.00 | 0.00 | 0.31 | 2.59 | 7.68 | 2191.90 | *** | 0.01 | ** | 0.00 | *** |
| **Brazil_Drought** | 0.19 | 0.00 | 1.00 | 0.00 | 0.40 | 1.55 | 3.41 | 442.19 | *** | 0.00 | *** | 0.00 | *** |
| **Brazil_Frost** | 0.08 | 0.00 | 1.00 | 0.00 | 0.27 | 3.18 | 11.11 | 4781.48 | *** | 0.01 | *** | 0.00 | *** |
| **Coffee_Rust** | 0.10 | 0.00 | 1.00 | 0.00 | 0.30 | 2.67 | 8.12 | 2463.69 | *** | 0.15 | | 0.00 | *** |
| **Mad_Cow_1** | 0.00 | 0.00 | 1.00 | 0.00 | 0.04 | 23.18 | 538.50 | 13013089.00 | *** | 0.00 | *** | 0.00 | *** |
| **Mad_Cow_2_Short** | 0.00 | 0.00 | 1.00 | 0.00 | 0.04 | 23.18 | 538.50 | 13013089.00 | *** | 0.00 | *** | 0.00 | *** |
| **CR_Asym_Centered** | 0.00 | 0.00 | 62.39 | -760.61 | 77.71 | -7.61 | 67.30 | 196673.70 | *** | 0.00 | *** | 0.00 | *** |
| **CR_Asym_Interaction** | 0.48 | 0.00 | 18.44 | -38.94 | 4.07 | -1.99 | 17.62 | 10334.97 | *** | 0.00 | *** | 0.00 | *** |

**Notes:** ***Real*** is weekly index of global business activity adapted from Kilian (2009). We compute weekly ***Real*** values using Tuesday settlement prices of the Baltic Dry index of shipping rates for dry bulk cargoes on oceanic routes (*Source*: Bloomberg), deflated and detrended using a methodology adapted from Kilian (2009) as described in Bruno, Büyükşahin, and Robe (2016). ***Real_95_Tue*** is the same variable, detrended over the 1995–2015 period (*vs*. 1985–2015 for ***Real***). ***Working_T*** is an index (Working, 1960) of speculation in commodity futures markets (*Source*: CFTC and authors' computations). The three ***Vol_Option_1m_Tue*** variables capture the Tuesday trading volume of the nearby option on futures contracts (*Source*: Bloomberg based on ICE data for coffee (***KC***) and sugar (***SB***) and CME Group data for live cattle (***LC***)). ***Brazil_Drought***, ***Brazil_Frost***, and ***Coffee_Rust*** are dummy variables set to 1 during extreme weather episodes in Brazil or amid the rust epidemic in Colombia (Jan. 2008 to Oct. 2011) and Central America (Nov. 2012 to Sept. 2014). Each dummy takes the value 0 in regular times and 1 otherwise; the ***Brazil_Frost*** dummy is estimated as in Igami (2015). ***Mad_Cow_1*** and ***Mad_Cow_2*** are two dummies set equal to 1 for the first two weeks of, respectively, the Canadian and U.S. episodes of mad cow disease (bovine spongiform encephalopathy, or BSE) in 2003, as described in Adjemian, Bruno, Robe, and Wallen (2016). ***CR_Asym_Centered*** is the Bruno, Büyükşahin, and Robe (2016) weekly index of the U.S. corn crop's progress.

## Table III: Predictors of Near-dated Implied Volatilities

| | Coffee | Sugar | Live Cattle |
|---|---|---|---|
| **Lagged Ivol** | 0.616989*** *(0.023297)* | 0.797064*** *(0.016824)* | 0.856754*** *(0.013642)* |
| **VIX** | 0.058919** *(0.025142)* | 0.103094*** *(0.019361)* | 0.017489*** *(0.006291)* |
| REAL_95 - **World Business Cycle** (*Tuesday-to-Tuesday change)* | -5.651287 *(5.509306)* | -2.311818 *(4.179183)* | 1.22811 *(1.439667)* |
| **Unusual inventory conditions** *(Short-term, Tuesday)* | 12.93224*** *(2.091107)* | 5.573329*** *(1.112202)* | 0.23776 *(0.566749)* |
| **Unusual inventory conditions** *(Corn, short-term, Tuesday)* | | | 0.553336 *(0.386879)* |
| **Time-to-maturity** *(nearby contract)* | -0.060252*** *(0.008296)* | -0.030049*** *(0.003983)* | -0.008633*** *(0.002565)* |
| **Financial Speculation** *(Working's T, Tuesday-to-Tuesday change)* | 9.42068 *(5.880677)* | 20.33697*** *(7.545885)* | 1.347309 *(1.210967)* |
| Option market **volume** *(Tuesday-to-Tuesday change)* | 0.000286*** *(0.0000632)* | 0.0000145 *(0.0000161)* | 0.000022 *(0.0000216)* |
| **Coffee rust** *(dummy, Central America)* | -1.608235** *(0.725673)* | | |
| **Brazil frost** *(rough dummy)* | 3.134952*** *(0.797589)* | | |
| **Brazil drought** *(rough dummy)* | 3.069562*** *(0.540734)* | -0.29849 *(0.376282)* | |
| **Brazil drought** *(non-rolling dummy)* | 5.705479 *(4.361554)* | -2.086806 *(3.207254)* | |
| **India drought** *(non-rolling dummy)* | | -0.371765 *(3.366752)* | |
| **India rain** *(non-rolling dummy)* | | -3.093941 *(1.99399)* | |
| **Mad cow** - episode 1 (**Canada**, May 2003) | | | 2.721945** *(1.182557)* |
| **Mad cow** - episode 2 (**USA**, Dec. 2003) | | | 11.64354*** *(1.218813)* |
| **US corn crop condition** *(asymmetric index)* | | | 0.000454 *(0.00069)* |
| **US corn crop/inventories interaction** | | | 0.006859 *(0.013588)* |
| **Constant** | 16.22757*** *(1.208563)* | 5.816307*** *(0.624283)* | 2.190186*** *(0.290471)* |

***Notes:*** **Table III** shows the estimated coefficients from the model described in Sections 4 and 5.2 (Wednesday nearby IVols on weekly variables in Tables I-II), 1995-2015. Stars (*, **, ***) indicate levels (10%, 5%, 1%) of statistical significance.

## Table IV: Predictors of 6-Month Implied Volatilities

| | Coffee | Sugar | Livecattle |
|---|---|---|---|
| **Lagged Ivol** | **0.891283***<br>*(0.014153)* | **0.953046***<br>*(0.009046)* | **0.929649***<br>*(0.010927)* |
| **VIX** | **0.023817**<br>*(0.010197)* | **0.022425***<br>*(0.008375)* | **0.010702***<br>*(0.004053)* |
| REAL_95 - **World Business Cycle** (*Tuesday-to-Tuesday change)* | -1.300947<br>*(2.236814)* | -0.91387<br>*(1.778454)* | 1.118421<br>*(0.88639)* |
| **Unusual inventory conditions** *(6-month, Tuesday)* | **1.844805**<br>*(0.903222)* | **0.945993***<br>*(0.536401)* | **0.925449**<br>*(0.441474)* |
| **Unusual inventory conditions** *(Corn, 6-month, Tuesday)* | | | 0.287121<br>*(0.278301)* |
| **Time-to-maturity** *(nearby contract)* | -0.005453<br>*(0.003365)* | -0.002156<br>*(0.00168)* | -0.000649<br>*(0.001582)* |
| **Financial Speculation** *(Working's T, Tuesday-to-Tuesday change)* | **5.196814**<br>*(2.362526)* | **12.47108***<br>*(3.210022)* | 0.48443<br>*(0.74936)* |
| Option market **volume** *(Tuesday-to-Tuesday change)* | **0.000213***<br>*(0.0000571)* | 0.0000151<br>*(0.0000095)* | 0.000036<br>*(0.0000282)* |
| **Coffee rust** *(dummy, Central America)* | -0.422247<br>*(0.301295)* | | |
| **Brazil frost** *(rough dummy)* | **0.712654**<br>*(0.324556)* | | |
| **Brazil drought** *(rough dummy)* | **0.90506***<br>*(0.235578)* | -0.041505<br>*(0.160678)* | |
| **Brazil drought** *(non-rolling dummy)* | 2.180689<br>*(1.774115)* | -0.805961<br>*(1.364949)* | |
| **India drought** *(non-rolling dummy)* | | 0.368514<br>*(1.432171)* | |
| **India rain** *(non-rolling dummy)* | | -1.29657<br>*(0.851298)* | |
| **Mad cow -** episode 1 **(Canada**, May 2003) | | | 0.515299<br>*(0.729416)* |
| **Mad cow -** episode 2 (**USA**, Dec. 2003) | | | **3.195745***<br>*(0.738028)* |
| **US corn crop condition** *(asymmetric index)* | | | 0.000185<br>*(0.000424)* |
| **US corn crop/inventories interaction** | | | 0.005516<br>*(0.008256)* |
| **Constant** | **3.587321***<br>*(0.618139)* | **0.939438***<br>*(0.2708)* | **0.636723***<br>*(0.17529)* |

***Notes:*** **Table IV** shows the estimated coefficients from the model described in Sections 4 and 5.2 (Wednesday 6-month IVols on weekly variables in Tables I-II), 1995-2015. Stars (*, **, ***) indicate levels (10%, 5%, 1%) of statistical significance.

**Table V: Predictors of Softs-Equity Linkages (Macro View)**

| | <u>**Coffee**</u> | <u>**Sugar**</u> | <u>**Live Cattle**</u> |
|---|---|---|---|
| REAL_95 - **World Business Cycle** *(level, Tuesday)* | 0.115393<br>*(0.103907)* | -0.1207<br>*(0.096817)* | 0.024719<br>*(0.076238)* |
| **VIX** | **0.015974*****<br>*(0.004416)* | **0.016226*****<br>*(0.004213)* | **0.014897*****<br>*(0.003084)* |
| **Unusual inventory conditions** *(Short-term, Tuesday)* | 0.03259<br>*(0.334298)* | **0.496584****<br>*(0.230284)* | 0.44922*<br>*(0.271529)* |
| **Unusual inventory conditions** *(Corn, Short-term, Tuesday)* | | | **-0.410918****<br>*(0.190699)* |
| **Financial Speculation** *(Working's T, level, Tuesday)* | **0.77119****<br>*(0.368725)* | **0.660865***<br>*(0.38757)* | 0.047081<br>*(0.240442)* |
| **Coffee rust** *(dummy, Central America)* | -0.061761<br>*(0.129408)* | | |
| **Brazil frost** *(rough dummy)* | 0.12068<br>*(0.133313)* | | |
| **Brazil drought** *(rough dummy)* | **-0.143201***<br>(0.082473) | -0.063139<br>*(0.080285)* | |
| **Brazil drought** *(non-rolling dummy)* | -0.557905<br>*(0.707115)* | 0.599512<br>*(0.6925)* | |
| **India drought** *(non-rolling dummy)* | | -0.850485<br>*(0.725595)* | |
| **India rain** *(non-rolling dummy)* | | -0.031685<br>*(0.426615)* | |
| **Mad cow -** episode 1 **(Canada**, May 2003) | | | 0.504667<br>*(0.559815)* |
| **Mad cow** - episode 2 (**USA**, Dec. 2003) | | | **-2.394085*****<br>(0.696415) |
| **US corn crop condition** *(asymmetric index)* | | | -0.000137<br>*(0.000337)* |
| **US corn crop/inventories interaction** | | | 0.001017<br>*(0.006411)* |

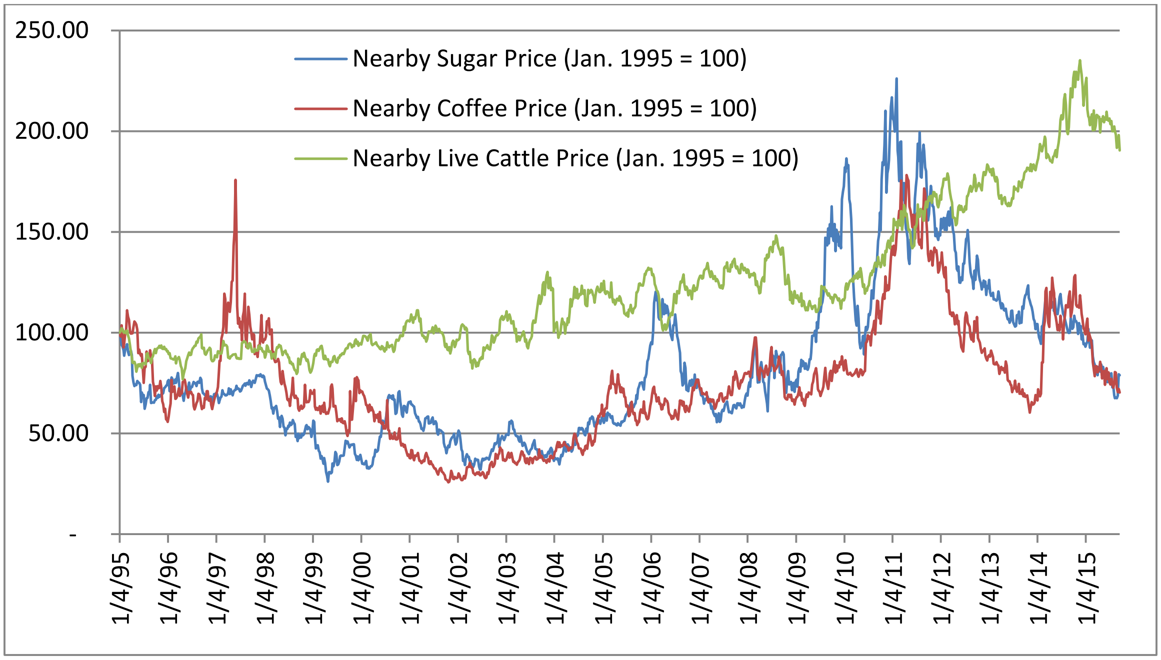
***Notes:*** **Table V** shows the estimated long-run coefficients from the two-step ARDL (p,q) model described in Sections 4 and 5. Long-run estimates are from the two-step ARDL(p,q) estimation approach of Pesaran and Shin (1999). We follow Büyükşahin and Robe (2011, 2014) and set p=q=1. The independent variables are described in Tables I and II. Sample period: January 4$^{th}$, 1995 to September 15$^{th}$, 2015. Stars (*, **, ***) indicate different levels of statistical significance (10%, 5% and 1%, respectively).

## Table VI: Predictors of Softs-Equity Linkages (Finance View)

| | Coffee | Sugar | Live Cattle |
|---|---|---|---|
| **GSCI *v*. S&P_500 Correlation** | **0.385839*****<br>*(0.102822)* | **0.435375*****<br>*(0.102295)* | **0.1584***<br>*(0.08569)* |
| **VIX** | **0.00777****<br>*(0.003524)* | **0.00936*****<br>*(0.003456)* | **0.012929*****<br>*(0.002894)* |
| **Unusual inventory conditions** *(Short-term, Tuesday)* | 0.237686<br>*(0.266922)* | 0.300822<br>*(0.188252)* | 0.487812*<br>*(0.252056)* |
| **Unusual inventory conditions** *(Corn, Short-term, Tuesday)* | | | **-0.419701****<br>*(0.177279)* |
| **Financial Speculation** *(Working's T, level, Tuesday)* | **0.629584****<br>*(0.295285)* | 0.142976<br>*(0.33498)* | -0.140051<br>*(0.236557)* |
| **Coffee rust** *(dummy, Central America)* | **-0.172313***<br>*(0.100231)* | | |
| **Brazil frost** *(rough dummy)* | 0.132967<br>*(0.106806)* | | |
| **Brazil drought** *(rough dummy)* | -0.029501<br>*(0.071484)* | 0.049749<br>*(0.068696)* | |
| **Brazil drought** *(non-rolling dummy)* | -0.664253<br>*(0.569651)* | 0.226213<br>*(0.551844)* | |
| **India drought** *(non-rolling dummy)* | | -0.588586<br>*(0.579931)* | |
| **India rain** *(non-rolling dummy)* | | 0.101737<br>*(0.34345)* | |
| **Mad cow -** episode 1 (**Canada**, May 2003) | | | 0.568027<br>*(0.523505)* |
| **Mad cow -** episode 2 (**USA**, Dec. 2003) | | | **-2.156237*****<br>*(0.6407)* |
| **US corn crop condition** *(asymmetric index)* | | | -0.000081<br>*(0.000312)* |
| **US corn crop/inventories interaction** | | | 0.000396<br>*(0.005986)* |

***Notes:*** **Table VI** shows the estimated long-run coefficients from the two-step ARDL ($p$,$q$) model described in Sections 4 and 5.3. Long-run estimates are from the two-step ARDL($p$,$q$) estimation approach of Pesaran and Shin (1999). We follow Büyükşahin and Robe (2011, 2014) and set $p$=$q$=1. The independent variables are described in Tables I and II. Sample period: January 4th, 1995 to September 15th, 2015. Stars (*, **, ***) indicate different levels of statistical significance (10%, 5% and 1%, respectively). **Table VI** is constructed like **Table V** – the only difference is the first explanatory variable.

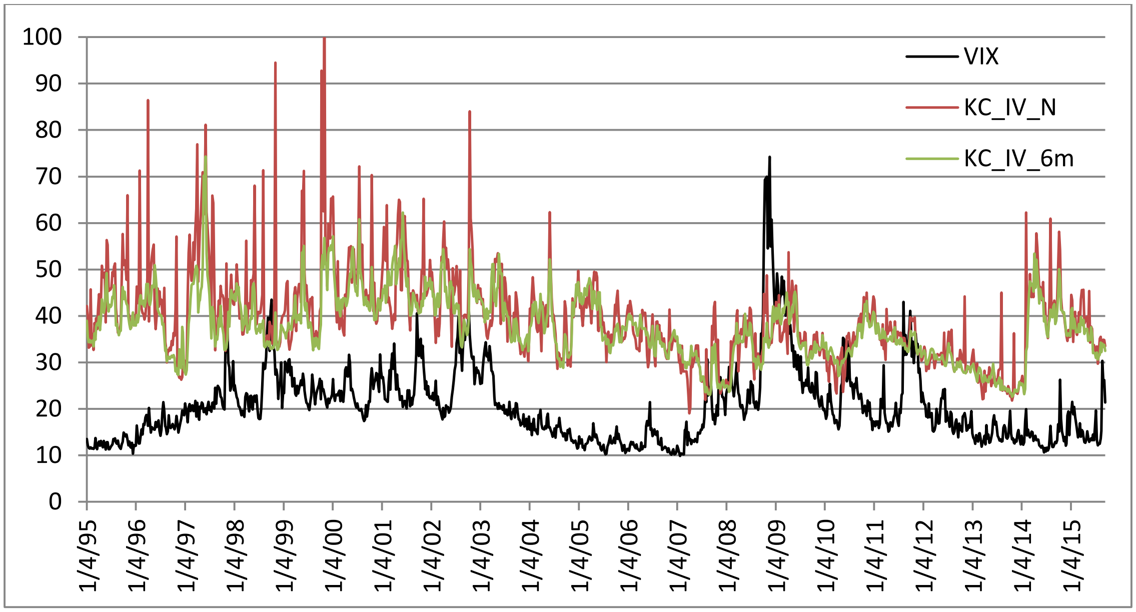
**Figure 1: Coffee, Sugar and Live Cattle Prices, 1995-2015**



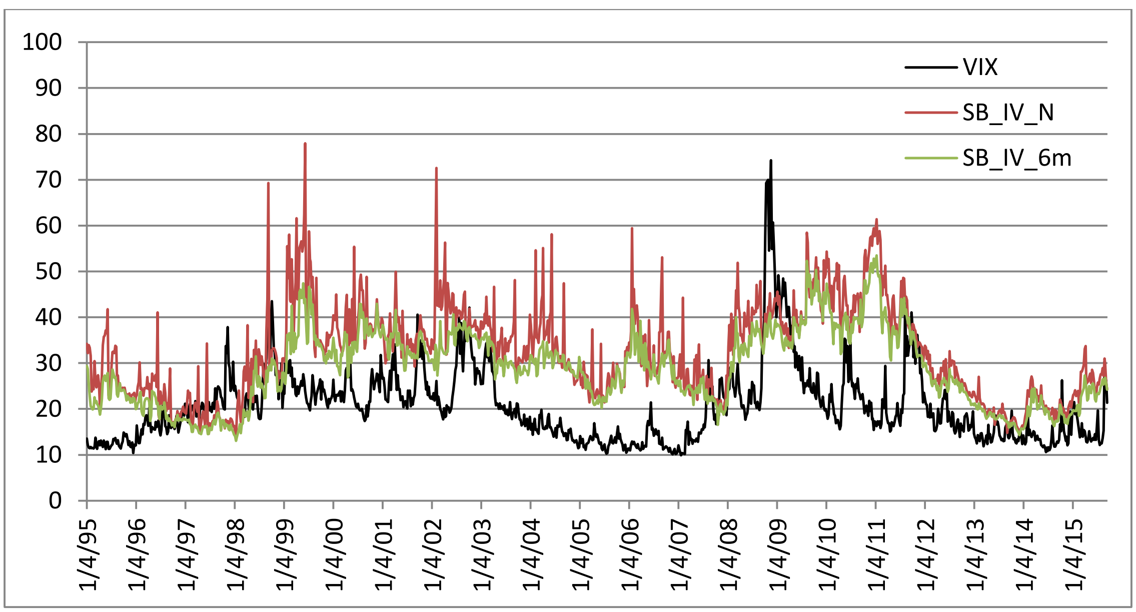

***Notes*: Figure 1** plots nearby-futures settlement prices (*Source*: Bloomberg) of three major Latin American agricultural export commodities: sugar (SB, ICE; **light blue**), coffee (KC, ICE; **red**) and live cattle (LC, CME Group; **green**). For comparability, all prices are sampled at the Wednesday close and scaled relative to their value on January 4th, 1995 (*Base*: 1995 = 100). For each commodity, the "nearby" contract is defined as either the prompt or the first-deferred futures based on the preponderance of the futures open interest. Figure 1 highlights that, while long-term cycles appear similar for coffee and sugar, the timing of short term deviations generally differ markedly for these two "soft" commodities. Live cattle's price path stands apart, with lower volatility and an upward trend throughout the sample period.

**Figure 2: Forward-Looking Volatility in Softs and Equity Markets**

**Panel A: Coffee**



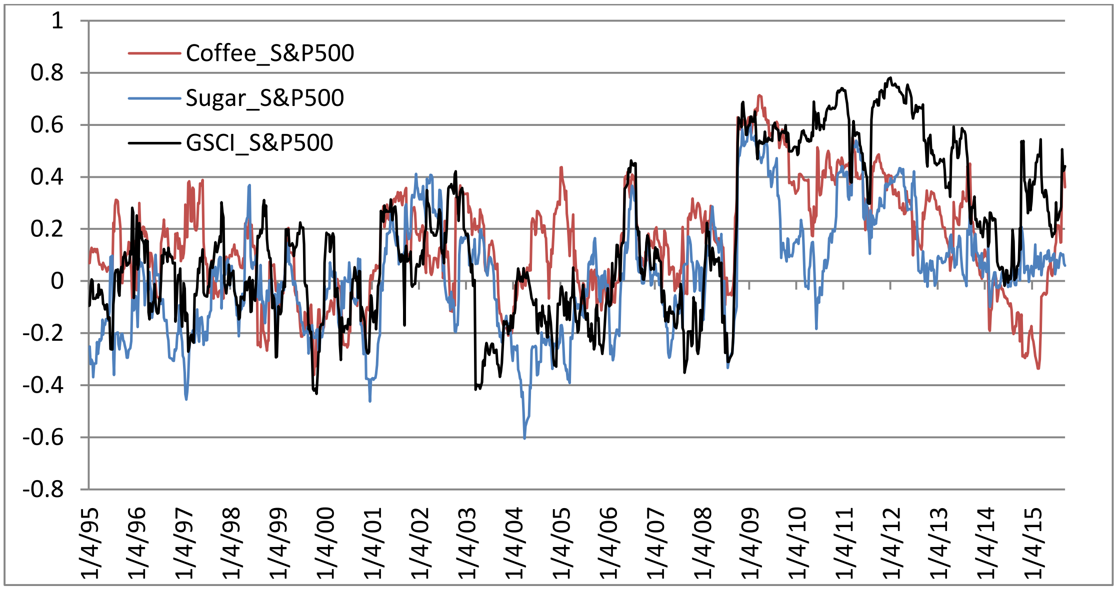

**Panel B: Sugar**



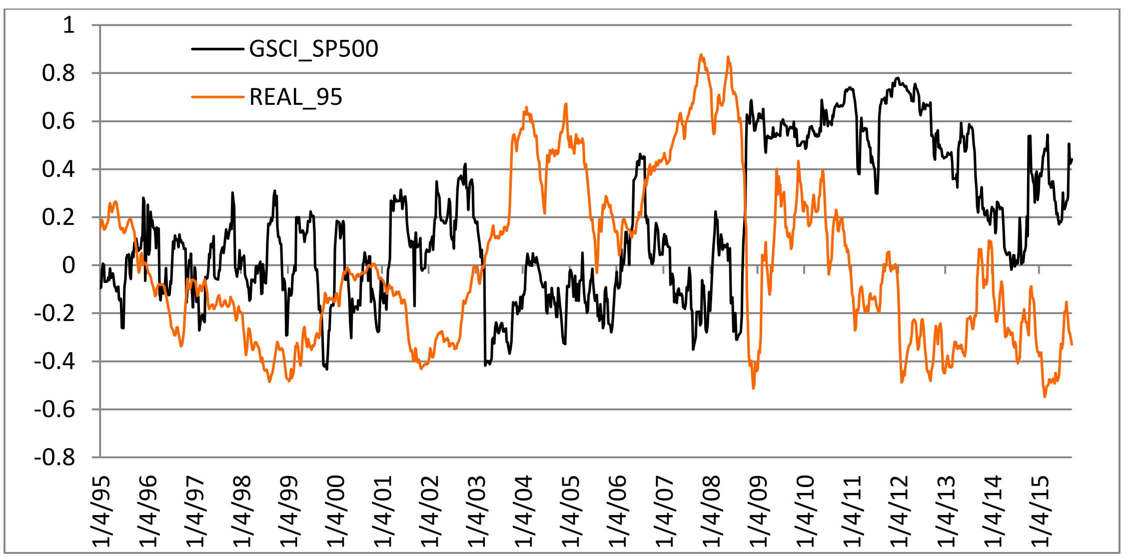

***Notes***: **Figure 2** plots, from January 1995 to September 2015, the forward-looking volatilities implied by prices of nearby (**red**) and six-month-out (**green**) at-the-money call options on futures for coffee in Panel A and sugar in Panel B (*Source*: Bloomberg). In both panels, we also plot the corresponding volatilities implied by near-dated equity options prices (VIX, in **black**; *Source*: CBOE – Chicago Board Options Exchange). For both softs, near-dated forward-looking volatility is itself much more volatile than longer-dated (6-month out) figures. Although all series show concomitant increases from the third quarter of 2008 to the first quarter of 2009 (after the demise of Lehman's Brothers), both panels show commodity-specific spikes unrelated to the VIX.

**Figure 3: Cross-Market Linkages**

**Panel A: Return Correlations on Passive Equity, Coffee and Sugar Investments**

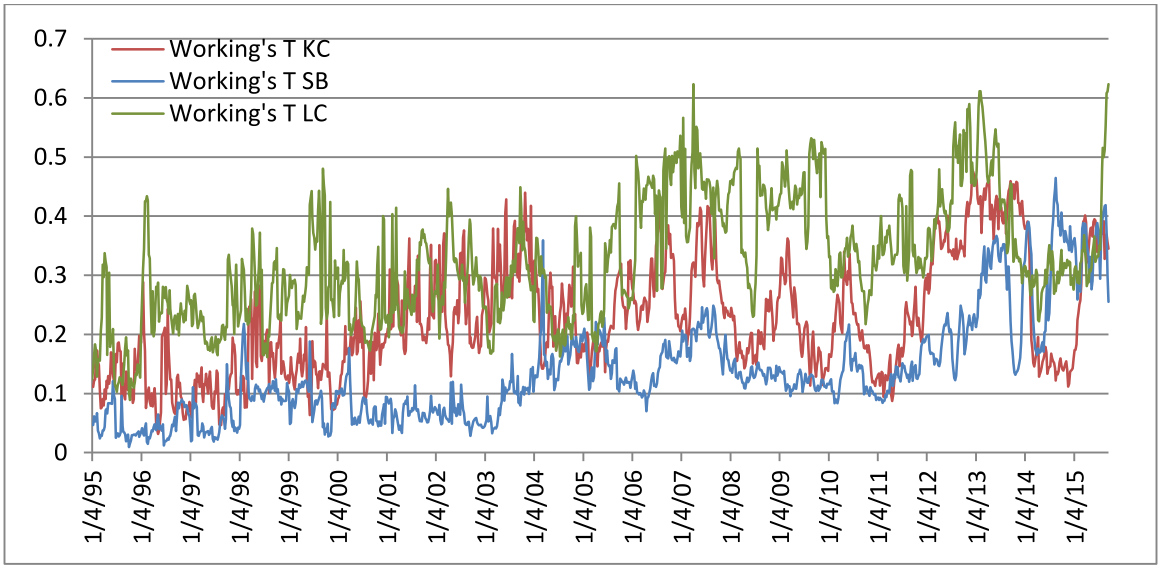



**Panel B: Commodity-Equity Correlations *vs*. World Business Cycle**




***Notes*: Panel A of Figure 3** plots rolling (exponential-smoothing) correlations between the **weekly** unlevered rates of return (precisely, changes in log prices) on the S&P 500 equity index and three investable commodity indices: the S&P GSCI total-return index (**black**) as well as commodity-specific S&P GSCI total-return indices for coffee (**red**) and sugar (**blue**). The estimation period is January 1983 to September 2015: Figure 3 plots our estimates for our sample period, Wednesday January 4th, 1995 to Wednesday September 15th, 2015. A direct relationship is clearly visible between the three time series. **Panel B** shows an inverse relationship between commodity-equity correlations and the global business cycle, captured by a weekly index (*REAL_95*, **orange**) that we construct based on the methodology of Kilian (2009).

**Figure 4: Financial Speculation in Softs Markets, 1995–2015**




***Notes*: Figure 4** plots, for our entire sample period (January 4th, 1995 to September 15th, 2015), indices of speculative intensity (Working's (1960) *T* index *minus* 1) in coffee (**red** series), sugar (**blue** series), and live cattle futures markets (**green** series). We use data regarding end-of-Tuesday trader positions published every Friday in our sample period by the U.S. Commodity Futures Trading Commission (CFTC Commitments of Traders Reports) to compute weekly *T* values for each market. All series trend upward in the sample period, with the weakest growth experienced by the coffee market and growth visible starting in 2003-2004 for sugar and 2004-2005 for live cattle.

# Appendix 1: Cattle.

### *A.1.a. Data.*

We obtain implied volatilities and live cattle market variables using Wednesday (IVol, returns) or Tuesday (volume, open interest, futures term structure slope) data from the U.S. live cattle futures market (*Source*: Bloomberg, based on CME Group data).

### *A.1.b. Estimating Cross-correlations*

We use Wednesday-to-Wednesday returns on the S&P 500 equity and S&P GSCI "All Cattle" Total Return index. As do Büyükşahin, Haigh, and Robe (2010), we set the smoothing parameter $\lambda = 0.94$ to compute the ES correlations. The estimation period for the ES correlations is the same as for coffee and sugar, i.e., 1983–2015; again, we only use the 1995–2015 correlation estimates in our live cattle analysis.

### *A.1.c. Inventories*

In livestock markets, physical inventory data do exist in the shape of the U.S. Department of Agriculture's (USDA) cold-storage reports. These reports, however, are monthly while our analysis requires weekly data. Furthermore, they are released several weeks after the time when the stocks were actually measured. As we do for sugar and coffee, we therefore use a proxy for inventories based on the futures term-structure slope.

### *A.1.d. Exogenous shocks in the livestock space*

We include dummy variables to account for unexpected shocks to beef markets due to the revelation of mad cow disease (bovine spongiform encephalopathy, or BSE) in North America. Adjemian *et al*. (2016) propose two dummies covering May 20th to 27th, 2003 and December 23rd to 30th, 2003 to account for the impacts on uncertainty of, respectively, Canadian and U.S. episodes of mad cow disease. We follow their approach.

Bruno *et al*. (2016, Section 5.1.4) argue that the price impact of the second event (i.e., of the first U.S. mad cow episode) lasted approximately four months (December

23rd, 2003 to April 30th, 2004). While numerous papers back up that choice,[20] our analysis suggests that only the first two weeks of that 4-month period are significant. A four-month dummy is statistically insignificant. Put differently, the uncertainty brought about by news about the epidemic was mostly resolved after two weeks.

### *A.1.e. Results*

Our results for live cattle are qualitatively similar to those derived for sugar and coffee, in three respects. First, market sentiment matters for both commodity-market uncertainty and co-movements with equities, although the magnitude of the regression coefficient is much smaller than for coffee and, especially, sugar. The smaller importance of global uncertainty in the cattle market confirms a similar finding obtained by Adjemian *et al*. 2016) using structural vector autoregression model and data similar to ours. Second, the world business cycle has statistically insignificant explanatory power beyond the VIX. Third, idiosyncratic shocks (in this case, disease outbreaks) increase uncertainty and help disconnect the commodity from other asset markets (the mad cow episode of 23 December 2003 to 30 April 2004, captured by our second "Mad_Cow dummy, is highly significant in all regressions).

The main difference between live cattle *vs*. softs dynamics relates to inventories. (i) Beef inventories, as proxied by the live cattle futures term structure slope, help explain longer-dated live cattle IVols (as predicted, extreme inventory levels boosting long-term cattle price uncertainty) but not near-dated Ivols. They are barely significant (and do not have the expected sign) as a predictor of the co-movements between live cattle and equity markets. (ii) Abnormal levels of corn inventories, the main cattle feedstock in the United States, do boost live cattle IVols but are not statistically significant (they are almost significant, at the 10 percent level, in the case of near-dated volatility). Still, cattle and equity markets are less connected when corn stocks are abnormal, which establishes the importance of carefully modeling the behavior of key inputs to the production process.

[20] Bruno *et al*. (2015) cite Brittain, Garcia and Irwin (2011); Coffey, Mintert, Fox, Schroeder, and Valentin (2005); Devadoss, Holland, Stodick, and Ghosh (2006); Ding, Veeman, and Adamowicz (2011, 2013); Pozo and Schroeder (2012); Schlenker and Villas-Boas (2009); Thomsen, McKenzie, and Power (2009); Tse and Hackard (2006); UN-WHO (2009); and, U.S. Department of Agriculture (2004, 2005, 2006, 2013).

## Appendix 2: Brazilian droughts and Indian Precipitations.

### *A.2.a. Brazil*

To construct our second Brazilian drought dummy, we draw on monitoring-station-level precipitation data obtained from UCAR-NCAR (University Corporation for Atmospheric Research – National Center for Atmospheric Research) as downloaded in February 2016 from http://rda.ucar.edu/datasets/ds570.0/#!subset.html

In order to be considered, a station must have monthly data starting in January 1995 at the latest, with the time series after 1995 being (almost) complete. We also impose the following requirements for locations:

a. ***coffee***: to be selected, a station must be located in the states of Parana,[21] Sao Paulo, Bahia,[22] or Minas Gerais[23] or be in an area known for growing coffee.[24]
b. ***sugar***: to be selected, a station must be located in the states of Parana, Sao Paulo,[25] Bahia, or Pernambuco[26] (plus Paraiba, Alagoas or Sergipe – but there are no useful stations there, see below[27]) or be in an area known for growing sugar.[28]

Dummy construction:

We first average precipitations state by state, because the average precipitation levels seem to be close by state but differ across states. Next, we create standardized

[21] For the state of Parana, there is only one station (Londrina) located in the middle of the coffee area that goes back to 1995. Hence, we also pick Fernado Pinheiro, located in the middle of the state and with data back to 1988, and Curitiba (inside a city, not the coffee growing area) with data going back to 1955, and averaged the results.

[22] For the state of Bahia, we use the Vitoria da Conquista station (in a coffee growing region closer to Minas Gerais) but ignore Barreiras because too many observations are missing. We add Bom Jesus de Lapa, although it is not in a coffee area, to get an average; we ignore Petrolina, also not in a major coffee area, as it has too many missing observations.

[23] For the state of Minas Gerais, Araxa and Monte Claros are the only weather stations with long data series that are also located in coffee-growing areas. Hence, we also use Caratinga, which is more sugar oriented.

[24] See, e.g., http://www.fivesenses.com.au/blog/2014/02/06/part-ii-brazil-one-country-many-flavours and http://www.brasilbar.com/blog/archives/brazils-coffee-regions.

[25] For the state of Sao Paulo, none of the stations in coffee-growing areas go back far enough (before 2001) so we use the stations of Sao Paulo (city) itself, and Catanduva (sugar), and averaged the figures for both.

[26] For the state of Pernambuco (sugar), only the Recife station has sufficient data available.

[27] For the state of Paraiba, only the Patos station has data going back far enough (to 1961) but these data are spotty so we ignore the state. For the states of Alagoas or Sergipe, the only station with enough data is Aracaju; precipitations there are much lower than in Pernambuco or Paraiba, so we omit it.

[28] See, e.g., https://upload.wikimedia.org/wikipedia/commons/2/2c/Goldemberg_2008_Brazil_sugarcane_regions_1754-6834-1-6-1_Fig_1.jpg ). Matto Grosso's sugar output has been increasing a lot in the past decade, but it remains outside the top states, so we ignore it.

values by state and by month. Then, we create monthly state-level dummies (set equal to 1 when the monthly precipitation is 2 standard deviations below the state/month-specific sample mean, and 0 otherwise). Finally, we use state-production-inspired weights to create a Brazilian dummy variable.

### *A.2.b. Indian variables*

We construct two Indian weather dummies to capture months when precipitations were extremely low ("drought dummy") or high ("rain dummy"). To do so, we draw on data made available by the India Meteorological Department (IMD), a part of the Indian Ministry of Science.[29]

We download state-level, area-weighted monthly rainfall data (in mm) for the four states that account for most of the Indian sugar production: Uttar Pradesh, Madhya Maharashtra, and Tamil Nadu. Data are available for several decades before the beginning of our sample period (1995), so we use a 30-year rolling window to identify exceptional precipitations (either 2 standard deviations above or below the state/month specific mean). We use a long window prior to the date of measurement in order to make sure that only information that would have been available to sugar futures traders at the time is taken into account. A maintained assumption is that there is no long-term trend in each state's output shares, which is consistent with visual inspection of the time series (only Tamil Nadu seems to show an upward trend, but it is the smallest producer).

<u>Dummy construction</u>:

We first create standardized values of the precipitations (in mm) by month (for seasonality) and by state (as the average precipitation levels differ across states). Then, we create monthly state-level dummies (set equal to 1 when the monthly precipitation is 2 standard deviations above ("Rain") or below ("Drought") of the state/month-specific sample mean, and 0 otherwise). Finally, we use state-production-inspired weights to create an Indian dummy variable.

[29] Data were downloaded for this project in February 2016 from https://data.gov.in/catalog/area-weighted-monthly-seasonal-and-annual-rainfall-mm-36-meteorological-subdivisions

## Appendix 3: Financial Speculation in Softs Markets

In Section 5, we test empirically if the intensity of financial speculation in softs markets is informative regarding market expectations of softs price volatility or the strength of softs-equity linkages. As a proxy for the intensity of financial speculation, we employ the widely used Working's (1960) *T*.[30] This Appendix explains how the *T* index is constructed. It reproduces, with minor adaptations, Section 4 of Bruno, Büyükşahin, and Robe (2016) with permission from the paper's authors.

### 4.1 Data

Weekly *T* values may be computed from trader position data published in 1995–2015 by the U.S. Commodity Futures Trading Commission (CFTC) for softs (coffee, sugar) and live cattle futures markets. For all major U.S. futures markets, the CFTC gathers information on the activities of every trader holding positions above a certain level. Every Tuesday, it aggregates this trader-level information and, the next Friday, publishes a "Commitments of Traders Report" (COT) showing the overall long, short and spread end-of-day positions of two ("legacy" reports) or four ("disaggregated" reports, starting in 2009) categories of traders.

The "legacy" COT reports classify large traders as either "commercial" or "non-commercial."[31] A trading entity generally gets all of its futures and options positions in a given commodity classified by the CFTC as "commercial" if it is commercially "engaged in business activities hedged by the use of the futures or option markets" as defined in CFTC regulations. The "non-commercial" group includes various types of mostly financial traders including floor brokers and, crucially for our query, hedge funds and similar institutional financial traders.

The CFTC's COT reports started differentiating between "managed money traders" (i.e., hedge funds) and "other non-commercial traders with reportable positions"

[30] See, e.g., Sanders, Irwin, and Merrin (2010), Alquist and Gervais (2013), Bruno, Büyükşahin and Robe (2015) and numerous references cited in those papers. Sanders *et al* (2010) provide empirical evidence of the continued ability of the *T* index to capture speculative activity in agricultural futures markets. Büyükşahin and Robe (2014) present evidence, based on non-public CFTC position data in 2000-2010, that changes in the *T* (computed from the same public data as in the present paper) can provide a useful proxy to capture changes in the actual importance of hedge funds in commodity futures markets.

[31] COT reports also provide data on the positions of non-reporting (i.e., small) traders.

on September 4th, 2009. Because the CFTC has not made these more disaggregated data available retroactively before 2006, we rely on the legacy classification scheme in order to obtain a sufficient time series of trader positions for our entire sample (1995–2015).

### 4.2 Financial speculation

Working's (1960) *T* index relates the aggregate positions of "non-commercial" commodity futures traders (often called "speculators") to the net demand for hedging originating from "commercial" traders (typically known as "hedgers").

In general, when seeking to answer some research questions about speculation, a potential issue with the *T*'s relying on the CFTC's simple commercial/non-commercial dichotomy is that a substantial fraction of "commercial" traders (all of whom Working's (1960) methodology classifies as "hedgers") seem in real life to engage in "selective hedging" or even to outright speculate.[32] In the present paper, however, we are interested in the activities of hedge funds and similar financial institutions – all of which are classified as "non-commercial" in agricultural markets. Thus, the reality that some "commercial" traders may effectively be speculating should in no way reduce the *T*'s usefulness in capturing the relative importance of *financial* institutions in softs markets. Consistent with this intuition, Büyükşahin and Robe (2014) present empirical evidence that the *T* index acts, in the critical middle part of our sample period (2000–2010), as an "effective public-data substitute" for finer measures of financialization and cross-market trading activity that could otherwise only be computed with the CFTC's non-public trader-level futures position data.[33]

#### *4.2.1 Measuring the intensity of financial speculation*

Working's *T* is predicated on the idea that, if long and short hedgers' respective positions in a given futures market were exactly balanced, then their positions would

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[32] and Xiong (2014) present evidence that, in various agricultural futures markets, "traditional" commercial traders (i.e., producers, transformers, physical commodity dealers, etc.) change their aggregate positions in reaction to futures price changes – a behavior characteristic of speculation rather than hedging. Fishe, Robe and Smith (2016) document a similar pattern for foreign central banks in U.S. interest rate futures markets.

[33] Using the same confidential daily CFTC trader-level data, Raman, Robe, and Yadav (2014) document that the relative contribution of floor brokers to the total commodity futures open interest did not fluctuate substantially in 2000–2010. This fact may explain the finding that "changes in Working's *T* can provide, absent access to the CFTC's proprietary disaggregated LTRS data, a useful proxy to capture changes in hedge fund activity measures during the 2000–2010 sample period" (Büyükşahin and Robe, 2014, p.65).

always offset one another and speculators would not be needed in that market. In practice, of course, long and short hedgers do not always wish to trade at the same time or in the same quantity. Speculators must therefore step in to fill the unmet hedging demand. Working's $T$ measures speculative intensity in terms of how much financial speculation exceeds the minimum required to offset any unbalanced commercial hedging at the market-clearing price (i.e., to satisfy hedgers' net demand for hedging at that price).

For each commodity market in our sample, we use public COT data to compute Working's *T* every Tuesday in our sample (January 3rd, 1995 to September 15th, 2015). This *T* index covers all contract maturities. Formally, in the *i*th commodity market in week *t*:

$$Working's\ T_{i,t} \equiv Ti,t \quad = \begin{cases} 1 + \dfrac{SS_{i,t}}{HL_{i,t} + HS_{i,t}} & if\ HS_{i,t} \geq HL_{i,t} \\ 1 + \dfrac{SL_{i,t}}{HL_{i,t} + HS_{i,t}} & if\ HL_{i,t} \geq HS_{i,t} \end{cases} \qquad (i = 1, \ldots, 7),$$

where $SS_{i,t} \geq 0$ is the (absolute) magnitude of the short positions held in the aggregate by all non-commercial traders ("Speculators Short"); $SL_{i,t} \geq 0$ is the (absolute) value of all non-commercial long positions; $HS_{i,t} \geq 0$ stands for all commercial short positions ("Hedge Short"); and $HL_{i,t} \geq 0$ stands for all long commercial positions.

We then average individual index values in the corn, soybean, and Chicago wheat markets (*hogs and live cattle markets*) to provide an overall picture of financial activity in grain (*livestock*) futures markets:

$$T_t = \sum_i w_{i,t}\, T_{i,t},$$

where we use equal weight $w_{i,t}$ for commodity *i* in a given week *t*.[34]

[34] We exclude from our equally-weighted indices the Kansas City wheat and the feeder cattle markets in order not to give undue importance to two smaller futures contracts that were not part of the S&P GSCI in the early part of our sample period. As an alternative measure, we included those two smaller markets while assigning to each commodity, each year, a weight proportional to its weight in the S&P GSCI index that year (source: *Standard and Poor's*). The resulting value weighted financial speculation patterns are qualitatively similar to their equally weighted counterparts, with the correlation between equally-weighted (three grains, two meats) and value-weighted (four grains, three meats) *T* indices exceeding 0.90 *(0.90)* for livestock and 0.98 *(0.96)* for grains in levels *(first differences)* in our 1995-2015 sample period.