SPECULATIVE BUBBLES IN AGRICULTURAL COMMODITY PRICES: DETECTION AND FORECASTING VIA MARKET INDICATORS

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1. Introduction

Following the period of economic expansion starting in the early 2000s in developing countries, i.e., Brazil, Russia, India, China, and South Africa (BRICS), commodity prices were characterized by sharp increases and high volatility, achieving their peak at the beginning of 2011. However, the global financial crisis has affected industrial production with consequences for economic growth and financial asset returns. Thus, investors have started to use commodities to hedge their positions against inflation risk because of their low correlation with traditional assets such as stock and bonds. Such behavior by investors has led researchers and scholars to believe that commodities constitute an independent asset class (Radetzki, 2006; Daskalaki, 2011). The emergence of commodities as an independent asset class has also been encouraged by events such as the Internet bubble in the late 2000s, the financial crisis in 2008, and the sovereign debt crisis, which have encouraged investors to diversify portfolios to also include safer and more profitable alternatives. The sharp increase in trading volume of commodity futures in the 2000s and the increased volatility of spot prices has led to the "Financialization of Commodities" phenomenon. This occurs every time the growth in trading activity is linked to an increase in commodity spot prices and volatility (Chari, 2017). In addition, fluctuations in the trend of commodity prices seem to contrast with the dominant vision that non-emotive agents impose market prices of capital equal to the present value of expected future cash flows.

This contrast has led to an extension of this mainstream view that accounts for two findings: i) investors act following the sentiment (Delong et al., 1990); and ii) dealing with sentiment-driven investors is costly and risky (Shleifer & Vishny, 1997). Market sentiment is intended as the expectation of future cash flows and investment risks not justified by objective facts (Baker & Wurgler, 2007). Thus, empirical researchers began to focus on measuring and quantifying a sentiment index. The literature presents two main approaches.

The first is a "bottom up" approach based on the psychology of the individual investor (overconfidence, representativeness, conservativeness) and is aimed at detecting the reaction of a single investor to past returns or fundamentals. Hong & Stein (2007) and Shefrin (2008) analyze investors' misevaluations of stock prices while considering the differences of opinion across investors combined with some sales constraints.

The second is the "top down" approach (Baker & Wurgler, 2007): the focus is the empirical effect of the sentiment, which has exogenous origins. This work highlights the possibility of measuring investors' sentiment and analyzing its effect on the individual firm and the stock market.

This work aims to develop an index of commodity prices inspired by the Bull and Bear Indicator by Bank of America Merrill Lynch (henceforth BofAML Bull and Bear Indicator). Roughly speaking, this indicator is basically the ratio of the share of individuals with bullish sentiment to the share of individuals with bearish sentiment. Values of this ratio larger than one indicate a market where bullish sentiment is dominant, while values smaller than one indicate the prevalence of a bearish sentiment.

The paper is organized as follows. Section 2 presents a short literature review of the pioneering switching model known as the Kirman's ants model (Kirman, 1993) on which the indicator we propose is based. Section 3 is devoted to the definition of our index and a rough comparison of its trend with that of the BofAML Bull and Bear Indicator. Section 4 provides some descriptive statistics of the data used in the empirical analysis. Section 5 shows the results of the empirical analysis. Section 6 illustrates the combined use of the indicator and a correlation analysis to detect the presence of speculative bubbles and to forecast their presence in advance. Section 7 contains some concluding remarks.

2. Herding behaviour

Kirman's seminal paper in 1993 shows the herding, epidemics, and polarization of agents in financial markets using a simple stochastic model of information transmission. This is suggested by macroscopic behaviors observed in entomological experiments in ant colonies when foraging for food.

In Kirman's stochastic model, an environment is considered in which there are two sources of food — black and white — and a colony of N ants feeding on one source or the other. The number of ants feeding at the black source, k, represents the state of the system, $k \in (0,1, \ldots N)$.

The author explains this phenomenon by introducing an interaction mechanism, i.e., exchange of information by pheromones, combined with an autonomous switching probability given by the stochastic search. In fact, when exploring a given searching area, *S*, ants may act as independent units or may signal the presence of food in the vicinity by exchanging pheromones with a companion met at random. The transmitted signal is more like "follow me" rather than information concerning the exact spatial position where the food is located. Furthermore, this signal may be caught with probability b by the other ant.

The ant can also decide independently to change the color of the source of food, with a given probability. The probabilities of the two sources can differ as proposed in Alfarano et al. (2005).

The exchange of information between ants constitutes the recruitment based on the herding behavior since the ant, after being informed, decides not to use its private information while following its companion's "suggestion". The model limits random meeting to pair-wise, excluding multiple encounters, so the density of the ants in area S is low. A further hypothesis is that ants lack memory, that is, the outcome of previous meetings does not influence either the probability of following the companion or the success in recruiting companions.

The transition probabilities of a single switch are:

$$p_1 = P(n+1, t+\Delta t | n, t) = \left(1 - \frac{n}{N}\right)\left(a_1 + b\,\frac{n}{N}\right)\Delta t, \tag{1}$$

$$p_2 = P(n-1, t+\Delta t | n, t) = \frac{n}{N}\left(a_2 + b\,\frac{N-n}{N}\right)\Delta t \tag{2}$$

while the probability of not switching is:

$$p_3 = 1 - p_1 - p_2\ . \tag{3}$$

As the strength of the herding component increases, the stationary probability distribution of the model switches from unimodal, which implies an equal exploitation of both sources, to a bi-modal probability distribution following the model hypothesis and experimental observations.

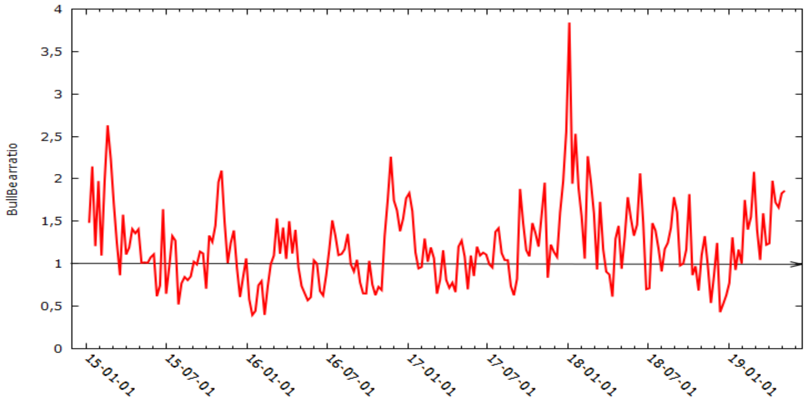
3. Implementation of the commodity sentiment index

Our aim is to implement an indicator to detect and forecast speculative bubbles inspired by sentiment indicators such as the BofAML Bull and Bear Indicator but based on more objective information than sentiment. In fact, the BofAML Bull and

Bear Indicator is based on market agents' opinion of market trends. Specifically, Investor Intelligence carries out a survey every week of over 100 top investment operators, questioning their sentiment regarding the market, (bullish, bearish or neutral). The BofAML Bull and Bear Indicator is, then, the ratio of bullish sentiment to bearish sentiment, but when the market is bullish, the indicator suggests behaving in a bearish way while the opposite is true when the market is bearish. For this reason, it is also called the "contrarian indicator."

Figure 1 shows the time series of the BofAML Bull and Bear Indicator from January 2015 to January 2019.

Figure 1 – *Trend of the Bull and Bear Index of Bank of America Merrill Lynch from January 2015 to January 2019.*



Our analysis aims to infer the sentiment of the agricultural commodity market from the co-movement of the prices of different commodities. This indicator is constructed by considering *N* commodities and their daily prices.

We use x^i_t to denote the logarithm of the price of the commodity *i* at time *t* and μ_t^i to denote its average, $i = 1,2,3, \dots N$, and $t > 0$.

We use as a proxy of the bullish sentiment the fraction of the commodities whose log-price is above its average. Specifically, for any time *t*, we use a time window of two-year back to compute the average price of each commodity. We then measure the bullish sentiment in the agricultural commodity market as the fraction, Z_t, of the commodities with observed log-price higher than the corresponding average. That is, we define Z_t as follows:

$$Z_t = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1} \left\{ x_t^i - \mu_t^i > 0 \right\} \tag{4}$$

where $\mathbf{1}\cdot$is the indicator function of the set in parentheses. The proposed indicator of market sentiment reads as:

$$i_t^{BB} = \frac{Z_t}{(1-Z_t)} \quad . \tag{5}$$

It is easy to see that, $0 \leq Z_t \leq 1$ so to prevent the indicator from exploding, we set the values of Z_t less than 0.1% to 0.001 and those larger than 99.9% to 0.999.

The index i_t^{BB} is a proxy for market sentiment since it is an odds ratio that measures the propensity to buy with respect to the propensity to sell a basket of a given agricultural commodity. When i_t^{BB} is significantly larger than one, the market experiences a sharp increase in the prices of many commodities, while the opposite occurs when $i_t^{BB}$is significantly smaller than one.

We now detail the dynamics of the ratio measuring bullish sentiment in the market. Following the generalization of the Kirman ant model proposed by Alfarano et al. (2005), the variable Z_t introduced above can be interpreted as the limit when the number of traders goes to infinity, while the fraction of bullish traders to the total number of traders, i.e., *n/N* in equations (1) - (2) is kept constant. Thus, the dynamics of Z_t reads as (see Alfarano et al. 2005):

$$Z_{t+\Delta t} = Z_t + (\varepsilon_1 - (\varepsilon_1 + \varepsilon_2)Z_t)b\Delta t + \sqrt{2bZ_t(1 - Z_t)}\Delta t\lambda, \tag{6}$$

where λ is distributed as $\lambda \sim N(0,1)$ while the parameters ε_1 and ε_2 are related to the Kirman model parameters a_1 and a_2 as follows:

$$\varepsilon_1 b = a_1 \,, \qquad\qquad \varepsilon_2 b = a_2 \,. \tag{7}$$

Since the quantities $a_1\Delta t, a_2\Delta t$ are probabilities we should expect that:

$$(a_1 + a_2)\Delta t = (\varepsilon_1 b + \varepsilon_2 b)\Delta t \leq 1. \tag{8}$$

In our work, we start with Larsen and Sørensen (2007) and adopt their formulation in the continuous time of equation (6), which is the Jacobi equation to compute the expectation of Z_T given Z_t:

$$E(Z_T/Z_t) = \frac{\varepsilon_1}{\varepsilon_1+\varepsilon_2} - \left(\frac{\varepsilon_1}{\varepsilon_1+\varepsilon_2} - Z_t\right) e^{-b(\varepsilon_1+\varepsilon_2)(T-t)}. \tag{9}$$

Here, $b_t(\varepsilon_1 + \varepsilon_2)$ indicates the speed of mean reversion and defines how fast the price converges to its long term mean, i.e., $\frac{\varepsilon_1}{\varepsilon_1+\varepsilon_2}$. We use the expectation to forecast Z_t and then to forecast the indicator i_t^{BB}.

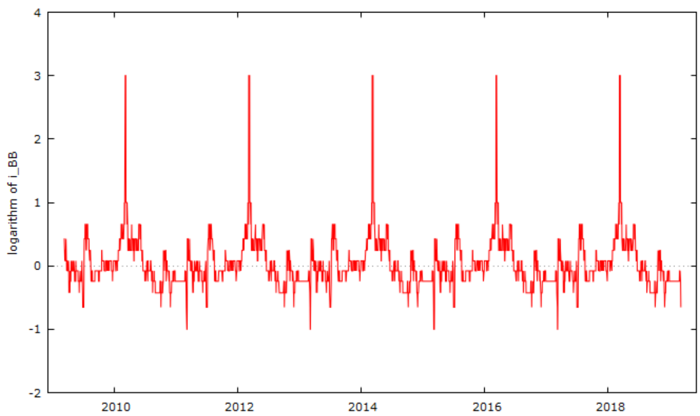
4. Description of the data

The empirical analysis proposed here uses the daily close prices of some agricultural and soft commodities gathered from the Thomson Datastream Database. Specifically, we deal with eleven commodities — cocoa, coffee, corn, cotton, oats, rice, soybean, soybean meal, soybean oil, sugar, and wheat — traded on the American CBOT and ICE_US markets from March 10, 2009 to March 6, 2019, i.e., a ten-year time series.

For calibration and estimation purposes, we use a two-year window of data, estimating the data using the indirect inference method (Gouriéroux and Valéry, 2004). Roughly speaking, we apply a regression that accounts for the heteroskedasticity of equation (6). As mentioned above, the weekly time series of Z_t is computed using a window of consecutive prices going back two years from date t. The rolling window moves along the panel data, discarding the oldest data and inserting the newest data.

Figure 2 shows the time series of the indicator, i_t^{BB}, which reveals a cycle in the market with peaks of bullish sentiment in the spring. In the next section, we distinguish seasonal peaks from market anomalies by using the parameters of the dynamics of Z_t (see equation (6)) estimated from the observed values of Z_t.

Figure 2 – *Time series of the logarithm of the indicator* $\boldsymbol{i_t^{BB}}$ *from March 2009 to January 2019.*



5. Results of the empirical analysis

In this section, we show the time series of the parameters appearing in equation (6), estimated using a two-year rolling window of data. These data are used first to compute the process Z_t as well as the indicator i_t^{BB} and then to estimate the model parameters in (6).

Table 1 shows the parameters estimated using the log-price average computed over the rolling window (changing average, or c.a., for short), and those obtained by computing the price average over the entire ten years (fixed average, or f.a., for short). From left to right, Table 1 shows the parameters ε_1, ε_2, b, the speed of mean reversion (s.m.r.) and the long-term mean (l.t.m.). The values of the parameters are rather similar except for ε_1 and the long-term mean. Specifically, Table 1 reveals that for short runs (i.e., computing the average of the log-price over the rolling window), the number of bullish and bearish traders are very similar (l.t.m. = 0.5174), while for long runs it can be seen that there are twice as many bullish traders as bearish traders, with a long term mean equal to 0.6155. Thus, in the long term, the market expectation on future sentiment is 60% in favor of bullish traders.

Table 1 – *Estimation of parameters of the indicator* $\boldsymbol{i_t^{BB}}$.

	ε_1	ε_2	b	s.m.r.	l.t.m.
M(daily_f.a.)	4.4651	2.62969	0.048406	0.06558	0.6155
M(daily_c.a.)	2.2297	2.30731	0.047961	0.06223	0.5174

Figure 3 – *Estimated values of the long term mean $\varepsilon_1/(\varepsilon_1 + \varepsilon_2)$ as a function of time.*

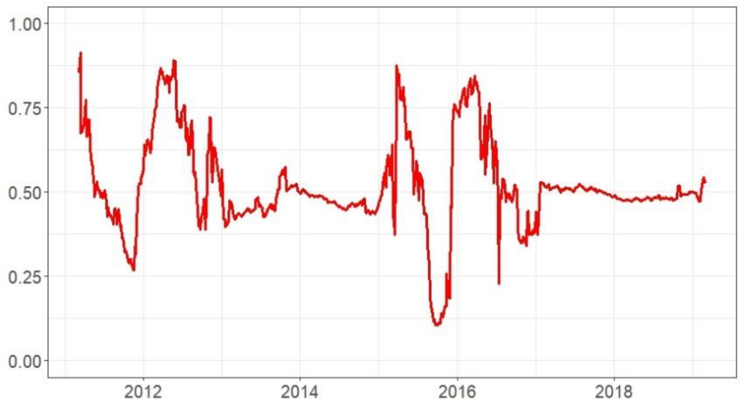
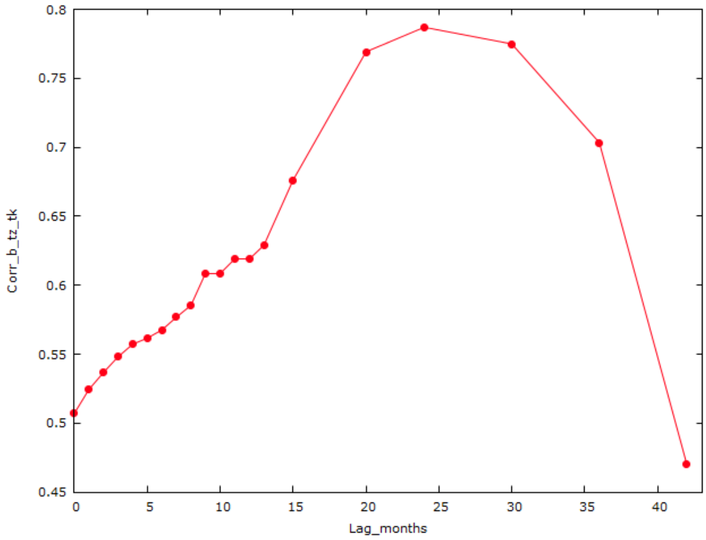


Figure 3 shows the time series of the long term mean $\varepsilon_1/(\varepsilon_1 + \varepsilon_2)$ as a function of time. No seasonality is evident, although four bubbles emerge: at the beginning of 2011, 2012, 2015, and 2016. From the beginning of 2017, the market sentiment is in equilibrium in that the fractions of bullish and bearish traders are equal. This equilibrium seems to persist today as confirmed by the signal the BofAML Bull and Bear Indicator.

Figure 4 – *Correlations between the herding parameter b_t and Z_{t+k} as a function of the lag k (expressed in months).*

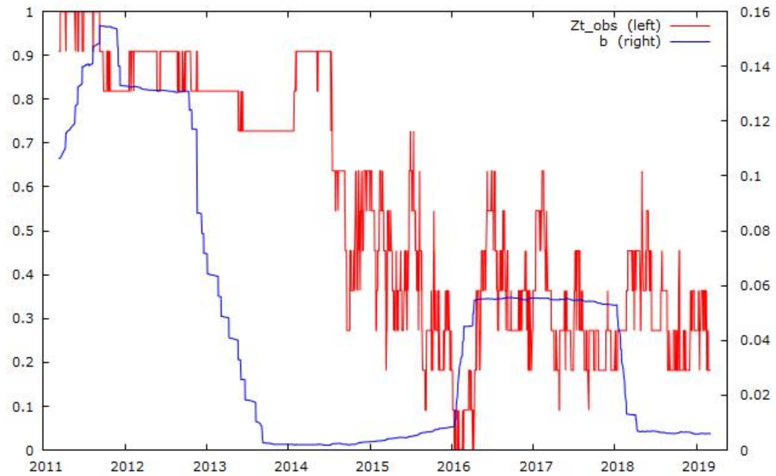


6. The detection and forecasting of speculative bubbles

The detection and forecasting of speculative bubbles in the agricultural commodity market seem to be revealed by the parameter b, which measures the herding behavior. In fact, in periods preceding high uncertainty, traders who are in a better position from the informational point of view show a tendency to herd. We try to capture this finding through the correlation analysis. Specifically, we compute the correlation between the time series of b and the share of traders belonging to the bull category lagged for different time periods, namely months (Figure 4). The analysis shows that there is an increase in correlation for a lag of one and a half years. This means that abrupt changes in the herding parameter reflect abrupt changes in the bullish sentiment in the market, Z_t. Hence, an increase in b may imply an increase in the share of bull agents in the market about one and a half years later, thereby implying an increase in prices.

Figure 5 shows the time series of parameter b (blue line) and the time series of the fraction of bullish traders in the market Z_t (red line). This figure reveals the forecasting potential of the herding parameter b one and a half years ahead. As we can see from the figure, the parameter b starts to decrease in 2013, followed by the fraction Z_t in the second half of 2014. And then when b starts to increase in the second half of 2014, Z_t starts to increase in early 2016. From 2016 to 2018, b remains constant and the fraction Z_t displays oscillations around a fixed value. A decreasing trend is exhibited by parameter b starting in 2018, and we expect a decrease in the fraction Z_t in the middle of 2019.

Figure 5 – *Time series of the herding parameter b and the fraction of the bullish traders in the market (Z_t).*



7. Conclusions

In this work, our aim is to develop a composite indicator based on prices of agricultural commodities that could detect and forecast bubbles in the agricultural commodity market. Interest in Financialization of Agricultural Commodities has grown, especially since the crisis of 2007 (i.e. subprime mortgages crisis), the moment in which investors began to realize that agricultural commodities could be chosen as a safer investment than those in intangible assets. Our index was built based on the sentiment index by Bank of America Merrill Lynch, but estimating market sentiment from prices. The index is based on a fraction of bullish traders whose dynamics was described using a suitable stochastic model. The time series of the model parameters estimated by the data panel with a suitable regression are the tools used to detect and forecast bubbles. Interestingly, despite the fact that no seasonality treatment is applied, the time series of the model parameters are not affected by seasonality, although bubbles are revealed. The most predictive model parameter is *b*, i.e., the parameter governing the herding behavior, since in periods of fear and uncertainty, the tendency to imitate is higher than in normal periods. Thus, the correlation analysis shows that an increase in *b* implies an increase in the fraction of bullish traders about one and a half years ahead.

References

ALFARANO S., LUX T., WAGNER F. 2005. Estimation of agent-based models: the case of an asymmetric herding model, *Computational Economics*, Vol. 26, No. 1, pp. 19-49.

BAKER M., WURGLER J. 2007. Investor sentiment in the stock market. *Journal of economic perspectives*, Vol. 21, No. 2, pp. 129-152.

CHARI V. V., CHRISTIANO L. 2017. Financialization in commodity markets, No. w23766. National Bureau of Economic Research.

DASKALAKI C., SKIADOPOULOS G. 2011. Should investors include commodities in their portfolios after all? New evidence, *Journal of Banking & Finance,* Vol. 35, No. 10, pp. 2606-2626, Elsevier.

GOURIÉROUX C., VALÉRY P. 2004. Estimation of a Jacobi process, *Preprint*, Vol. 116.

HONG H., STEIN J. C. 2007. Disagreement and the stock market. *Journal of Economic perspectives*, Vol. 21, No. 2, pp. 109-128.

KIRMAN A. 1993. Ants, rationality, and recruitment, *The Quarterly Journal of Economics*, Vol. 108, No. 1, pp. 137-156, MIT Press.

LARSEN K.S., SØRENSEN M. 2007. Diffusion models for exchange rates in a target zone, *Mathematical Finance*, Vol. 17, No. 2, pp. 285-306, Wiley Online Library.

RADETZKI M. 2006. The anatomy of three commodity booms, *Resources Policy,* Vol. 31, No. 1, pp. 56-64, Elsevier.

SHEFRIN H. 2008. *A behavioral approach to asset pricing*. Elsevier.

SHLEIFER A., VISHNY R. W. 1997. A survey of corporate governance. *The Journal of Finance*, Vol. 52, No. 2, pp. 737-783.

SUMMARY

Speculative bubbles in agricultural commodity prices: detection and forecasting via market indicators

Starting in the 2000s, commodity prices experienced a sharp increase and high volatility, reaching their maximum value in 2011. The hedging role of commodities and their low correlation with traditional assets such as stock and bonds means they can be defined as an independent and different asset class. The considerable increase of trading in agricultural commodity futures markets and the increased volatility of spot prices is known as the "financialization of commodities."

The aim of this paper is to detect and forecast speculative bubbles in the agricultural commodity market. Our framework models the ratio between two consecutive prices as the ratio between demand and supply of a certain commodity.

We model the demand as a Jacobi diffusion process to grasp its trend in continuous time and consequently the ratio of two consecutive prices as an odds ratio. Our approach belongs to agent-based modeling and is able to capture different market features such as herding behavior, the long-term mean (i.e., the expectation on the prices that agents have in the future), and the speed of mean reversion. In addition, the estimated model provides us with a tool to forecast prices.

We propose the sentiment indicator to summarize the behavior of market agents. Our proposal is inspired by the Bank of America Merrill Lynch indicator tied to market sentiment. This indicator is based on the deviations of each commodity price from its respective average, detecting extreme fluctuations and summarizing the behavior of market agents.

We model this indicator via a Jacobi diffusion process and estimate the parameters to investigate the presence of the excess of demand due to speculative behavior.

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