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A market sentiment indicator, behaviourally grounded, for the analysis
and forecast of volatility and bubbles

Abstract

Purpose

This work aims at designing an indicator for detecting and forecasting Price Volatility and Speculative Bubbles in three markets dealing with agricultural and soft commodities, i.e., IFEU, CBOT, IFUS. This indicator, designed as a demand/supply odds ratio, intends to overcome the subjectivity limits embedded in sentiment indexes, as the Bull and Bears ratio by the Bank of America Merrill Lynch.

Design/Methodology/Approach

Data evidence allows for the parameter estimation of a Jacobi diffusion process that models the demand share and leads the forecast of speculative bubbles and realized volatility. Validation of outcomes is obtained through the dynamic regression with ARIMA error. Results are discussed in comparison with those from the traditional GARCH models. The database is retrieved from Thomson Reuters DataStream (nearby futures daily frequency).

Findings

The empirical analysis shows that our indicator succeeds in capturing the trend of the observed volatility in the future at medium and long time horizon. A comparison of simulation results with those obtained with the traditional GARCH models, usually adopted in forecasting the volatility trend, confirms that our indicator is able to replicate the trend while providing turning points, that is, an additional information completely neglected by the GARCH analysis.

Originality

Our commodity demand, modeled as discrete-time process, is capable of replicating the observed trend in a continuous-time framework, as well as turning points. This process is suited for estimating behavioural parameters of the agents, i.e., long-term mean, speed of mean reversion and herding behaviour. These parameters are used in the forecast of speculative bubbles and realized volatility.

Keywords: *sentiment indicator, behavioural models, herding, speculative bubbles, realized volatility*

JEL Codes: *Q02, Q14, G15, G17, G41.*

Introduction

Since the post “dot com” bubble burst in early 2000s, agricultural commodity prices experienced significant increases, reaching their highest values in years 2007-2008 and 2010-2011. In late 2008 during the financial and economic crisis, the increasing trend of prices decelerated sharply and then increased again starting from 2009, going beyond the levels of 2008. In these periods large increases in volumes of traded agricultural commodities, mostly employed for hedging against inflation risk and portfolio diversification, are also shown. The observed low correlation between these kinds of commodities and traditional financial commodities, i.e., stocks and bonds, led researchers to view them as a “standing alone” asset class (Shamsher (2021)). This feature of independence justified the definition of the phenomenon as “Financialization of Commodities”. Evidence on fluctuations in the trend of commodity prices and speculative bubbles contradict the prevalent belief of non-emotive agents setting market prices of capital equal to the present value of expected future cash flows. Within this framework, the mainstream vision must consider that (i) agents’ actions are motivated by sentiment (De Long et al. (1990)); (ii) trading with sentiment-driven agents is costly

and risky (Shleifer & Vishny (1997)). The action of these, so called, “noise traders”, leads to the burst of speculative bubbles and generates volatility in commodity prices (Black (1986)). Therefore, social interaction between agents in the stock market reveals to be a relevant source of price deviations from their fundamental value (Shiller (2015)). The relationship between price fluctuations and social interactions, in finance, have been studied by means of Agent-Based Models (hereafter ABM). These kinds of models contain, in their dynamics, several behavioural features as herding parameter, long term mean and propensities to change behavior. Within this framework, Kirman (1993) represents the pioneering work. Its model, based on entomological observations of the ants’ behaviour in the food provision, introduces a stochastic mechanism of information transmission. In financial market, characterised by the interaction of “informed” and “not informed” agents in their investment decisions, the model has been adopted to explain some observed empirical regularities, e.g., heteroskedasticity and unpredictability of fluctuation of financial returns (Kyle (1985)). These empirical regularities are not only a result of the new market information, but also emerge from the interaction of the different groups of agents. The psychology of market agents and the measurement of their sentiment become, then, of primary importance when dealing with financial markets. Investor sentiment is quantified through proxy indicators expressing investors’ beliefs in their own market choices (Baker & Wurgler (2007)). The behavioural literature contains two main types of proxy indicators of investor market sentiment. In single objective sentiment indicators, i.e., proxies based on actual market behaviour, the index is computed indirectly from market trends, e.g., closed-end fund discounts and put-call ratios. Single subjective sentiment indicators are based on individual surveys directed at agents, e.g., the Yale School of Management’s Stock Market Confidence Index and the University of Michigan’s Consumer Confidence Index (Zhang (2008); Brown & Cliff (2004)). One relevant indicator of subjective sentiment has been provided by Bank of America Merrill Lynch, (hereafter BofAML). To build this indicator, Investor Intelligence performs a weekly survey of over 100 top investment operators, to know their sentiment when acting in the market, (bullish, bearish or neutral). This indicator is a contrarian indicator, since when the market shows a bullish attitude, it suggests the bearish behaviour, viceversa, in presence of bearish attitude.¹ Our work is addressed at investors in agricultural markets concerned in long time horizon forecasts. The contribution is twofold.

First, we build a market sentiment indicator based on the dynamics of three agricultural and soft commodities markets, i.e., IFEU, CBOT, IFUS. We ground our analysis on data on historical prices of nearby (3-months) futures, with daily frequency. The indicator, designed as a demand/supply odds ratio, intends to overcome the subjectivity limits embedded in survey-based sentiment indexes. The odds ratio has been designed based on an ABM of commodity markets, which considers two types of agents, i.e., fundamentalist agents and noise traders. The dynamics of the bullish share of agents, (share of demand in agricultural market), modelled as a discrete-time process, is suited for estimating behavioural parameters of the agents, i.e., long-term mean, speed of mean reversion and herding behaviour. Second, we make an attempt to forecast speculative bubbles and the trend of realized volatility in long-time horizons. The forecast is based on the estimated herding parameter and the trend of the share of bullish agents (Z_t). It suggests a good performance of the herding parameter in long time horizons predictions of speculative bubbles, up to 21-months ahead in IFUS, 18-months ahead in IFEU and 11-months ahead in CBOT. In addition, the variable Z_t is capable to predict up to 36-months ahead in CBOT, 22-months ahead in IFUS and 15-months ahead in IFEU. A comparison of these outcome with those of the traditional GARCH models, usually adopted for volatility forecasts, confirms that Z_t

¹more information on BofAML at: <https://www.aaii.com/sentimentsurvey>

performs well in replicating the trend, also providing turning points, an additional information completely neglected by GARCH.

This work is organized as follows. Section 1 consists of a literature review on sentiment indicators. Sections 2, 3 and 4 are devoted to the implementation and calibration of the sentiment indicator and other methodological issues. In Section 5, data used for the study and the main features of the indicator are described. In this section, results on the detection and forecast of speculative bubbles are also provided. Section 6 discusses the results of the realized volatility forecasts. Section 7 contains the conclusions.

1 Literature Review

Starting from the early 2000s agricultural commodities acquired a relevant role in further development of financial and non-financial markets. Agricultural markets have always been considered as hedgers-driven, i.e., driven by agents aimed at hedging commodities' prices with futures contracts, (hedgers). Hedgers are further complemented with speculators, i.e., investors speculating on the price increase of commodities (Working (1961)). The "Financialization of Commodities" enables agents to invest in a wider range of commodities through different financial instruments, e.g., over-the-counter swaps, exchange-traded funds and exchange-traded notes, without concretely holding commodities (Domanski & Heath (2007)). This fact leads to relevant increases in trading volume of commodity futures exchanges and the development of a new class of speculative oriented market agents, e.g., commodity index traders and long-short speculators. The outcomes of the observed interaction between agents, often driven by sentiment, result in wide market fluctuations. The convenience of adopting sentiment-based indexes in the forecast of future market trends have been explored by several empirical studies. In general, in Behavioural Finance literature, investors act in response to market news. The leading tendency is that of taking investments decisions on the basis of bad news rather than good ones. In particular, special attention has to be given to the origin and contents of texts providing basis of sentiment analysis with financial purposes. A study of Kearney and Liu (2014), examined the qualitative information from annual reports and press releases and try to build a relationship between future stock returns and qualitative information extracted from publicly available reports. Significant findings have been described analysing the tone of narrative sections used in their 10-ks and its effects on financial entities like returns, trading volume, return volatility and unexpected earnings (Tetlock (2007), Jegadeesh & Wu (2013)). The main highlight of these works is that lexicon used by newspapers and social networks plays a relevant role in delivering financial information, in shaping the sentiment of investors and determining with a higher precision the appropriate forecasting model (Loughran & McDonald (2011)). This qualitative information constitutes the basis for the design of "subjective" market sentiment indicators. When sentiment indicators show that a "predominant number of market analysts are bullish [bearish], it is quite likely that the market is approaching an overbought [oversold] condition, and that a reversal in trend may be imminent" (Sanders et al. (2003)). This approach led to the flourishing of several survey-based contrarian sentiment indicators which suggest to take a market position opposite to the dominant market opinion, quantifying the prevailing market belief within the agents. Among others, the i) AAII Investor Sentiment Survey, ii) the Investors Intelligence Advisors Sentiment Report (Clarke & Statman (1998)) and the iii) Barron's Big Money Poll.

A study of Schmeling (2009) highlights the relevant effect of sentiment on stock market returns within many industrialised countries, with higher impact on countries with less market integrity characterised by herding behaviour of agents. Among others, Borovkova (2011) investigates the response of crude oil future markets to negative and positive sentiment in news, as measured by Thomson Reuters Data News Analytics. The study shows that strong or weak sentiment could affect the slope and level of the forward curve. Lv et al. (2020) explore the dimension of sentiment in predicting the price of Shanghai International Energy Exchange’s (INE) crude oil futures market, highlighting the valuable performance of a long-term memory model combined with composite sentiment indexes in forecasting one-day ahead prices.

With reference to agricultural markets, among others, Wang (2003) forecasts future prices in six major agricultural futures markets by means of a trader position-based sentiment index, while, Liu et al. (2022) study the impulse responses of agricultural prices to online negative sentiment.

Generally speaking, in sentiment analysis literature, subjective sentiment is based on the personal opinions of agents, usually expressed in linguistic terms. Preferences expressed by each agent for a specific decision are measured and ranked using different scales, depending on each individual sentiment. This causes a meaningless translation of words into numerical values when aggregating individual evaluations using different classifications of an equivalently ordered qualitative levels (Franceschini et al. (2004)).

In Behavioural Finance, the issue of subjectivity of sentiment indicators has been addressed introducing a range of objectively-determined indicators. These indicators rely on actual market data, e.g. Vidal and Alfarano (2020), and measure the collective movement of stock prices. The most relevant objective indicators are the i) Chicago Board Options Exchange (CBOE) Put-Call Ratio, ii) CBOE Volatility Index (VIX) and iii) Volume of trades.

The CBOE put-call ratio, usually adopted as a contrarian indicator, relates the number of put-options purchased by bearish agents, i.e., hedgers, to the number of call-options purchased by bullish traders (Bathia & Bredin (2013)). The CBOE volatility index, VIX, is computed aggregating the weighted prices of put and call options on the S&P500 index and measures the expected 30-day volatility of the US stock market. Finally, the volume of trades is considered a direct measure of market activity and a proxy of investors sentiment (Baker & Wurgler (2007)).

Our indicator, designed as a demand/supply odds ratio, is based on the “theory of contrary opinion” (Sanders et al. (2003)). Its power resides in the fact that, differently from the objective indicators existing in literature, its dynamics allows for the estimation of behavioural parameters useful for forecast purposes.

2 The bull-bear market sentiment indicator

This section introduces an indicator able to forecast price volatility dynamics. Price volatility is defined as the variability of the price series around its average value, i.e. the tendency for individual price observations to vary far from its mean value, but also the propensity to deviate from the global trend (Dehn et al. (2005)). In agriculture, the relevance of volatility in food prices is highlighted in several respects. Firstly, poor farm households in developing countries spend large amounts of their incomes on food. Secondly, most of these households are small-scale farmers who mainly sell their produce on the market, which may happen to be net buyers. Third and lastly, most small-scale farm households fully rely on the sale of food commodities to meet their basic needs, e.g., health and education. To

formalize volatility, we refer to the realized volatility RV_t defined by:

$$RV_t = \sqrt{\frac{1}{N} \sum_{i=1}^N \log^2 \left(\frac{P_{t-(i-1)\Delta t}}{P_{t-i\Delta t}} \right)} \quad (1)$$

where Δt denotes the time interval which depends on price frequency, N the number of the observed prices, and t the date of the most recent observation used in Eq. (1).

To the aim of forecasting realized volatility with a special focus on speculative bubbles in the three markets, here we introduce and detail our “objective” market sentiment indicator. We start by defining the market bullish sentiment, further modeled using a process originated from a biological model, whose parameters can be behaviourally interpreted. Bullish sentiment is defined as the fraction of commodities with the settlement price above the corresponding average over the total number of commodities in a given market. Specifically, for any market we consider N_C commodities and define the share of bullish agents as:

$$Z_t = \frac{1}{N_C + 2\psi} \left(\psi + \sum_{m=1}^{N_C} \mathbb{1}_{\{x_{t,m} - \mu_{t,m} > 0\}} \right), \quad (2)$$

where $\mathbb{1}_{\{\cdot\}}$ is the indicator function, $x_{t,m}$ is the log-price at time t of the m -th commodity, $\mu_{t,m}$ is the average of the m -th commodity log-price over the time window $[t - N\Delta t, t]$, that is

$$\mu_{t,m} = \frac{1}{N} \sum_{i=t-(N-1)\Delta t}^t x_{i,m}, \quad m = 1, 2, \dots, N_C, \quad t > (N-1)\Delta t, \quad (3)$$

and ψ is a regularization parameter ($\psi = 0.05$).

Now, we define the market sentiment indicator as the logarithm of the ratio of Bullish sentiment, Z_t , to Bearish sentiment, $1 - Z_t$:

$$i_t^{BB} = \log \left(\frac{Z_t}{1 - Z_t} \right), \quad t > 0. \quad (4)$$

The structure of Eq. (2) has been implemented to satisfy the constraint $0 < Z_t < 1$, thus preventing the explosion of the indicator i_t^{BB} .

Roughly speaking, associating Z_t to the probability of a price increase (success) and $1 - Z_t$ to the probability of a price decrease (failure), at a fixed time t , the ratio $\frac{Z_t}{1 - Z_t}$ reads as the expected value of the negative binomial random variable, i.e., the average number of successes (increase in price) before a failure (decrease in price). The logarithm symmetrizes the indicator with respect to the origin. The process Z_t depends on the interaction of two kinds of agents, i.e. Bears and Bulls, taking trading decisions based on market trends. Information asymmetries among market operators imply that only a limited group owns complete information. For this reason herding behaviours may emerge, and their level and extent has to be detected and evaluated. At the end of each period there are two possible scenarios: (i) the fraction of Z_t is higher than the fraction $1 - Z_t$, i.e., the share of Bulls is higher than the share of Bears, meaning that the indicator i_t^{BB} is larger than zero; (ii) the fraction Z_t is lower than the fraction $1 - Z_t$, i.e., the share of Bulls is lower than the share of Bears. The value of our indicator, i_t^{BB} , will be, then, smaller than zero. Volatility can be,

then, determined by measuring the size of the difference between the two shares of agents. Equilibrium (i.e. same weight in the market) between the two groups is reached for values of Z_t around 50%.

In the further analysis, we use Z_t , to forecast the trend of realized volatility in the three markets, being preferred to the indicator, for the better distribution of its random component².

3 The herding model

Kirman's work (1993) describes the behaviour of agents in financial markets using a simple stochastic model of information transmission derived from the macroscopical behaviour of ants' colonies in the food provision, (see Fig.1). Some experiments of entomologists highlight an asymmetric behaviour of ants in presence of two identical sources of food close to their nest. In Kirman's stochastic model, two sources of food – black and white – are placed close to the ants' habitation. The colony of N ants could feed to each of the two food sources and the states of the system is the number n of ants choosing the black option, where n ranges from 0 to N . The number of ants at white source is given by $N - n$. Only ants' pair-wise random meetings are allowed.

Figure 1

When exploring the area, ants may act independently or introduce an interaction mechanism to signal the presence of food in the vicinity to a random companion. The transmitted signal does not concern the exact spatial location of the food source but is a signal like “follow me”. This signal, at a certain probability, could be caught by the other ant. Nevertheless the “informed” ant could autonomously decide to change the colour of the source of food, with a certain probability. This exchange of information between ants represents the recruitment based on the herding behaviour, since the “informed” ant can decide to follow the companion's “suggestion” regardless its private information on the food location. In addition, due to the lack of memory hypothesis, the outcome of previous encounters does not affect either the probability of following the companion or the success of the recruiting. Then, the transition probabilities of a single switch from n at time t to $n \pm 1$ at time $t \pm \Delta t$ are given by:

$$p_1 = P(n + 1, t + \Delta t | n, t) = \left(1 - \frac{n}{N}\right) \left(b\varepsilon_1 + b\frac{n}{N}\right) N\Delta t \quad (5)$$

$$p_2 = P(n - 1, t + \Delta t | n, t) = \frac{n}{N} \left(b\varepsilon_2 + b\frac{N - n}{N}\right) N\Delta t \quad (6)$$

where ε_1 and ε_2 define the idiosyncratic propensity to change the colour of food independently and b accounts for the herding effect. In addition, the probability of not switching is simply $p_3 = 1 - p_1 - p_2$.

Defining z_t as the concentration of the ants at the black-source and using a suitable limit when both the number of ants at black source, n , and the total number of ants, N , go to infinity, we have that z_t can be modeled by the

²Shapiro-Wilk normality test for the random component of Z_t shows p -values equal to 0.632, 0.190 and 0.046, respectively, in CBOT, IFUS and IFEU, while for the same markets the p -values corresponding to the random component of the indicator i_t^{BB} are lower than 0.000

following discrete stochastic process:

$$z_{t+\Delta t} = z_t + [\varepsilon_1 - (\varepsilon_1 + \varepsilon_2)z_t]b\Delta t + \sqrt{2b\Delta t(1 - z_t)z_t}\lambda. \quad (7)$$

Here $\theta = \varepsilon_1/(\varepsilon_1 + \varepsilon_2)$ is the z -long term mean, the quantity $b(\varepsilon_1 + \varepsilon_2)\Delta t$ is the speed of mean reversion while λ is a random variable, normally distributed, with zero mean and variance one (i.e., $\lambda \sim N(0, 1)$).

Similar values of ε_1 and ε_2 are associated with a similar probability to observe shifts from one group to the other; in these circumstances, the number of ants in each group can be considered in equilibrium.

Different values of the two parameters facilitate the acquisition of agents by one group with respect to the other, and there is an imbalance in the process $z_t/(1 - z_t)$, which can assume extreme values close to 0 or $(\rightarrow +\infty)$.

Starting from Eq. (7) we can estimate the parameters ε_1 and ε_2 as shown in the next section.

4 The model dynamics

Following several works on ABM in finance (Wagner (2003)) we employed the Kirman (1993) model and its generalization to describe the evolution of the dynamics of investors' sentiment indicator in agricultural markets, since it provides parameters that are easy to interpret. Specifically, in our framework, z_t is the stochastic process modeling the fraction of bullish traders, Z_t , and the process $1 - z_t$ models the fraction of bearish traders, $1 - Z_t$. In line with Alfarano et al. (2005) the evolution of the process z_t can be defined by Eq. (7).

The calibration procedure is carried out using a rolling window of 252 consecutive daily data. We re-calibrate the model every fifteen days including the new observations and excluding the oldest ones. Shifting this window over the whole time period, we obtain a two-weekly time series of the model parameters. The date attributed to the estimate corresponds to the last date of the time window. We then rearrange Eq. (7) as follows:

$$z_{t+\Delta t} - z_t = \varepsilon_1 b\Delta t - (\varepsilon_1 + \varepsilon_2) z_t b\Delta t + \sqrt{2b\Delta t z_t (1 - z_t)}\lambda. \quad (8)$$

The left side of the equation describes the difference between the Bullish sentiment at time $t + \Delta t$ and t , and the right side depicts the lagged value of the sentiment, herding behaviour, and parameters related to the agents' belief about the expected future price trend. The equation highlights that a higher value of Bullish sentiment leads to a greater variation between the present and lagged value of z_t . This autocorrelation is overcome estimating parameters through a weighted least squares regression whose coefficients are:

$$\begin{aligned} \beta_0 &= \varepsilon_1 b\Delta t, \\ \beta_1 &= -(\varepsilon_1 + \varepsilon_2) b\Delta t, \end{aligned} \quad (9)$$

and the regression weights are:

$$w_t = \sqrt{2z_t(1 - z_t)}. \quad (10)$$

Note that $\sqrt{b\Delta t}$ in Eq. (8) is the standard deviation of the residuals of weighted regression. In our work, we estimate $\sqrt{b\Delta t}$ over time, thus obtaining a time series $\sqrt{b_t\Delta t}$, and we use $\sqrt{b_t\Delta t}$ to forecast the trend of speculative bubbles, that is the dynamics of Z_τ , at $\tau = t + l$, ($l > 0$) i.e. the share of Bullish agents in the agricultural commodities markets. Hereafter, roughly speaking, we refer to $\sqrt{b_t\Delta t}$ as the square root of the herding parameter. The estimation of the two parameters, i.e., ε_1 and ε_2 , leads to the estimation of the equilibrium distribution of z_t , which is a Beta distribution:

$$W_0(z) = \frac{1}{B(\varepsilon_1, \varepsilon_2)} z^{\varepsilon_1-1} (1-z)^{\varepsilon_2-1}, \quad (11)$$

where

$$B(\varepsilon_1, \varepsilon_2) = \frac{\Gamma(\varepsilon_1)\Gamma(\varepsilon_2)}{\Gamma(\varepsilon_1 + \varepsilon_2)}, \quad (12)$$

where $\Gamma(\cdot)$ is the Gamma function.

It is worth noting that if z is drawn from a Beta distribution, the unconditional mean of z equals $\theta = \varepsilon_1/(\varepsilon_1 + \varepsilon_2)$. As a consequence, if $\varepsilon_1 \approx \varepsilon_2$, we have $\theta = E(z) \approx 0.5$, which implies an equilibrium between the two groups of markets agents. For this reason, 0.5 has been further considered as the “reference value”. If ε_1 differs from ε_2 , i.e. $\varepsilon_1 \neq \varepsilon_2$, the unconditional expected value of z is different from 0.5. In particular, when ε_1 is higher than ε_2 , Bulls dominate the market and the indicator increases, while in the opposite case the indicator decreases because Bears prevail in the market.

Table I shows the descriptive statistics of the two-weekly time series of the estimated parameters, $b_t\Delta t$ and θ_t , the herding parameter and the long term mean, respectively, for the three markets. The subscript t refers to the last date of the time window used for the calibration.

Table I

In Table II, we present the outcomes, (average values), of \bar{p}_{β_0} and \bar{p}_{β_1} that define, respectively, the average of the p -values of the estimated values of β_0 and β_1 in Eq. (9).

Table II

5 The detection and forecast of speculative bubbles

This section aims at verifying the empirically observed tendency of herding behavior to create speculative bubbles in the markets under scrutiny, i.e., IFEU, CBOT, and IFUS. Data on futures prices of the different commodities are provided by the Thomson Reuters Datastream. Corn, oats, rice, soybean, and Chicago Wheat, belong to the Chicago Board of Trade (hereafter CBOT) market. In addition, we consider two ramifications of the Intercontinental Exchange (ICE) market, i.e., ICE Futures U.S. (hereafter IFUS) including canola, cocoa, coffee, cotton, orange juice, and sugar, and ICE Futures Europe (hereafter IFEU), which includes cocoa, robusta coffee, sugar, and UK wheat. The analysed daily data cover 18 years for CBOT, 19 years for IFUS and 11 years for IFEU. We selected the information on the

trade-date, volume, expiration date, and settlement price. We use nearby futures, since better reflecting the real exchange volumes in a given market at a fixed year but the analysis could be also performed at different maturities (Tomek (1997)).

Further details on volumes can be found in Online Appendix A.1 and contract specifications are shown in Online Appendix A.2. The present section is split into four subsections. First, we decompose the indicator into seasonal, trend and residual components and analyse the trend in connection to seasonality, to establish the origin of the detected cycle, e.g., adverse weather conditions or financial events. We, then, perform correlation analysis between Z_{t+l} and $\sqrt{b_t \Delta t}$ (see Eq. (7)) of each market to highlight the forecasting ability of $\sqrt{b_t \Delta t}$ on speculative bubbles and determine the optimal forecast horizon. The third step consists of a multiple regression, further compared to a dynamic regression with ARIMA errors as robustness check. The last subsection shows the co-movements between the historical series of $\sqrt{b_t \Delta t}$ and Z_{t+l} at the optimal lag and the percent variations of Z_t from the reference value, thus providing information on which branch of the wave, i.e., increasing or decreasing, the agent is located at a give time period.

5.1 The Decomposition of the Indicator

The trends of the indicators for the three markets are plotted in Fig.2. In addition, Fig.3 shows the decomposition of IFUS-market indicator, into trend, seasonality and random components, obtained using Hodrick-Prescott Filter. Combining the series of trend and seasonality, the two observed consecutive peaks in Fig.3 highlight a 2-years cycle. The 2-years cycle is performed also by IFEU-market indicator, while CBOT indicator shows a 3-year cycle (Figs.??-?? in Online Appendix). The wide size of cycles, rather than seasonal determinants, suggests adverse weather conditions and financial crisis as possible driving factors.

Figure 2

The cyclical trend of the IFUS indicator is similar to that of the two main traded commodities in IFUS market, i.e., cotton and cocoa (Figs.4-5), performing well in the replication of speculative bubbles, empirically observed in correspondence of financial crisis of 2007 and 2010. In particular, a series of unfavourable events connected to cotton markets in 2010, e.g., the Chinese ban of exports, an unpredictable freeze in China's cotton producing areas, and an extensive flood in Pakistan, fueled a historical rise in cotton prices (Fig.4). In addition, in 2011-2012, a further speculative bubble arised, due to the so-called "bumper crop" of cocoa, i.e., an excess of supply generating a drop in cocoa prices between October and December 2011, followed by a drop in cocoa production due to the lack of rain at the beginning of 2012 (Fig.5). As shown in Figs. ??, ?? and ?? in Online Appendix, a sharp price spike of robusta coffee in IFEU, at the beginning of 2014, has been caused by the lack of rainfall (Fig. ??). Finally, in CBOT, wide increases in prices of fertilizers, farm machinery and biofuels impact the wheat prices and events like "corn borer" pest, affecting corn crops, led to increases in corn prices in years 2010-2011(Fig.??).

Figure 3

Figure 4

Figure 5

5.2 Speculative bubbles: correlation analysis

The detection of the optimal lag at which the square root of herding parameter, $\sqrt{b_t \Delta t}$, predicts speculative bubbles, i.e. the trend of Z_{t+l} , is based on a correlation analysis between the two time series at an increasing lag l , $l = 1, \dots, 42$ months.

Figure 6

Fig.6 shows that the maximum value of correlation in the IFUS is higher than 0.4 at a lag of $l = 18$ months. Outcomes related to IFEU and CBOT are shown in the Online Appendix. In IFEU, (Fig. ??), the highest value of the correlation, slightly higher than 0.1, is at a lag of $l = 27$ months, while the lowest value, observed at a lag of $l = 18$ months, is lower than -0.2, suggesting a countercyclical trend between Z_{t+l} and $\sqrt{b_t \Delta t}$. With reference to CBOT, Fig. ?? shows that the highest value, higher than 0.4, could be found at a lag of $l = 11$ months. Therefore, the correlation analysis highlights a predictive ability of $\sqrt{b_t \Delta t}$ towards Z_{t+l} of $l = 18$ months ahead in IFUS and $l = 11$ months in CBOT. In addition, a negative significant correlation at a lag of $l = 18$ months in IFEU seems to emerge.

5.3 Speculative bubbles: regression analysis

In this Section, we use the regression analysis to highlight the goodness of fit of our model to the observed data. The multiple regression adopted reads as:

$$Z_{t+l} = \beta_{0,t} + \beta_1 \varepsilon_{1,t} + \beta_2 \sqrt{b_t \Delta t} + error_t, \quad (13)$$

where, $\varepsilon_{1,t}$ defines the idiosyncratic propensity to the shift of state, and $\sqrt{b_t \Delta t}$ describes the square root of the herding parameter. At first, we implement an ordinary least square regression model, in which $error_t$ is a white noise. In consideration of the detected autocorrelation in the error term, we, then, perform a dynamic regression where the historical series of the errors follow an ARIMA model. In Table III, outcomes of the regression at the optimal time horizon, are presented. As expected, the square root of the herding parameter, $\sqrt{b_t \Delta t}$, has a highly significant relationship with Z_{t+l} both in OLS and ARIMA models, providing further evidence of the ability of $\sqrt{b_t \Delta t}$ to predict the trend of Z_{t+l} in the three markets at the stated optimal lags. In particular, in CBOT and IFUS, the increasing trend of the herding parameter, predicts a prevalence of Bullish behaviour in the market. The detected awareness of herding attitude, in fact, suggests a climate of uncertainty in which all the “uninformed agents” follow the “leaders”. The expectation of future increases in prices, induce the leaders to buy large amounts of goods, thus causing increases in prices and, in turn, speculative bubbles. The only exception to this tendency is in IFEU, where both the correlation and the regression, reveal a negative relationship between Z_{t+l} and $\sqrt{b_t \Delta t}$. Indeed, since IFEU shares some commodities with the other markets, an increase in $\sqrt{b_t \Delta t}$ in this market could induce the agents to shift to others.

Table III

5.4 Final comments on speculative bubbles

The forecasting ability of $\sqrt{b_t \Delta t}$ on the trend of Z_{t+l} historical series, lagged by the amount of period defined as optimal in previous sections, has been shown in Fig.7, with reference to IFUS. In particular, the Figure describes the outcomes at a lag of $l=21$ months. Results of IFEU market at a lag of $l=18$ months perform a counter-cyclical trend between $\sqrt{b_t \Delta t}$ and Z_{t+l} (Fig.?? in Online Appendix). This market, in fact, shares two commodities, i.e., cocoa and coffee, with IFUS. Therefore, in case of excessive price increases in one of the two markets, agents have the possibility to shift to markets with cheaper prices. This option could be exploited by agents also with reference to wheat, shared by IFEU and CBOT. Fig. ?? in Online Appendix, describes the forecasting ability of $\sqrt{b_t \Delta t}$ in CBOT at a lag of $l=11$ months.

Figure 7

We, therefore, made a rough attempt to describe the collocation of the agent on the wave of the speculative bubble in a specific instant using two approaches. Neither of them succeeds in this purpose, but, both of them provide clues on where the agent is located, i.e., the increasing or decreasing part of it. The first approach looks at the historical series of $\sqrt{b_t \Delta t}$ and is based on the already mentioned ability of the herding parameter to approximate the dynamics of Z_τ some periods ahead, being $\tau = t + l$, $l > 0$ the number of periods detected by the correlation analysis and verified, with reference to IFUS, in Fig.7. For instance, in this market the observed trend of $\sqrt{b_t \Delta t}$ is predictive for the dynamics of Z_{t+l} , $l = 21$ months ahead, and, if the agent is located at the peak of a bubble, he would expect that the next peak of Z_{t+l} will be performed in $l = 21$ months later. The past trend of $\sqrt{b_t \Delta t}$, is, then, informative on the position of the agent along the wave (increasing or decreasing part) of speculative bubble and enables to take a market decision even at “optimal for practitioners” lags, (hereafter OFP), i.e., $l = 9\text{--}10$ months, usually preferred by investors in their market decisions (Mahto et al. (2021)). The second approach is that of computing the percentage changes of Z_t with respect to the reference value, i.e. 0.5, in each time period. Results shown in Fig. 8 (and Fig. ?? and ??, in Online Appendix, respectively linked to IFEU and CBOT), are informative in the purpose of defining where the agent lies, i.e., increasing or decreasing part of the wave, depending on the positive or negative percentage change from the reference value, even failing in the determination of the exact position of the agent along the wave.

Figure 8

6 The detection and forecast of realized volatility

The last section shows the ability of Z_t to detect and forecast the trend and turning points of price volatility. Commodities under scrutiny have been chosen within the most traded ones, which perform better at both optimal lag and OFP lag, ($l = 9\text{--}10$ months). This latter time lag could be more conveniently adopted by agents when taking their investments decisions. Volatility is defined by Eq. (1) for the three different markets: IFEU, CBOT, and IFUS. This Section is split into three subsections. The first shows the results of the correlation analysis, the second, the results of linear regression and dynamic regression with ARIMA errors, and the concluding sections presents plots and descriptions of the main results of the estimates.

6.1 Realized volatility: correlation analysis

Graphical results on the correlation analysis between the realized volatility (RV_{t+l}) of cocoa and cotton in IFUS with Z_t , are shown in Figs. 9 and 10. High and significant correlations are found at a lag of $l = 24$ and $l = 22$ months, respectively. With reference to IFEU, we show the correlation between RV_{t+l} of white sugar and robusta coffee with Z_t . Significant correlations are observed, respectively, at lags of $l = 7$ and $l = 15$ months (Figs. ?? and ?? in Online Appendix). Finally, in CBOT, significant correlations emerge for commodities corn and wheat at a lag of $l = 33$ and $l = 15$ months (Figs. ?? and ?? in Online Appendix).

Figure 9

Figure 10

6.2 Realized volatility: regression analysis

This subsection goes through the results obtained in the correlation analysis and shows what happens when relating lagged realized volatility (RV_{t+l}) to the herding parameter $\sqrt{b_t \Delta t}$, and Z_t , i.e. the fraction of agents with a Bullish attitude. The use of these two regressors, provides the best combination of parameters to describe the trend of RV_{t+l} . The regression model is written as:

$$RV_{t+l} = \beta_{0,t} + \beta_1 Z_t + \beta_2 \sqrt{b_t \Delta t} + error_t. \quad (14)$$

This analysis is performed by using both OLS and, due to autocorrelation in the errors, also through a dynamic regression where the errors series follow an ARIMA model. The forecast of the trend of each commodity is made using both the optimal and the OFP lags. The latter seems to be significant when analysed by means of the regression model and, as observed in the next section, it performs well in predicting the volatility trend. Table IV shows that all the analysed goods in all markets perform a significant positive relationship between Z_t and RV_{t+l} both in OLS and ARIMA, so emphasizing the predictive ability of Z_t on RV_{t+l} at the optimal lags. Since the optimal lag of white sugar in IFEU is a short term lag, we will exclude this commodity from the further regression analysis at OFP lag, performed for the other goods. Table V describes the predictive power of Z_t in combination with $\sqrt{b_t \Delta t}$ for RV_{t+l} , at the OFP lag of $l = 9-10$ months. We remark that, also at OFP lag, at least in the dynamic regression, Z_t appears significant. With reference to commodity cotton in IFUS and robusta coffee in IFEU, results highlight a negative relationship, indeed a countercyclic trend between RV_{t+l} at the analysed lag and Z_t , implying a negative relationship between RV_{t+l} and Z_t , at the same time period $t + l$.

Table IV

Table V

6.3 Final comments on realized volatility

The forecasting ability of Z_t on the dynamics of realized volatility of the examined commodities in IFUS, is highlighted in Figs. 11 to 14. Outcomes for IFEU and CBOT are plotted in Figs. ?? to ?? (IFEU) and in Figs. ?? to ?? (CBOT),

of the Online Appendix. In general, Z_t seems to be able to catch peaks and troughs of RV_{t+l} at least in three points of each graph, even its speed in reaching the turning points could be different from that of volatility, thus justifying the different slopes of the two lines at a given time period. Figs. 11 and Fig.13 for IFUS, Fig.?? and Fig. ?? for IFEU and ?? Figs. ?? for CBOT show a cyclic trend, i.e., a direct relation between Z_t and RV_{t+l} when analysing the optimal time lag. At the OFP lag, these cyclic trends seems to be compromised, particularly in markets trading in commodities of different nature i.e. IFUS and IFEU, which, at the OFP lag, perform a countercyclic relation between RV_{t+l} and Z_t . In this case, in fact, the predictor, Z_t only considers the more volatile shorter-term information affected by the different paths of all commodities, thus excluding the stabilising long-term trend (Goedhart & Mehta (2016)). In particular, with reference to IFUS, cocoa maintains also in OFP lag (i.e. $l = 9$ months), a cyclical trend (Fig. 12). Differently, the regression and, in turn, the plot of the historical series of RV_{t+l} and Z_t of cotton, highlight an inverse relation and countercyclic trend (Fig. 14). When shifting to IFEU, the same countercyclic trend is performed also by robusta coffee (Fig. ??), while a direct relation between RV_{t+l} and Z_t is observed for sugar (Fig. ??), whose OFP lag corresponds to the optimal. In contrast, CBOT, which trades in similar commodities, performs, as expected, also at OFP lag, a positive relation between Z_t and the volatility of the different commodities. Outcomes of CBOT are shown in Figs. ?? and ??, for commodity corn and in Figs. ?? and ?? for commodity wheat. Generally speaking, figures depict a better forecasting ability of Z_t at the optimal lag, but also a rather effective performance at the OFP lag in the market trading in homogeneous commodities. In “heterogeneous” markets, the OFP forecast could be misleading since it neglects the adjustments due to the different paths in commodities prices. The performance of Z_t in catching, at least, the main turning points of the observed RV_{t+l} , is also more effective than GARCH, which informs only on the increasing or decreasing trend of forecasted volatility, (see Online Appendix A.9). Outcomes on the comparison between the lagged observed and estimated trends of RV_{t+l} at the optimal and “optimal for practitioners” lags are shown in Online Appendix A.10.

Figure 11

Figure 12

Figure 13

Figure 14

7 Conclusions

Volatility and speculative bubbles in commodity markets have been a great concern among scholars since the early 2000s, corresponding to the emergence of the Financialisation of agricultural commodities. This class of commodities began to acquire the importance of an asset class, alternative and independent from equities and bonds as a hedging tool against market risk. We have designed a market sentiment indicator, whose dynamics is defined by behavioural parameters estimated on the basis of available empirical data. The indicator, modeled as the logarithm of an odds ratio, provides information on the trend of demand and supply in the market (i.e., bullish and bearish behaviour) and performs well in identifying the crucial events affecting agricultural and soft commodity markets. Moreover, the numerator of the odds ratio, i.e., the share of bullish agents, could be also used to forecast the market volatility, while

speculative bubbles are determined by the herding parameter. Forecast experiments have been performed on three commodity markets, i.e. CBOT, IFEU and IFUS. The effectiveness of herding parameter in forecasting speculative bubbles can be notably appreciated at the lags of $l = 21$ months in IFUS, $l = 18$ months in IFEU, and $l = 11$ months in CBOT. We, then, analysed the forecasting ability of Z_t on the realized volatility of six commodities, two for each market, chosen among the most traded ones. Its predictive ability, detected at optimal lag, has been further complemented with that obtained at the “optimal for practitioners” lag, established in 9-12 months, generally preferred by market agents in their investments decisions. In both cases, the observed present value of Z_t , shows a good performance in forecasting the future trend of volatility. The capability of Z_t to capture the trend of future volatility at different time lags is an innovative result, since the GARCH models, usually adopted to forecast the trend of the volatility, fail in the purpose of catching the moments of peaks and troughs in the markets. Agricultural and soft commodities, directly or indirectly, constitute a relevant share of food demand. The indicator provides, through its components, a valid tool in the decision-making process since it allows traders, usually farmers, to know, in advance, the behaviour of agricultural markets, thus enabling them to hedge against future risks and to gather earnings to satisfy their basic needs.

References

- Alfarano, S., Lux, T., & Wagner, F. (2005). Estimation of agent-based models: the case of an asymmetric herding model. *Computational Economics*, 26(1), 19–49.
- Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 21(2), 129–152.
- Bathia, D., & Bredin, D. (2013). An examination of investor sentiment effect on g7 stock market returns. *The European Journal of Finance*, 19(9), 909–937.
- Black, F. (1986). Noise. *The Journal of Finance*, 41(3), 528–543.
- Borovkova, S. (2011). News analytics for energy futures. *Available at SSRN 1719582*.
- Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, 11(1), 1–27.
- Clarke, R. G., & Statman, M. (1998). Bullish or bearish? *Financial Analysts Journal*, 54(3), 63–72.
- Dehn, J., Gilbert, C., & Varangis, P. (2005, 01). Agricultural commodity price volatility. *Managing Economic Volatility and Crises: A Practitioner’s Guide*, 137–185. doi: 10.1017/CBO9780511510755.007
- De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4), 703–738.
- Domanski, D., & Heath, A. (2007). Financial investors and commodity markets. *BIS Quarterly Review*.
- Franceschini, F., Galetto, M., & Varetto, M. (2004). Qualitative ordinal scales: the concept of ordinal range. *Quality Engineering*, 16(4), 515–524.
- Goedhart, M., & Mehta, D. (2016). The long and the short of stock-market volatility. *McKinsey & Company*, May.
- Jegadeesh, N., & Wu, D. (2013). Word power: A new approach for content analysis. *Journal of Financial Economics*, 110(3), 712–729.
- Kearney, C., & Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, 33, 171–185.
- Kirman, A. (1993). Ants, rationality, and recruitment. *The Quarterly Journal of Economics*, 108(1), 137–156.
- Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315–1335.
- Liu, Y., Liu, S., Ye, D., Tang, H., & Wang, F. (2022). Dynamic impact of negative public sentiment on agricultural product prices during covid-19. *Journal of Retailing and Consumer Services*, 64, 102790.
- Loughran, T., & McDonald, B. (2011). When is a liability not a liability? textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, 66(1), 35–65.

- Lv, F., Yang, C., & Fang, L. (2020). Do the crude oil futures of the shanghai international energy exchange improve asset allocation of chinese petrochemical-related stocks? *International Review of Financial Analysis*, 71, 101537.
- Mahto, A. K., Alam, M. A., Biswas, R., Ahmed, J., & Alam, S. I. (2021). Short-term forecasting of agriculture commodities in context of indian market for sustainable agriculture by using the artificial neural network. *Journal of Food Quality*, 2021.
- Sanders, D. R., Irwin, S. H., & Leuthold, R. M. (2003). The theory of contrary opinion: a test using sentiment indices in futures markets. *Journal of Agribusiness*, 21(345-2016-15207), 39–64.
- Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance*, 16(3), 394–408.
- Shamsher, S. (2021). Financialisation of commodities – empirical evidence from the indian financial market. *IIMB Management Review*, 33(1), 38-49. Retrieved from <https://www.sciencedirect.com/science/article/pii/S0970389621000161> doi: <https://doi.org/10.1016/j.iimb.2021.03.001>
- Shiller, R. J. (2015). Irrational exuberance. In *Irrational exuberance*. Princeton University Press.
- Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, 52(1), 35–55.
- Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3), 1139–1168.
- Tomek, W. G. (1997). Commodity futures prices as forecasts. *Applied Economic Perspectives and Policy*, 19(1), 23–44.
- Vidal-Tomás, D., & Alfarano, S. (2020). An agent-based early warning indicator for financial market instability. *Journal of Economic Interaction and Coordination*, 15(1), 49–87.
- Wagner, F. (2003). Volatility cluster and herding. *Physica A: Statistical Mechanics and its Applications*, 322, 607–619.
- Wang, C. (2003). Investor sentiment, market timing, and futures returns. *Applied Financial Economics*, 13(12), 891–898.
- Working, H. (1961). New concepts concerning futures markets and prices. *The American Economic Review*, 51(2), 160–163.
- Zhang, C. (2008). Defining, modeling, and measuring investor sentiment. *University of California, Berkeley, Department of Economics*.

Tables

	IFUS			CBOT			IFEU		
	Mean	Median	St. Dev.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
$b_t \Delta t$	0.05017	0.04065	0.03366	0.13698	0.13113	0.05966	0.08367	0.07501	0.04561
θ_t	0.47840	0.48650	0.11305	0.50643	0.51269	0.20013	0.4801	0.4998	0.14203

Table I: Descriptive statistics of parameters $b_t \Delta t$ and θ_t

	IFUS	CBOT	IFEU
	Mean	Mean	Mean
\bar{p}_{β_0}	0.00527	0.04445	0.01140
\bar{p}_{β_1}	0.00048	0.00290	0.00207

Table II: Average values of \bar{p}_{β_0} , \bar{p}_{β_1}

$Z_{t+l} = \beta_0 + \beta_1 \varepsilon_{1,t} + \beta_2 \sqrt{b_t \Delta t} + error_t$										
Ordinary Least Squares						Dynamic Regr. with ARIMA errors				
	$\varepsilon_{1,t}$	$\sqrt{b_t \Delta t}$	R^2	adj. R^2	L.B.T.	$\varepsilon_{1,t}$	$\sqrt{b_t \Delta t}$	σ	ARIMA	L.B.T.
IFUS where l is 21										
t.h. 2009-2019	0.035	2.789***	0.172	0.161	NO	0.002	1.866***	0.158	(1,0,0)	YES
t.h. 2009-2013	1.104***	15.371***	0.750	0.74	NO	0.891**	13.093***	0.123	(1,0,0)	YES
IFEU where l is 18										
t.h. 2008-2019	0.012	-0.940	0.045	0.0334	NO	0.004	-2.085***	0.195	(2,0,0)	YES
t.h. 2008-2013	-0.254*	-3.953**	0.171	0.142	NO	-0.054	-1.497***	0.109	(1,0,0)	YES
CBOT where l is 10										
t.h. 2009-2019	-0.123	4.631***	0.218	0.208	NO	-0.135	4.614***	0.225	(1,0,0)	YES
t.h. 2009-2013	0.822•	8.585***	0.633	0.622	NO	0.561	8.826***	0.197	(1,0,0)	YES

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table III: OLS and Dyn. Regr. results ($Z_{t+l} - \varepsilon_{1,t}$, $\sqrt{b_t \Delta t}$) optimal lag, l is lags in months

$RV_{t+l} = \beta_0 + \beta_1 Z_t + \beta_2 \sqrt{b_t} \Delta t + error_t$										
Ordinary Least Squares						Dynamic Regr. with ARIMA errors				
	Z_t	$\sqrt{b_t}$	R^2	adj. R^2	L.B.T.	Z_t	$\sqrt{b_t} \Delta t$	σ^2	ARIMA	L.B.T.
IFUS_{CC} where l is 24										
t.h. 2000-2019	0.096 ^{***}	-0.157 ^{**}	0.164	0.158	NO	0.011 [*]	-0.009	0.015	(1,1,1)	YES
IFUS_{CT} where l is 22										
t.h. 2000-2019	0.117 ^{***}	0.083	0.160	0.154	NO	0.048 [*]	0.056	0.068	(1,1,1)	YES
IFEU_{RC} where l is 15										
t.h. 2008-2019	0.034 ^{**}	-0.172 ^{***}	0.231	0.221	NO	0.007 [•]	-0.004	0.010	(1,1,1)	YES
IFEU_{WS} where l is 7										
t.h. 2008-2019	0.060 ^{**}	-0.259 ^{***}	0.183	0.173	NO	0.022 [*]	0.105.	0.033	(2,1,0)	YES
CBOT_{WT} where l is 16										
t.h. 2001-2019	0.044 ^{***}	-0.025	0.111	0.104	NO	0.017 [•]	-0.037	0.038	(1,1,1)	YES
CBOT_{CR} where l is 36										
t.h. 2001-2019	0.068 ^{***}	-0.016	0.125	0.118	NO	0.086 [*]	0.068	0.148	(1,1,0)	YES

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table IV: OLS and Dyn. Regr. results (RV_{t+l} - Z_t , $\sqrt{b_t} \Delta t$) optimal l is lags in months

$RV_{t+l} = \beta_0 + \beta_1 Z_t + \beta_2 \sqrt{b_t \Delta t} + error_t$										
Ordinary Least Squares						Dynamic Regr. with ARIMA errors				
	Z_t	$\sqrt{b_t}$	R^2	adj. R^2	L.B.T.	Z_t	$\sqrt{b_t \Delta t}$	σ	ARIMA	L.B.T.
IFUS_{CC} where l is 10										
t.h. 2000-2019	0.032 [*]	0.184 ^{***}	0.050	0.044	NO	0.008 [•]	−0.003	0.015	(5,0,1)	YES
IFUS_{CT} where l is 9										
t.h. 2000-2019	0.062 ^{***}	0.150 ^{**}	0.063	0.056	NO	−0.038 [•]	−0.042	0.058	(1,1,1)	YES
IFEU_{RC} where l is 9										
t.h. 2008-2019	0.016	−0.175 ^{***}	0.174	0.164	NO	−0.006 [•]	0.013	0.010	(1,1,1)	YES
CBOT_{WT} where l is 9										
t.h. 2001-2019	0.041 ^{***}	−0.078 [*]	0.107	0.101	NO	0.015 [•]	−0.057	0.038	(1,1,1)	YES
CBOT_{CR} where l is 10										
t.h. 2001-2019	0.029 [*]	−0.056	0.026	0.019	NO	0.093 ^{**}	0.087	0.144	(3,1,1)	YES

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘•’ 0.1 ‘ ’ 1

Table V: OLS and Dyn. Regr. results ($RV_{t+l} - Z_t, \sqrt{b_t \Delta t}$) “optimal for practitioners” lag, l is lags in months

Figures

Figure 1: Scheme of Kirman model

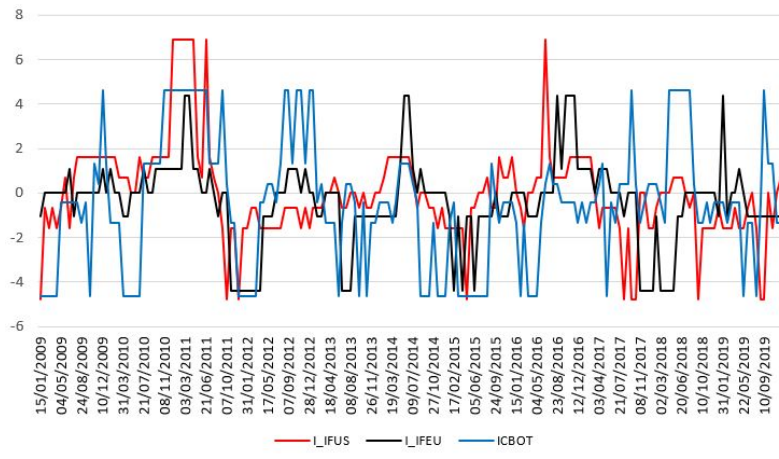


Figure 2: Trends of market indicators (i_t^{BB}) (2009-2019)

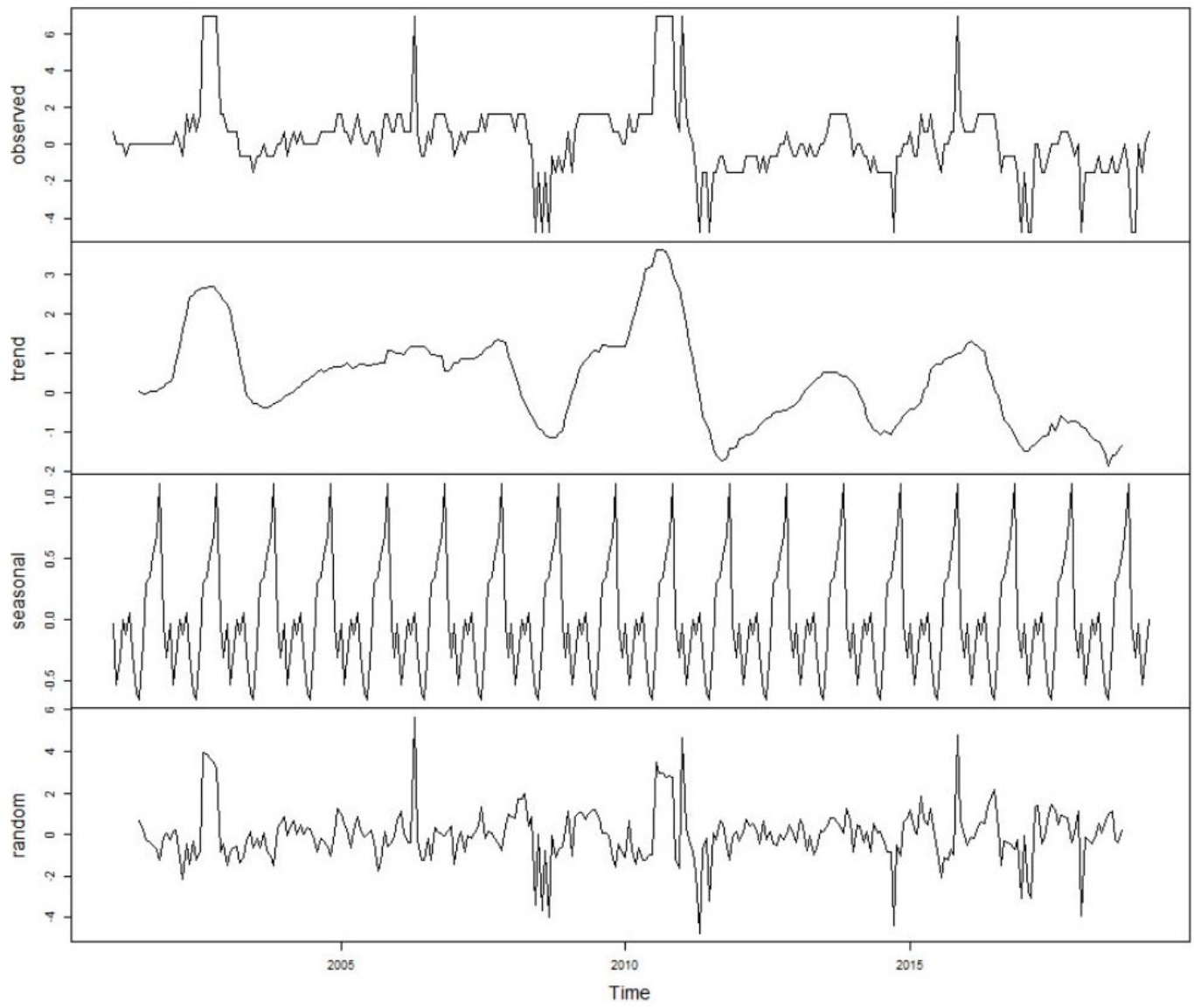


Figure 3: Decomposition of time series of i_t^{BB} of IFUS (2001-2019)

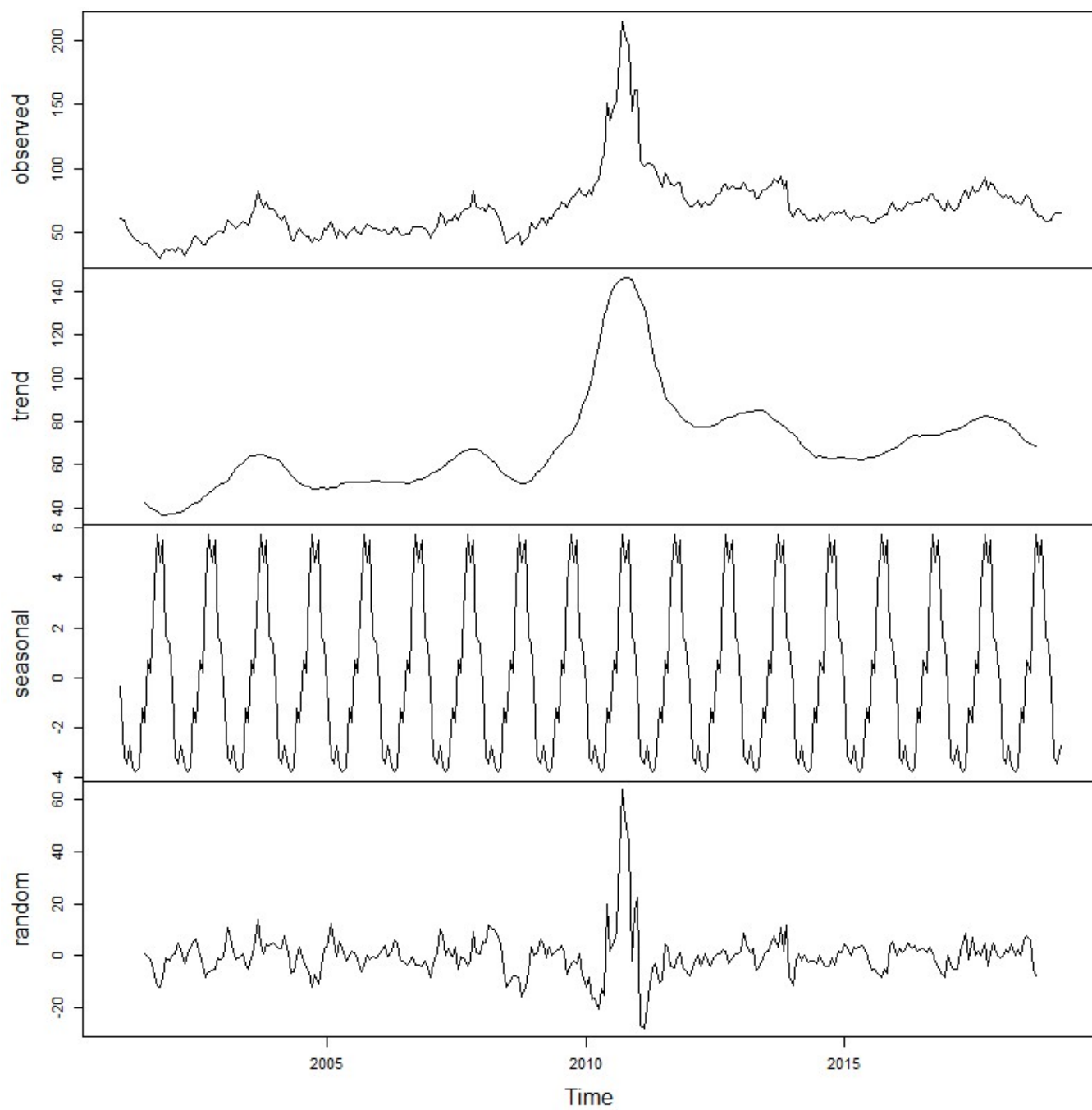


Figure 4: Decomposition of cotton price (IFUS) (2001-2019)

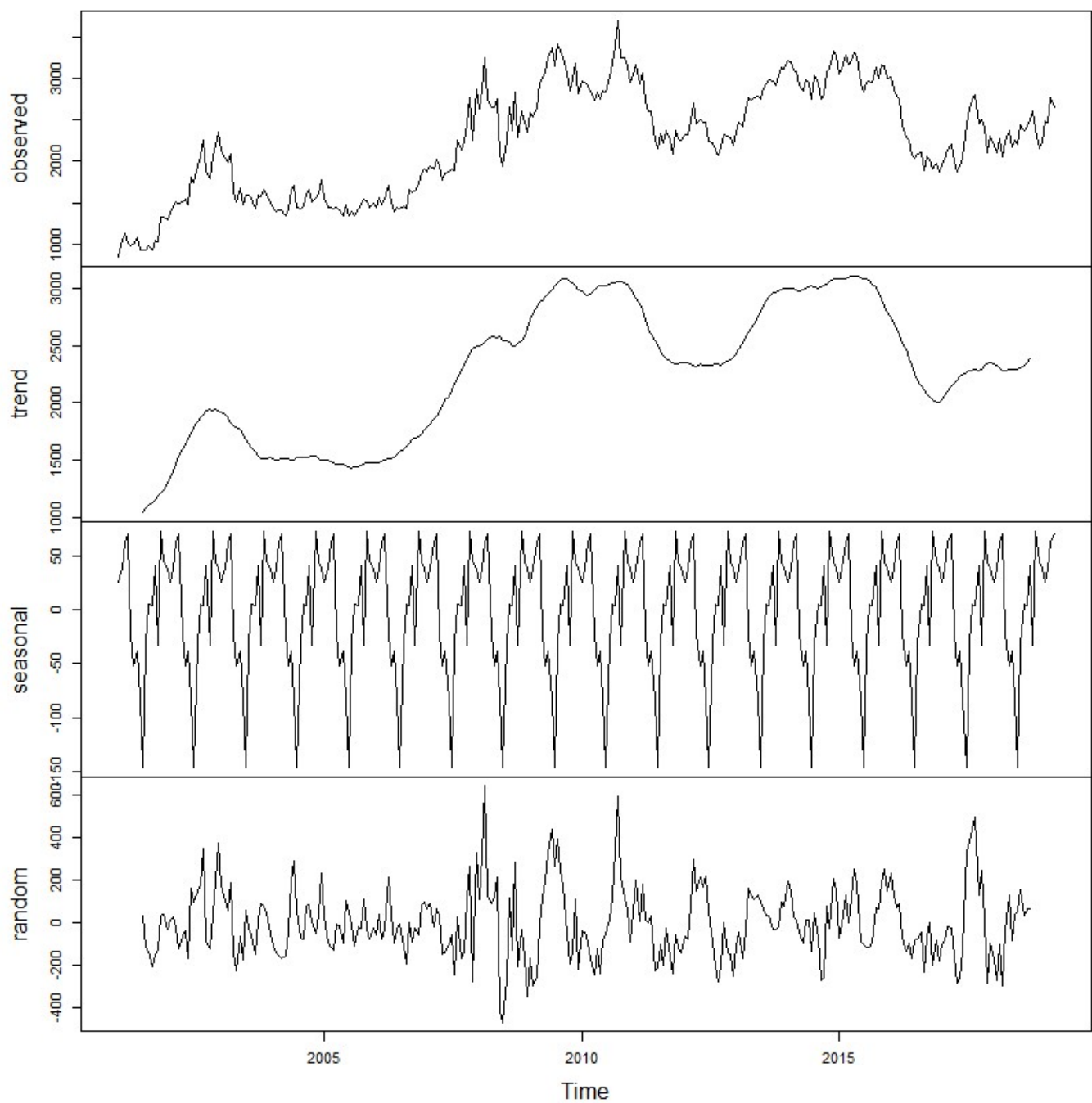


Figure 5: Decomposition of cocoa price (IFUS) (2001-2019)

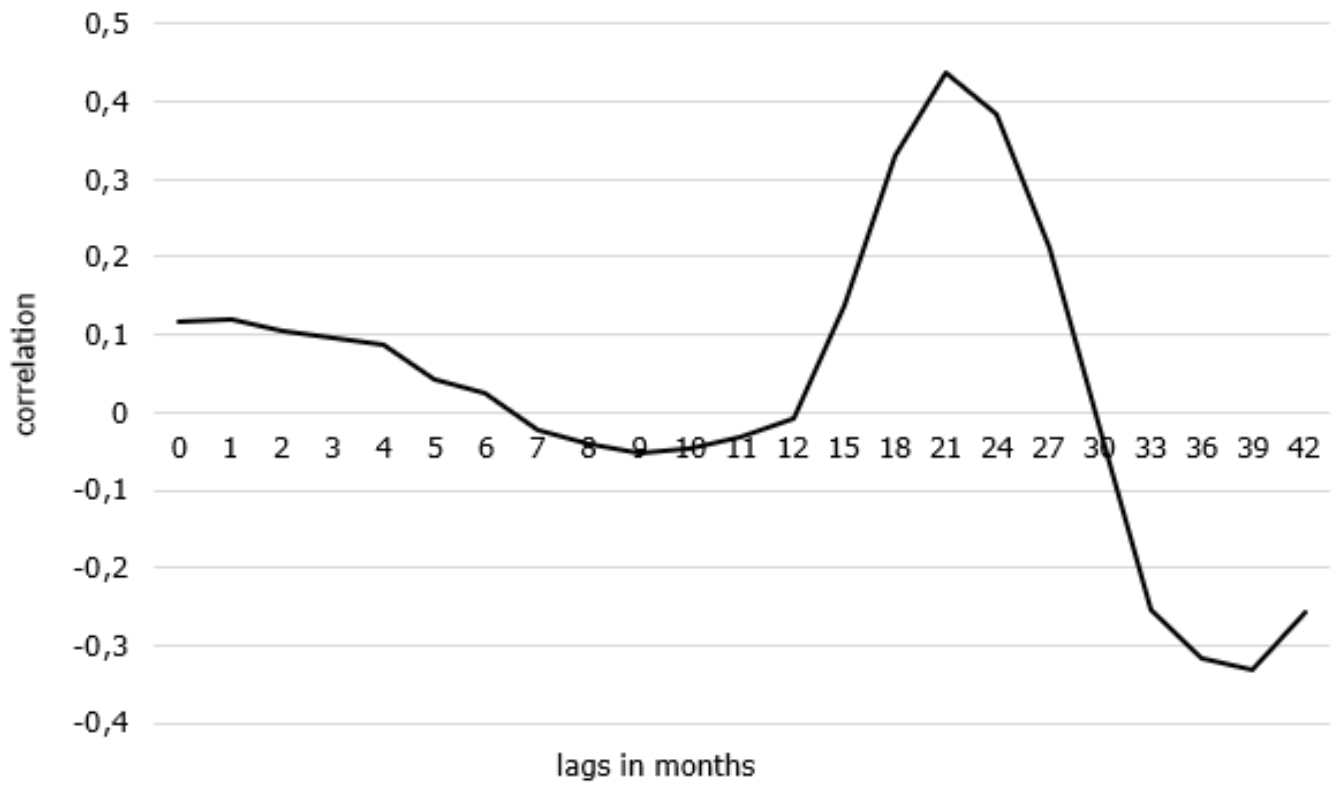


Figure 6: Correlation of Z_{t+l} and $\sqrt{b_t \Delta t}$ in IFUS, lags l , $l = 1, \dots, 42$, in months (2009-2019)

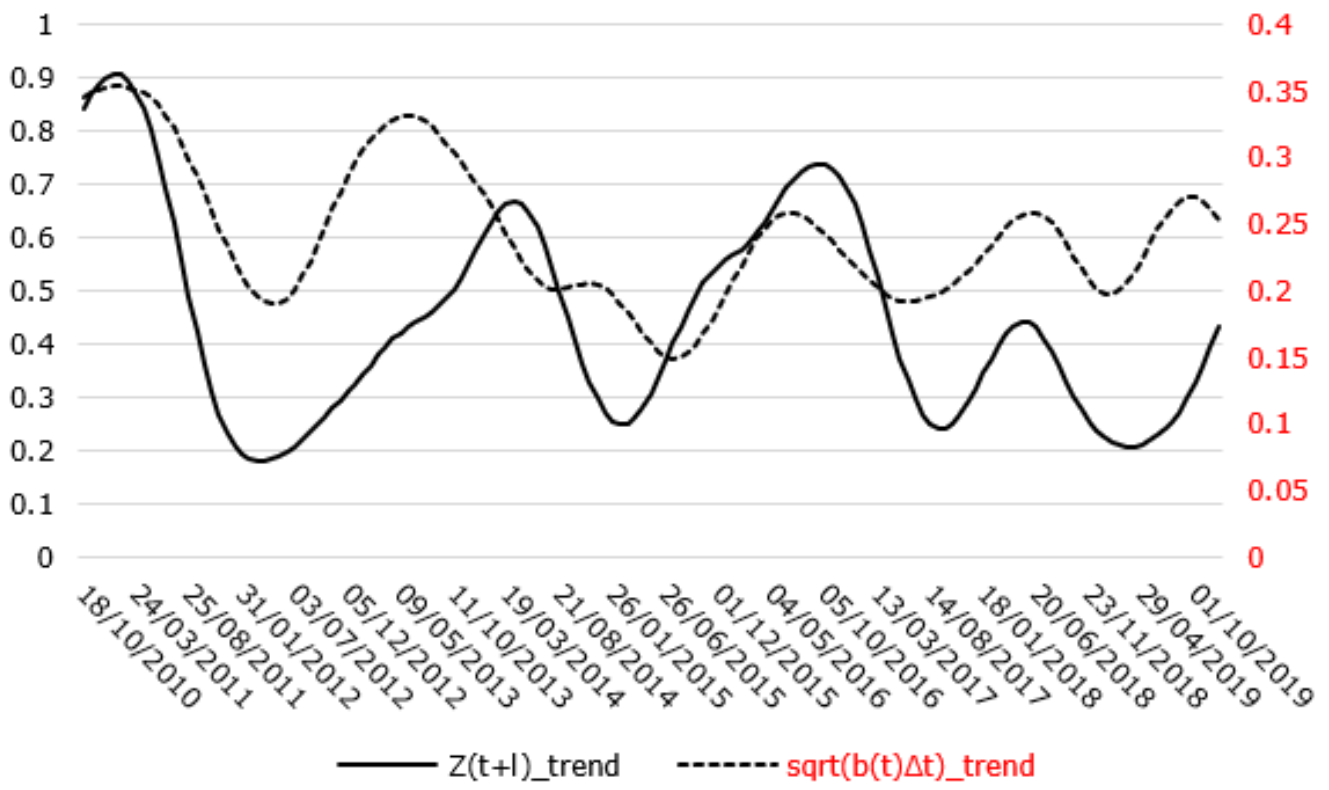


Figure 7: Z_{t+l} filt. and $\sqrt{b_t\Delta t}$ in IFUS at a lag of 21 months (2009-2019)

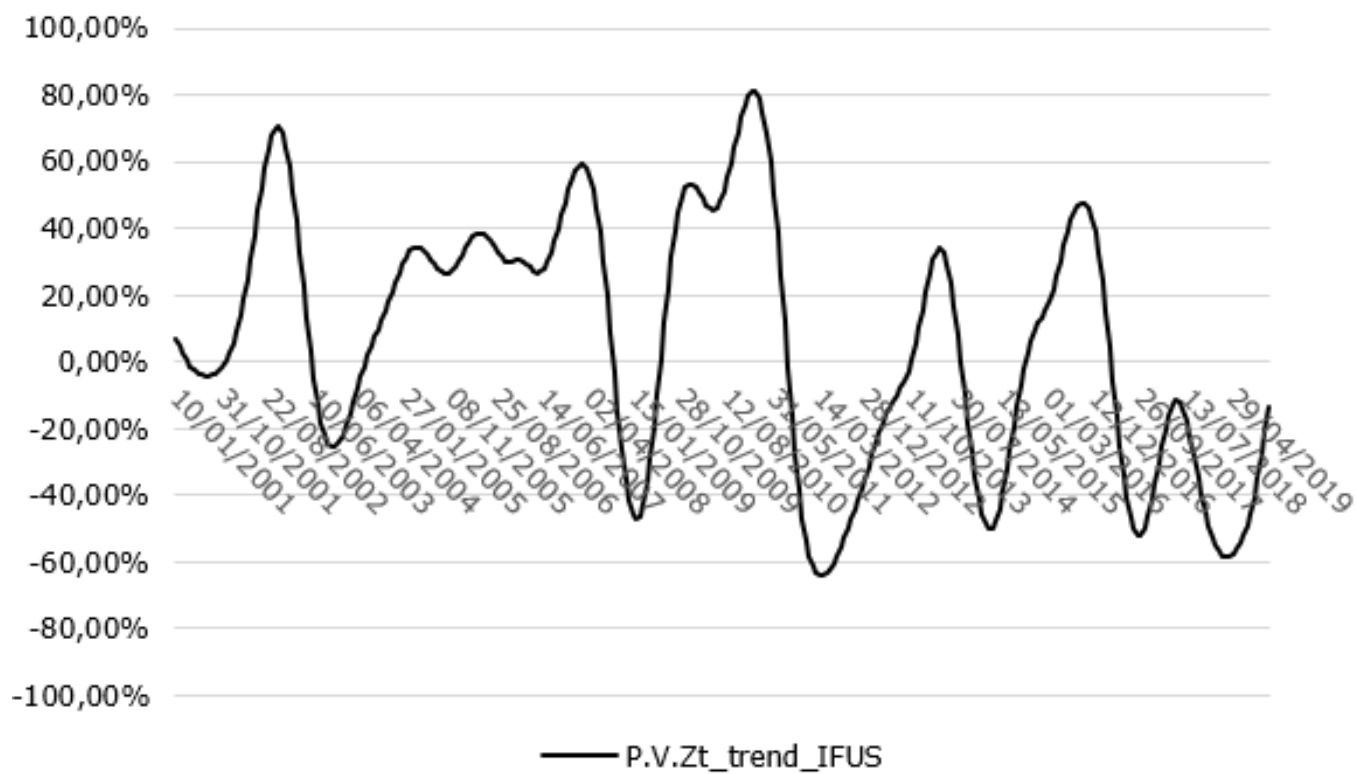


Figure 8: Percentage variation of Z_t IFUS w.r.t. the reference value (2001-2019)

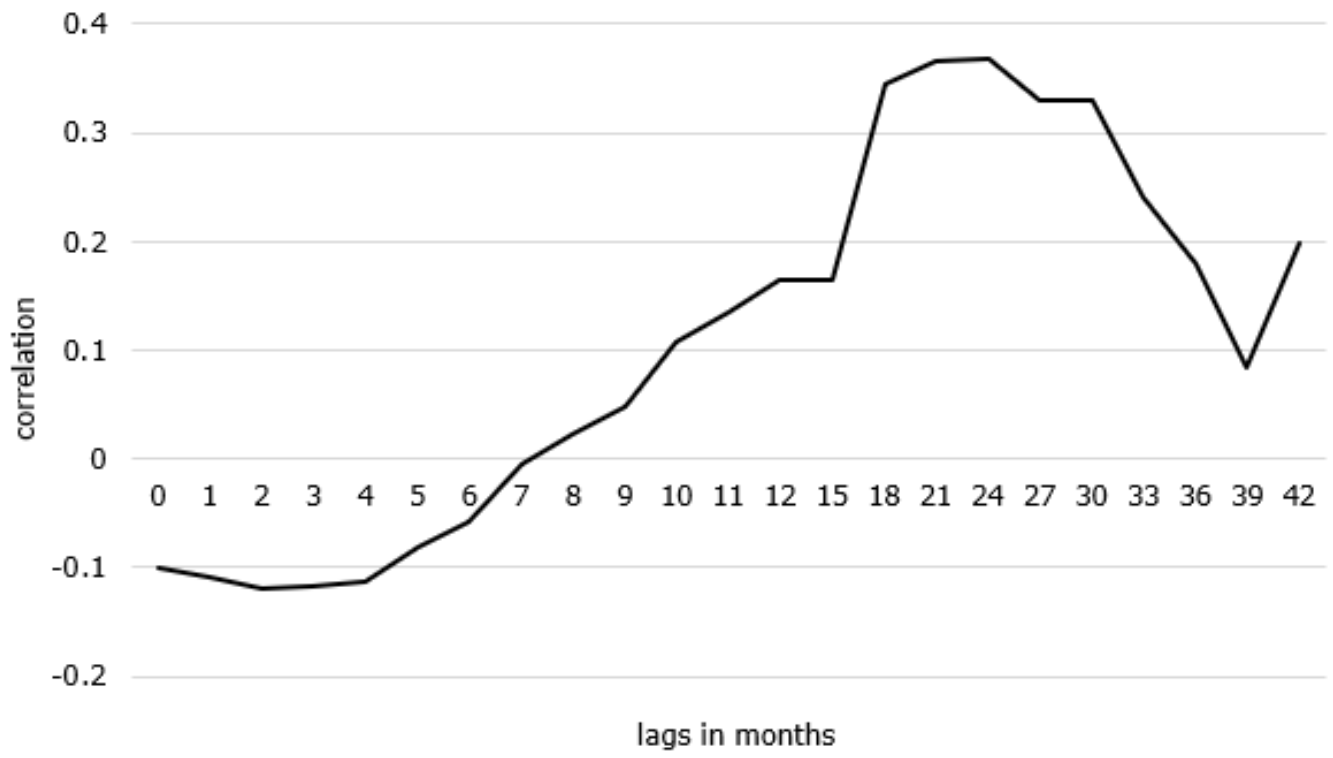


Figure 9: Correlation of RV_{t+l} of cocoa and Z_t in IFUS, lags l , $l = 1, \dots, 42$, in months (2000-2019)

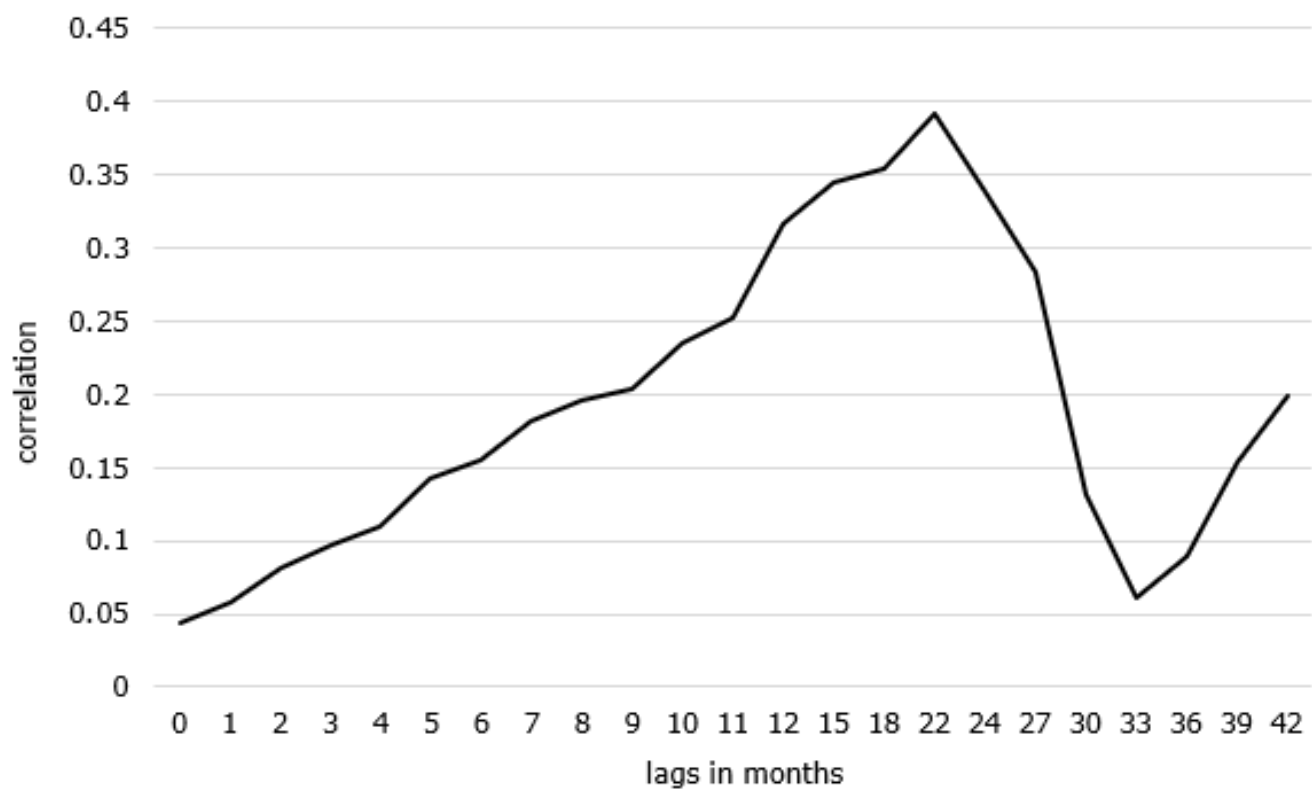


Figure 10: Correlation of RV_{t+l} cotton and Z_t in IFUS, lags l , $l = 1, \dots, 42$, in months (2000-2019)

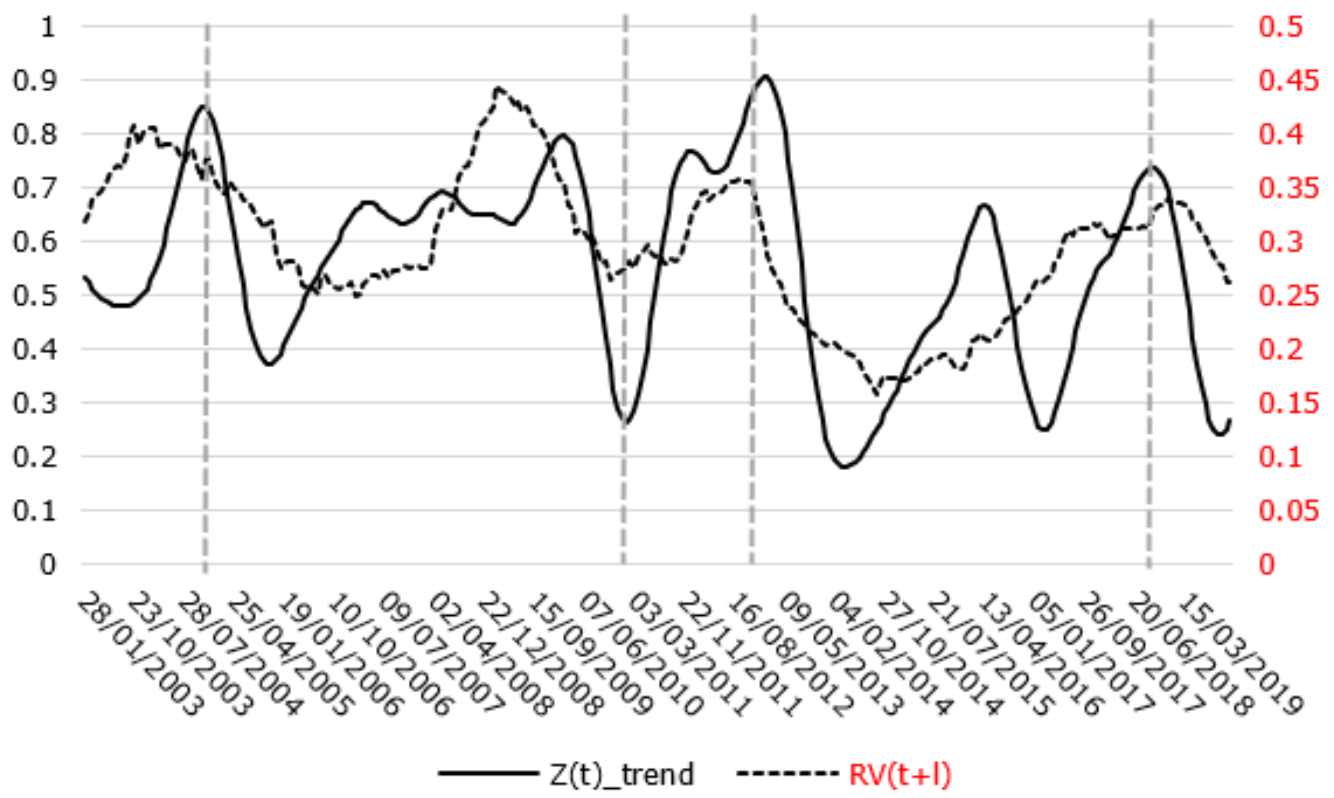


Figure 11: RV_{t+l} of cocoa and Z_t in IFUS at a lag of 24 months (2000-2019)

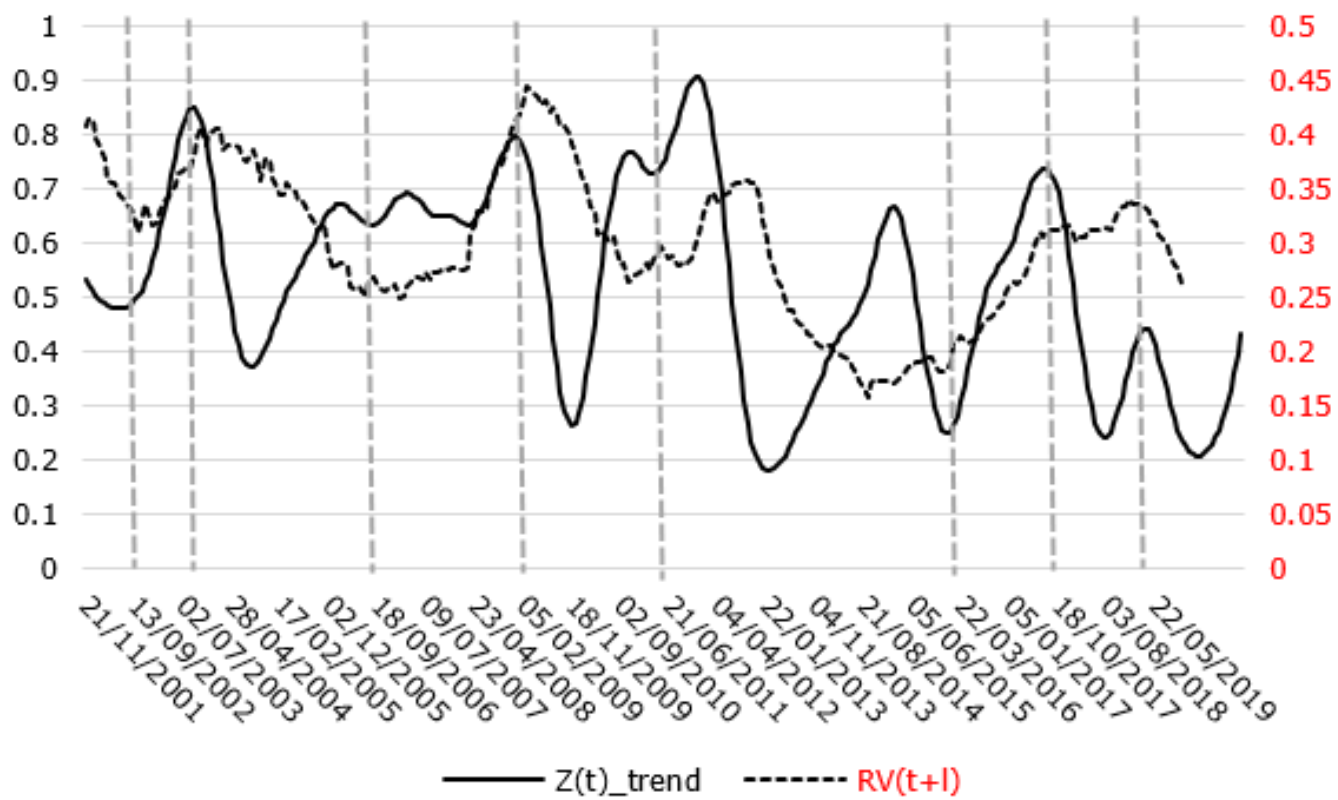


Figure 12: RV_{t+l} of cocoa and Z_t in IFUS at a lag of 10 months (2000-2019)

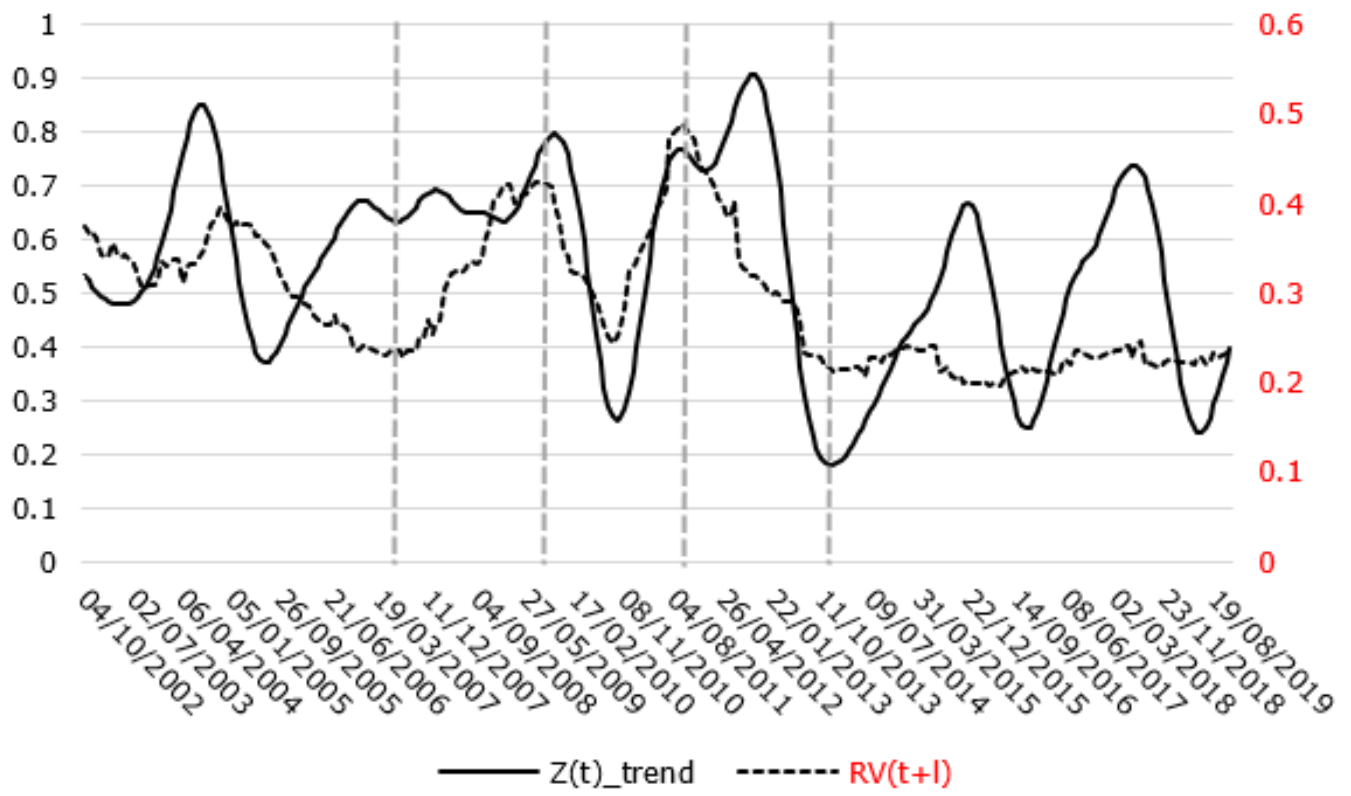


Figure 13: RV_{t+l} of cotton and Z_t in IFUS at a lag of 22 months (2000-2019)

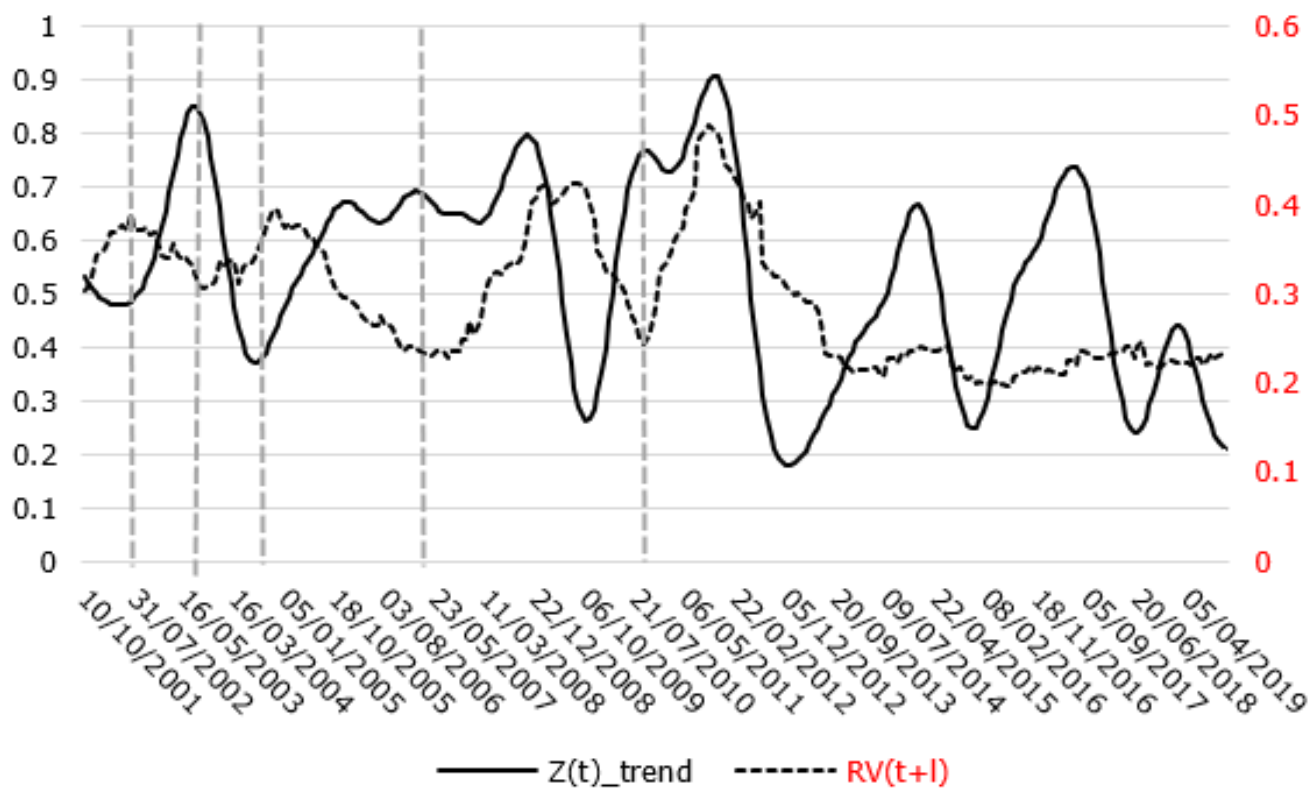


Figure 14: RV_{t+l} of cotton and Z_t in IFUS at a lag of 9 months (2000-2019)