

Article

Sugar Prices vs. Financial Market Uncertainty in the Time of Crisis: Does COVID-19 Induce Structural Changes in the Relationship?

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Abstract: Securitization of the agricultural commodity market has accelerated since the beginning of the 21st century, particularly in the times of financial market uncertainty and crisis. Sugar belongs to the group of important agricultural commodities. The global financial crisis and the COVID-19 pandemic has caused a substantial increase in the stock market volatility. Moreover, the novel coronavirus hit both the sugar market's supply and demand side, resulting in sugar stock changes. The paper aims to assess potential structural changes in the relationship between sugar prices and the financial market uncertainty in a crisis time. In more detail, using sequential Bai–Perron tests for structural breaks, we check whether the global financial crisis and the COVID-19 pandemic have induced structural breaks in that relationship. Sugar prices are represented by the S&P GSCI Sugar Index, while the S&P 500 option-implied volatility index (VIX) is used to show stock market uncertainty. To investigate the changes in the relationship between sugar prices and stock market uncertainty, a regression model with a sequential Bai–Perron test for structural breaks is applied for the daily data from 2000–2020. We reveal the existence of two structural breaks in the analysed relationship. The first breakpoint was linked to the global financial crisis outbreak, and the second occurred in December 2011. Surprisingly, the COVID-19 pandemic has not induced the statistically significant structural change. Based on the regression model with Bai–Perron structural changes, we show that from 2000 until the beginning of the global financial crisis, the relationship between the sugar prices and the financial market uncertainty was insignificant. The global financial crisis led to a structural change in the relationship. Since August 2008, we observe a significant and negative relationship between the S&P GSCI Sugar Index and the S&P 500 option-implied volatility index (VIX). Sensitivity analysis conducted for the different financial market uncertainty measures, i.e., the S&P 500 Realized Volatility Index confirms our findings.

Keywords: sugar prices; agricultural commodities; financial market uncertainty; VIX; global financial crisis; COVID-19 pandemic; structural break analysis

JEL Classification: G11; G15; G17; Q14; Q17



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1. Introduction

After the collapse of the equity market in 2000, commodities have become an important alternative investment asset class [1,2]. This includes insurance companies, financial institutions, pensions, hedge funds, and foundations, as wealthy individuals invested billions of dollars into commodities [3]. The process, also known as the financialisation of commodities [4], has been widely observed in the global markets [4–6]. It was partially a

result of neoliberal policies carried out in the 1980s, which advocated agricultural sector liberalisation [7]. Due to commodity market financialisation, the volatility in commodity markets and financial markets can feed on each other and constitute an inbuilt mechanism of destabilisation and uncertainty in the world economy [8].

The commodity market can be characterised by large price changes. It reacts strongly to unexpected events and involves many players who try to anticipate each other's actions, particularly in times of high uncertainty [9]. Bakas and Triantafyllou [10] found that uncertainty effects are lower in agricultural commodities than energy commodities. The empirical literature studies the relationship between economic and systemic shocks and the volatility in the commodity markets. It argues that some evidence shows the effects of market shocks in the time of crisis on commodity market volatility [10–12]. In the paper, we focus on the two main crisis periods in the 21st century, i.e., the global financial crisis and the COVID-19 pandemic.

One of the main effects of the global financial crisis of 2008–2009 was manifested in rapidly growing financial market uncertainty and extremely high volatility of commodity prices [13,14]. A significant increase of connectedness between the financial market and commodity market was found after the global financial crisis, and food has become the most influential commodity class in the system after the crisis [15]. During the global financial crisis and food crisis of 2008, investors were blamed for pushing prices above their fundamental values, creating a bubble. Masters [16] argues that this resulted in many policy responses [17]. Clapp [18] points out a change in narrative related to the 2008 food crisis. Before the 2008 global economic crash, the main global reports on rapidly rising food prices revealed that demand and supply fundamentals play a crucial role. Later in 2008, the Food and Agricultural Organization of the United Nations (FAO) changed the narrative and observed that June 2008 futures were way beyond market fundamentals, driven mainly by the increased popularity of agricultural commodity futures [18]. A simplified view of reality, referred to as the “Masters Hypothesis” [19], was questioned by Andreasson [20], who supported Irwin's [21] hypothesis rejection. Irwin [21] presents the bulk of the evidence indicating no or a negative relationship between index investment and price movements in agricultural futures markets. Increased volatility of commodities during crises is sometimes blamed on speculation rather than hedging [22].

The second crisis period we focus on is the COVID-19 pandemic. The novel coronavirus SARS-CoV-2 was declared a public health emergency of international concern by the World Health Organization (WHO) on 30 January 2020 [23], and officially classified as a global pandemic on 11 March 2020 [24]. COVID-19 is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) [25]. The global pandemic, causing fiscal and monetary interventions, social distancing, and nation-wide quarantine, has resulted in uncertainty among institutions, agents, and consumers. The novel coronavirus has shaken the global economy on an unprecedented scale [26], and as a black swan [27] has affected the global financial markets significantly [28,29]. There are numerous studies on the COVID-19 pandemic impact on agricultural commodity markets [30–33]. Some evidence shows the role of uncertainty shocks related to the novel coronavirus pandemic on commodity markets [10]. The findings of Bakas and Triantafyllou [10] present a strong negative impact of the pandemic on commodities volatility. Delatte and Lopez [34] find that the dependence between commodity and stock markets is time-varying and becomes unambiguously stronger with the global financial crisis. In the paper, we assume that the relationship between the agricultural commodities, including sugar and financial market uncertainty, changes structurally during the crisis periods.

Polcela et al. [35] show that financial market uncertainty plays an important role in determining short-run changes in non-energy raw material prices. Based on a factor-augmented vector autoregression, they reveal that an increase in the S&P 500 option-implied volatility index (VIX) leads to a decrease in non-energy commodity prices for 2 months. Gozgor et al. [36] found that the VIX Index has no significant effect on commodity returns in the pre-crisis period, including sugar. However, Huchet and Gueye Fam [37]

demonstrated a positive correlation between the VIX Index and selected soft commodities over the period of 1998 to 2013. Silvennoinen and Thorp [5] studied the relationship between the United States' stock market and commodity prices, including sugar, and found that regime changes in that relationship were observed even before the financial crisis, i.e., in 2001 and 2003. For sugar and cotton, the highest correlation with stock prices occurs during the most recent decade, when the VIX Index exceeded its average. Moreover, Delatte and Lopez [34] find that relationship between commodity and stock markets became unambiguously stronger with the global financial crisis after fall 2008.

We investigate the relationship between financial market uncertainty and commodity prices on the example of sugar. The world sugar market is one of the most rapidly developing [38], oscillating between surpluses and deficits [39]. The global sugar market is highly fragmented, and price levels and volatility differ across various national markets, mainly due to governmental protectionist measures. However, Kuzmenko et al. [38] revealed mutual interaction between selected stock exchanges and confirmed long-term equilibrium. Global sugar prices are recognised as highly volatile [40]; the volatility stems from the economic and physical characteristics of the sugar markets [41,42], as well as various support measures that benefit the subsector [43]. However, the international sugar agreement dissolution (1983) had a large impact on volatility, which resulted in an overnight drop in international sugar price by 38% [44]. Over the decades, price volatility has caused difficulties in developing commodity-dependent countries, possibly resulting in inequality, poverty, country vulnerability, and environmental degradation [18,44,45].

The paper aims to assess potential structural changes in the relationship between sugar prices and the financial market uncertainty in a crisis time. In more detail, using a sequential Bai–Perron test for structural breaks, we check whether the global financial crisis and COVID-19 pandemic induce the structural breaks in that relationship.

Our contribution is to supplement the research debate by evaluating the impact of increased financial market volatility induced by the global financial crisis and the COVID-19 pandemic on sugar prices. To our knowledge, there are no other studies that analyse changes in that relationship properties, particularly in the time of the novel coronavirus pandemic. An additional merit of our paper is that apart from the S&P 500 option-implied volatility index (VIX), we verify our study's robustness by supplementing our analysis with the additional measure of the financial market uncertainty, i.e., the S&P 500 Realized Volatility Index, developed by Oxford-Man Institute of Quantitative Finance.

2. Methodology and Data

This paper investigates the existence of structural changes in the relationship between sugar prices and financial market uncertainty. Babirath et al. [32] conclude that during the outbreak of the financial crisis in 2007, sugar served as a hedge against falling equity markets, while it did not serve as a hedge during the coronavirus pandemic. The above-mentioned leads to the question of whether global financial crisis and the COVID-19 pandemic impacted both markets identically through structural changes.

To achieve the main aim of the study, we build two research hypotheses:

- The global financial crisis has induced structural changes in the relationship between sugar prices and the financial market uncertainty;
- The COVID-19 pandemic has caused structural changes in the relationship between sugar prices and the financial market uncertainty.

In the research, sugar prices are represented by the S&P GSCI Sugar Index. The index belongs to the group of S&P Dow Jones sub-indices, and measures the sugar commodity market performance. It is considered a reliable and publicly available benchmark for investment in sugar. Moreover, it is designed to be a tradable index accessible to financial market participants. Moreover, the S&P GSCI Sugar Index reflects general price movement and inflation in the global economy, which enhances its suitability as a benchmark [46].

As a measure of the financial market uncertainty, we use the S&P 500 option-implied VIX. Additionally, to verify the research results, we apply the realized volatility of the S&P 500 in our analysis.

The VIX Index was introduced by Whaley in 1993 [47], and is computed on a real-time basis throughout each trading day. The VIX is a forward-looking index of the expected return volatility of the S&P 500 index over the next 30 days. It is implied from the prices of the S&P 500 index options, which are predominantly used by the market as a means of ensuring the value of stock portfolios [48]. The VIX Index is widely used as a barometer for market uncertainty, providing market participants and observers with a measure of the U.S. stock market's expected volatility. The VIX Index, as a proxy of global uncertainty, was validated by many studies [49].

The S&P 500 Realized Volatility Index data come from the Oxford-Man Institute of Quantitative Finance. The Oxford-Man Institute's "Realized Library" [50] contains daily non-parametric measures of how volatile the most popular stock market indices and assets were in the past, including the S&P 500 index. It should be stressed that realised volatility measures are not volatility forecasts. The institute uses the data from the Thomson Reuters DataScope Tick History database. The realised volatility of the S&P 500 index for a given day t refers to the square root of the sum of squares of 5 min log-returns during the day [51].

Christensen and Prabhala [52] found that implied volatility outperforms realized volatility in the financial market analyses, as it subsumes the information content of both past and expected future volatility. Thus, we apply the S&P 500 option-implied volatility index (VIX) as a main measure of the financial market uncertainty, and we use the S&P 500 Realized Volatility Index as a side measure to strengthen the validity of research results. Both above-mentioned financial market uncertainty measures are based on the S&P 500 index, the most popular benchmark for financial markets [53].

The research period covers the daily data on the S&P GSCI Sugar Index, the VIX Index, and the S&P 500 Realized Volatility Index since 3 January 2000 until 30 November 2020.

A regression model with a sequential Bai–Perron test for structural breaks was applied to identify structural changes in the relationship between the S&P GSCI Sugar Index and financial market uncertainty. Bai and Perron [54,55] proposed a sequential method that starts by testing for the existence of a single break date. The null hypothesis states that there is no structural break. If the null hypothesis is rejected, the sample is split into two subsamples. The sequence test is carried out until each subsample test fails to find evidence of a structural break. Identifying the time of the structural change allows researchers to get insight into the analysed problem. The classical test for structural change was introduced by Chow [56]. Hansen distinguished two main disadvantages of the Chow test [57]. First of all, the Chow test may be uninformative, because the true break date can be missed. Moreover, the Chow test may be misleading when the test indicates a break date when in fact, none exists. It is believed that a better approach to finding proper breakpoints is to treat the break date as an unknown parameter. This idea was developed by Quandt [58] and Andrews [59]. Moreover, Dufour [60] and Bai and Perron [54,55] extended Chow's test and have proposed a new test that detects multiple structural changes.

Based on Bai and Perron [54,55,61], we consider the following standard linear regression with t periods, m potential breaks (breakpoints), and j potential regimes ($m + 1$):

$$Y_t = X_t' \beta + Z_t' \delta_j + u_t \quad (1)$$

at time t for $j = 1, \dots, m + 1$. In the model (1), Y_t is the observed dependent variable at time t , X_t refers to a matrix of p regressors with regime invariant parameters, Z_t is a matrix of q regressors whose parameters vary between regimes, β and δ_j ($j = 1, \dots, m + 1$) are the corresponding vectors of coefficients, and u_t is the disturbance term at time t .

Bai and Perron [55,61] proposed the sup F type test of no structural break $m = 0$ vs. $m = k$ breaks, where F test statistics is defined as follows:

$$F_T(\mathfrak{I}_1, \dots, \mathfrak{I}_k; q) = \frac{1}{T} \left(\frac{T - (k+1)q - p}{kq} \right) \delta' R' (R \hat{V}(\hat{\delta}) R')^{-1} R \hat{\delta} \quad (2)$$

where $\hat{\delta}$ refers to the optimal k break estimate of δ , and R is a conventional matrix, such as that $\delta' R' = (\delta_0' - \delta_1', \dots, \delta_k' - \delta_{k+1}')$. $\hat{V}(\hat{\delta})$ is an estimate of the covariance matrix of $\hat{\delta}$ robust to serial correlation and heteroscedasticity. In addition,

$$V(\hat{\delta}) = p \lim_{T \rightarrow \infty} T \left(\bar{Z}' M_X \bar{Z} \right)^{-1} \bar{Z}' M_X \Omega M_X \bar{Z} \left(\bar{Z}' M_X \bar{Z} \right)^{-1} \quad (3)$$

where $M_X = I - X(X'X)^{-1}X'$, and $\bar{Z}$ is the matrix that diagonally partitions Z For each m -partition $(T_1, \dots, T_m)$.

$$\sup F_T(k; q) = F_T(\mathfrak{I}_1, \dots, \mathfrak{I}_k; q) \quad (4)$$

where $(\mathfrak{I}_1, \dots, \mathfrak{I}_k)$ minimizes the total sum of squared residuals under the specified trimming, i.e., equivalent to maximizing the F -test assuming spherical errors. However, this procedure is much simpler to construct than maximizing the F -test (2).

We applied the Bai–Perron sequential test with structural breaks. The simulation results show [62] that sequential testing performs much better than the information criteria methods proposed by Liu et al. [63] and Yao [64].

In the paper, we employ a regression model with Bai–Perron structural breaks with t periods, m potential breaks (breakpoints), and j ($m + 1$) potential regimes (5):

$$S_t = \alpha + \delta_j FMU_t + u_t \quad (5)$$

where the dependent variable (S_t) is sugar prices, FMU_t is an independent variable that reflects the financial market uncertainty, i.e., the S&P 500 option-implied volatility index (VIX) or the S&P 500 Realized Volatility Index, α and δ_j are the corresponding vectors of coefficients, and u_t is the disturbance term at time t . Parameter α is assumed to be non-breaking, while δ_j varies between j potential regimes. We do not include in the model (5) independent variable X_t whose parameters are regime invariant.

Parameter δ_j in model (5) reflects potential changes in direction, strength, and statistical significance of the relationship between sugar prices (S_t) and financial market uncertainty (FMU_t).

Taking into account the changes in the financial markets, including the financialisation of agricultural commodities, we expect the existence of structural breaks in the analysed relationship between the S&P GSCI Sugar Index and the VIX Index, as well as the existence of structural breaks in the relationship between the S&P GSCI Sugar Index and the S&P 500 Realized Volatility Index.

3. Sugar Market Review

The international trade of sugar is becoming the main income source for many economies, whose economic stability is thus dependent on global sugar prices. As an important agricultural and food commodity, sugar is highly integrated into many developing and less developed economies. As regional sugar markets create a single price organism [38], unpleasant events on one market can affect global price. Today, highly volatile sugar prices not only have global significance, but determine many individuals' livelihoods. Sugar-rich commodities, such as sugar cane and sugar beet, are still important cash crops. Sugar cane is expected to provide income for about a hundred million people worldwide [65]. Sugar production in developed countries (including those in the European Union (EU)) is minor in relation to sugar production in developing countries. Developing countries account for 76% of global sugar production [66], and are expected to increase

before 2027. Leading regions like Asia, Latin America, and the Caribbean will be accompanied by Africa, where the output will be driven by strong domestic demand for sugar and trade opportunities. It is argued that sugar cane cultivation supports many countries' development and social needs, including those in Sub-Saharan Africa [67].

The volatility of world sugar prices is explained by the nature of supply response to price changes resulting from the high fixed costs of sugar production [68]. In 2000–2020, the sugar markets were under pressure several times (Figure 1). Peaks were observed in the first quarter (1Q) of 2006, 1Q of 2010, 1Q and third quarter (3Q) of 2011, and the fourth quarter (4Q) of 2016. Bottoms were seen in the 1Q of 2000, second quarter (2Q) of 2002, 2Q of 2004, 2Q of 2007, 3Q of 2015, 3Q of 2018, and 2Q of 2020. Compared to food price volatility, sugar prices tend to be more volatile, with more extreme up and downs. However, prices do not reflect the situation of the global stock markets. About 80% of sugar is still traded in direct contracts out of the global stock markets [69,70]. Therefore, sugar price is rather determined by market fundamentals as supply and demand. Taylor [68] argued that the sugar price follows an opposite relationship with the stocks-to-use ratio, which reflects the global situation in demand and supply. When stocks are high, prices tend to be low. Among stocks, supply is further dependent on sugar price in the previous period and acreage of sugarcane [71]. The sugar price peak of 2006, the largest increase since 1997, was mainly caused by the global oil crisis and the use of alternative fuels as bioethanol and fall in the U.S. dollar (USD) exchange rate. Low prices in 2007 were caused by increased production among exporting nations [68]. High production costs, growing ethanol use in Brazil, and policy-induced production swings among Asian countries [72] affected the 2010 peak sugar price. After 2014, the stock-to-use ratio increased and explained the fall of sugar prices in 2014 and 2015 [68]. However, poor production years in 2016 and 2017 resulted in low stock levels with strong prices [73].



Figure 1. Food and Agricultural Organization of the United Nations (FAO) food price index and sugar price index for 2000–2020. Source: authors' own elaboration based on FAO [74].

Recently, the international sugar price has been under pressure since 2017. Main determinants are record production in Brazil, favourable weather conditions in Thailand and India, the end of production quotas in the European Union (September 2017), and area expansion in China [75]. After the sugar price increase in the 2Q of 2019, the price indicated by the Food and Agricultural Organization of the United Nations (FAO) was already trending downward in early 2020, even before the COVID-19 crisis, mainly due to the situation in the crude oil market [76]. According to a sugar industry journal, in late February 2020 sugar prices increased to values last seen in August 2017, due to insufficient supply expectations. However, after the first reports on the coronavirus outbreak, the price drop was followed by unsuccessful oil talks between Russia and Saudi Arabia [76].

COVID-19 demand and supply shock further decreased prices, and consequently, farm revenues observed by the WTO (World Trade Organizations) [77].

The COVID-19 outbreak has strengthened negative-demand side effects that have impacted commodity prices [78]—for example, meat prices have decreased by 7–18% and dairy products by 4–7%. Similarly, the novel coronavirus pandemic also affects the international situation with sugar, impacting sugar industry stakeholders and its integrated industries worldwide [77]. Prices of vegetable oils and sugar were affected the most, according to the FAO price index [77]. The important decline in prices has been observed among biofuels, whose price has fallen strongly [78], causing difficulties for American (decreasing by USD 10 bn) and Brazilian markets [79]. However, after the sharp drop in prices of early 2020, in the second half of the year, funds started to rebuild their long-term positions in sugar futures, indicating optimism among fund financial managers [80].

Global sugar consumption was affected by the pandemic. The sugar industry's entire value chain, including sugarcane/sugar beet, sugar, molasses, ethanol, and their subsequent marketing and export, has been adversely affected by the spill-over impacts [81]. In many countries, sales of durable food items (sugar, flour, cookies, and convenience food) soared due to panic shopping [82]. For example, French sugar retail sales increased by 50%, 27%, and 13% in March, April, and May respectively. However, the United States Department of Agriculture (USDA) expected that increased in-house sugar consumption could not fully compensate for lost eating-out sugar consumption in the EU [83]. The report also does not anticipate changes in the EU food industry's sugar demand [83].

In Brazil, low gasoline prices are negatively affecting the dynamics of the Brazilian sugar/ethanol industry [84], and sugar consumption is down by 6% relative to the original expectations due to general gross domestic product (GDP) slowdown [84]. In India, a long-lasting national lockdown affected mostly the hospitality (HORECA) sector, which accounts for about 65% of India's sugar consumption [81].

Global expectations of sugar demand effects vary. Solomon et al. [81] expect an Indian decrease in consumption of between 1.0–1.5 million tonnes. Rabobank [85] expects demand to lower by 1.7 million tonnes; F.O. Licht predicted global consumption to decrease by 1.2 million tonnes by the end of July [86], while in September the EU estimated lower global consumption by 2.7 million tonnes [87], resulting in higher EU sugar stocks (700,000 higher in July compared to the previous year).

Quarantine (of confirmed COVID-19 cases) leads to overeating and emotional eating of mostly food rich in salt, fats, and sugar [75]. An Italian sample proved that people consumed desserts, chocolate, and ice cream excessively during the pandemic [76]. Simultaneously, eating home cannot fully compensate for food consumed when eating out, which is mostly high in sugar [83], as the consumption of savoury snacks, snacks, and carbonated and sugary drinks has decreased [88]. Social distancing and global-spread quarantine measures have negatively harmed global sugar demand [81,82,85,87]. As indicated above, unexpected global events, such as global pandemics, have an impact on global sugar markets.

4. Research Results and Discussion

This paper investigates the structural changes in the relationship between sugar prices and financial market uncertainty, measured by the VIX Index. We consider the two most severe global crises periods in the 21st century, namely the global financial crisis and the COVID-19 pandemic. We distinguished four sub-periods to assess the 6 month periods preceding and following the global financial crisis and the COVID-19 pandemic. As the global financial crisis starting point, we have chosen the day of the Lehman Brothers bank's bankruptcy, i.e., 15 September 2008. Similarly, 30 January 2020, the day the WHO declared the novel coronavirus SARS-CoV-2 a public health emergency of international concern, has been selected as the start of the COVID-19 epidemic. Descriptive statistics presented in Table 1 imply that mean and median sugar prices during crisis periods were lower than in pre-crisis periods, while mean and median VIX levels were higher during crisis

periods than in pre-crisis terms. That might indicate the existence of a negative relationship between sugar prices and financial market uncertainty. We investigate whether the above-mentioned relationship is statistically significant, and there are potential structural changes in that relationship particularly induced by the crisis.

Table 1. Descriptive statistics: S&P Sugar Index and the VIX Index daily data for 2000–2020.

Index	Period	Mean	Median	Min	Max	Standard Deviation	Coefficient of Variation (%)
S&P GSCI Sugar	Full period (3 January 2000–30 December 2020)	146.204	134.630	50.840	371.680	61.520	42.08
	Pre-global financial crisis announcement period (15 March 2008–14 September 2008)	130.524	132.265	100.210	149.370	12.599	9.65
	Post-global financial crisis announcement period (15 September 2008–14 March 2009)	129.214	126.530	111.260	153.160	9.927	7.68
	Pre-COVID-19 announcement period (31 July 2019–29 January 2020)	133.337	132.635	115.470	154.320	9.904	7.43
	Post-COVID-19 announcement period (30 January 2020–30 July 2020)	124.767	123.265	98.740	160.040	16.216	13.00
	Full period (3 January 2000–30 November 2020)	19.922	17.595	9.140	82.690	8.924	44.80
VIX	Pre-global financial crisis announcement period (15 March 2008–14 September 2008)	22.052	21.565	16.300	32.240	2.838	12.87
	Post-global financial crisis announcement period (15 September 2008–14 March 2009)	50.956	47.560	30.300	80.860	11.048	21.68
	Pre-COVID-19 announcement period (31 July 2019–29 January 2020)	15.024	14.135	11.540	24.590	2.708	18.03
	Post-COVID-19 announcement period (30 January 2020–30 July 2020)	34.710	31.775	13.680	82.690	14.396	41.48

Source: authors' own calculations based on Refinitiv Datastream data.

Table 1 shows that sugar prices have been characterised by the high volatility, particularly in the time of COVID-19. The coefficient of variation equals 13%, compared to 7.68% in the first phase of the global financial crisis. Interestingly, the mean and median VIX levels in the novel coronavirus crisis period were about 50% lower than in the 15 September 2008–14 March 2009 period, but almost twice as volatile.

For 2020, the development of uncertainty and sugar price is depicted in Figure 2. Concerning the VIX Index, Altig et al. [89] present various uncertainty measures that all show huge uncertainty jumps in reaction to the pandemic. At the same time, most indicators reach their highest values on record. As a result of the COVID-19 pandemic, the VIX Index rose from 14 to values close to around 83 points, also the highest in recent history [90]. The peak value of the VIX Index was recorded in March 2020. However, the VIX Index volatility increased even before the global pandemic was announced (11 March 2020). The VIX Index uncertainty growth started during the weekend of 22–23 February 2020, as the index increased from a pre-weekend value of 17.08 to 25.30 on that Monday. From this perspective, the COVID-19 pandemic announcement by the World Health Organization was not the starting point for global uncertainty. Concerning the sugar price evolution, immediately after the abovementioned weekend, the sugar price stagnated. A fall in the sugar index value, opposite VIX development, was further strengthened at the beginning of March by the crash in oil production negotiations between the Russian Federation and Saudi Arabia on 8 March 2020—the sugar–oil relationship has been widely observed [91]. The above-mentioned leads us to the question of whether the COVID-19 pandemic, likewise the global financial crisis, has led to changes in the relationship between sugar prices and financial market uncertainty, which could be identified by a structural break.

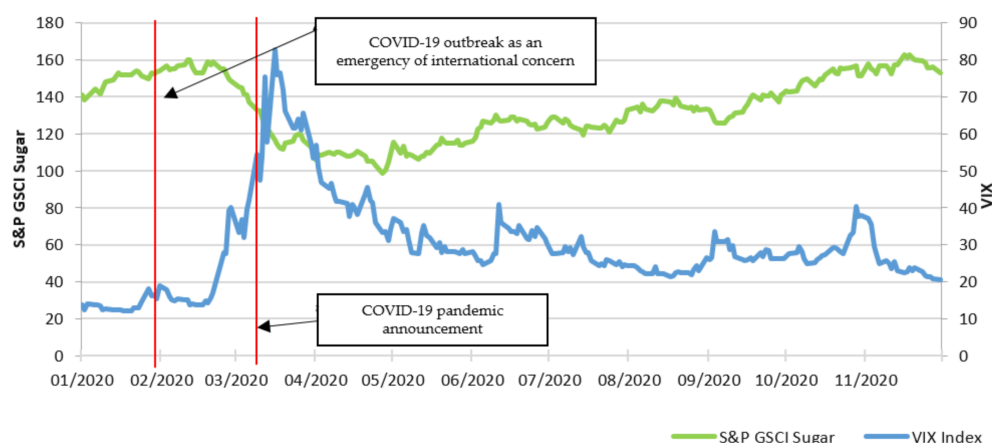


Figure 2. The S&P GSCI Sugar Index and the VIX Index between 2 January 2020—8 October 2020. Source: authors' own elaboration based on Refinitiv Datastream data.

Structural changes in the relationship between the S&P GSCI Sugar Index and the VIX Index are identified based on the regression model (5) with the Bai and Perron structural break sequential test. Considering that the slope coefficient δ represents the relationship between S&P GSCI Sugar and the VIX Index, we tested whether the parameter δ changed during the sample period. We assume that the intercept α is non-breaking. The model is built for the first differences of the logarithmic values of the analysed time series. The series are stationary. Table 2 displays the estimated F -statistic, Bai–Perron critical values, and break dates.

Table 2. Bai–Perron sequential test results for the S&P GSCI Sugar Index and the VIX Index.

Break Test	F -Statistic	Critical Value *	Break Date
S&P GSCI Sugar Index vs. VIX Index			
0 vs. 1	14.8911	8.58	23 September 2008
1 vs. 2	38.6522	10.13	8 December 2011
2 vs. 3	7.3529	11.14	-

* Bai–Perron [61] critical values for significance level 5%. Source: authors' own calculations based on Refinitiv Datastream.

The sequential Bai–Perron test reveals two breakpoints: 23 September 2008 and 8 December 2011. A null hypothesis of three breakpoints ($m = 3$) cannot be rejected for a 5% significance level (F -statistic equals 7.36 and is lower than the critical value of 11.14). As we suspected, the global financial crisis caused structural change in the relationship between sugar prices and financial market uncertainty. However, surprisingly, the novel coronavirus pandemic has not induced the statistically significant structural change in that relationship.

Figure 3 depicts the analysed relationship in 2000–2020. Yellow vertical dashed lines indicate the expected structural changes in the relationship, i.e., 15 September 2008 (crash of Lehman Brothers) and 30 January 2020 (WHO announced COVID-19 international concerns). Red vertical lines indicate structural changes obtained based on the sequential Bai–Perron test.

The results in Table 3 present the estimated coefficients of model (5) for the S&P GSCI Sugar Index and the option-implied VIX. Based on the of the sequential Bai–Perron test results presented in Table 2, we distinguished two breakpoints. Thus, the regression model with structural breaks (5) has three regimes. From 2000 until the beginning of the global financial crisis, the relationship between the sugar prices and the expected stock market volatility (VIX) was insignificant. This proves that there was no link between the above-mentioned variables. However, the 2008–2009 crisis substantially changed the

situation. The collapse of the Lehman Brothers bank hit the financial markets and caused a rapid growth of market uncertainty. Investors moved their funds from equity to other asset classes, including commodities [32]. Capital movement from portfolio investments to agricultural commodities resulted in price pressure, as noted above. Extreme events are rare, and their occurrence is unexpected. Thus, it is difficult to prepare and cope with them. However, the risk of extreme price events can intensify social risks, such as human development, food security, and political stability [92].

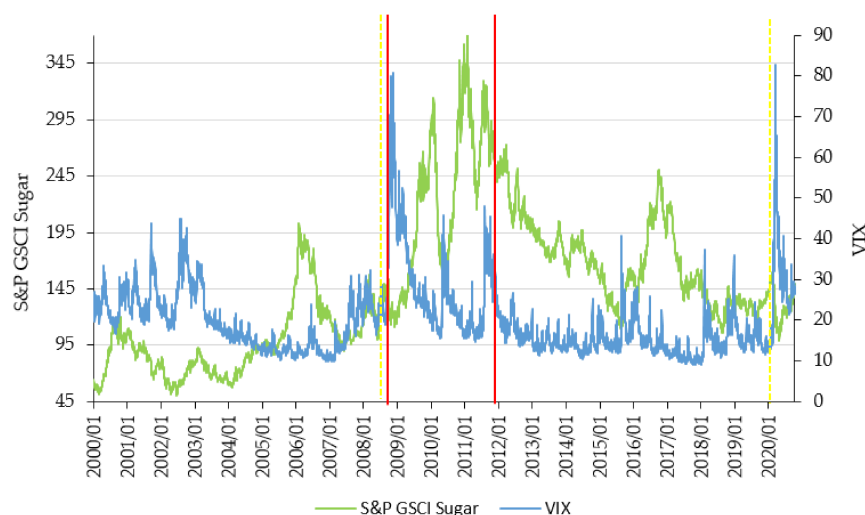


Figure 3. The S&P GSCI Sugar Index and the VIX Index between 3 January 2020–30 November 2020. Source: authors’ own elaboration based on Refinitiv Datastream data.

Table 3. Regression model (5) with sequential Bai–Perron test for structural breaks for the S&P GSCI Sugar Index and the VIX Index.

Parameter	Estimated Coefficient	Std. Error	T-Test Statistics	p-Value
3 January 2000–22 September 2008				
δ	0.0011	0.0072	−0.1561	0.8760
23 September 2008–7 December 2011				
δ	−0.0883	0.0091	−9.1344	0.0000
8 December 2011–30 November 2020				
δ	−0.0179	0.0052	−3.4210	0.0006
non-breaking variable				
α	0.0002	0.0003	0.5839	0.5593

Source: authors’ own calculations based on Refinitiv Datastream data.

The results in Table 3 show that since 23 September 2008, the relationship between sugar prices and stock market uncertainty changed into significant and negative. The second break is close to the 2011 VIX spike, caused by renewed fears about a slowing global economic recovery due to “policy errors” in the United States and Europe [86]. However, the 2011 break does not change the direction of the relationship, as only the regression coefficient decreases. Between September 2008 and December 2011, we observe high uncertainty during the era of relatively high sugar prices. Between 23 September 2008 and 7 December 2011, the mean S&P GSCI Sugar price equalled 225.4 and VIX equalled 28.7. In general, VIX values above 30 indicate that investors are worried [93]. For the period between September 2008 and December 2011, the estimated coefficient δ was defined as −0.0883. These results are in line with Jebabli et al. [57], as well as Karyotis and Alijani [58], who observed volatility spill-over to food and agricultural commodities. Since 2011, the

relationship has still been negative and statistically significant, but weaker (coefficient δj decreased from -0.0883 to -0.0179). Surprisingly, the COVID-19 pandemic did not increase the strength of dependence; during the pandemic period, the coefficient δj has not increased and not reached values similar to those in regime 2, i.e., during the global financial crisis. However, it should be noted that during the novel coronavirus pandemic, this relationship has still been negative and statistically significant, indicating that the enormous increase in uncertainty about financial markets was accompanied by a fall in sugar prices.

To verify our analysis's robustness, we supplemented the study with a different measure of the financial market uncertainty, i.e., the S&P 500 Realized Volatility Index, in order to check whether the test results are coherent with the above-presented analysis for the S&P 500 option-implied volatility index (VIX).

We applied the sequential Bai–Perron test to investigate structural breaks in the relationship between sugar prices and the S&P 500 realized volatility (RV). The regression model with structural breaks (5) also has three regimes with two breakpoints: 28 August 2008 and 10 November 2011 (Table 4). The obtained results confirm the test results for the VIX Index and indicate the structural change in the relationship between sugar prices and financial market uncertainty driven by the global financial crisis. The results in Table 5 present the estimated coefficients of model (5) for the S&P GSCI Sugar Index and the S&P 500 Realized Volatility Index. For the period between August 2008 and November 2011, the estimated coefficient $\delta = -0.0054$, and after November 2011, the coefficient δ decreased to a lower value (-0.0008), remaining statistically significant at the 10% significance level. The novel coronavirus pandemic has not changed the relationship mirrored by structural break analogously for the VIX's results.

Table 4. Bai–Perron sequential test results for the S&P GSCI Sugar Index and the S&P 500 Realized Volatility Index.

Break Test	F-Statistic	Critical Value *	Break Date
S&P GSCI Sugar Index vs. S&P 500 Realized Volatility Index			
0 vs. 1	8.8874	8.58	29 August 2008
1 vs. 2	31.3864	10.13	10 November 2011
2 vs. 3	1.5929	11.14	-

* Bai–Perron [61] critical values for a significance level of 5%. Source: authors' own calculations based on Refinitiv Datastream and Oxford-Man Institute of Quantitative Finance data.

Table 5. Regression model (5) with sequential Bai–Perron test for structural breaks for the S&P Sugar Index and the S&P 500 Realized Volatility Index.

Parameter	Estimated Coefficient	Std. Error	T-Test Statistics	p-Value
4 January 2000–28 August 2008				
δ	-0.0002	0.0005	-0.2993	0.7647
29 August 2008–9 November 2011				
δ	-0.0054	0.0007	-7.6306	0.0000
10 November 2011–30 November 2020				
δ	-0.0008	0.0004	-1.9018	0.0573
Non-Breaking Variable				
α	0.0002	0.0003	0.6096	0.5421

Source: authors' own calculations based on Refinitiv Datastream and Oxford-Man Institute of Quantitative Finance data.

The S&P Sugar Index was tested alone by a Bai–Perron structural break sequential test. The test did not reveal any structural break for the sugar price itself (F -statistic = 1.85 and critical value = 8.58). This implies that structural breaks do not result from the changes in sugar prices themselves, but from structural changes in the relationship between sugar prices and financial market uncertainty.

Based on the model with a sequential Bai–Perron test, we have not observed any unexpected change in the regression model's parameters as an effect of the COVID-19 pandemic. This pandemic character is determined by a combination of multiple problems [91], and therefore comparison to other historical events is not relevant. However, we can say that the interactions between market volatility and sugar price did not change under COVID circumstances. It should be emphasized that there is a catalogue of other factors influencing the world sugar prices' volatility. Among market fundamentals, those include (1) cost of production in the largest sugar-producing countries (Brazil and India) related to exchange rate parity; (2) medium-term supply and demand imbalances and the effects of unanticipated events [94]; (3) the price of other determining commodities, such as crude oil [32]; and (4) weather patterns, which are crucial short-term market drivers [80].

The challenge for future research is to explore the investigation of the relationship between sugar price volatility and the S&P 500 option-implied volatility index (VIX) by applying the test proposed by Chang and McAleer [95], and also to investigate the volatility spillover effect from commodities, including sugar, to the stock market, as in Candila and Farace [96]. Moreover, further studies conducted for longer time series covering the COVID-19 pandemic period might provide different results and verify our findings' robustness.

5. Conclusions

We assessed structural changes in the relationship between sugar prices and financial market uncertainty in crisis times. We focused on two main crisis periods in the 21st century: the global financial crisis and the COVID-19 pandemic. During both the global financial crisis and the novel coronavirus pandemic, sugar prices were on average lower than in the pre-crisis periods. On the other hand, lower sugar prices were accompanied by increased S&P 500 option-implied volatility index (VIX) levels. Moreover, sugar prices were characterised by the high volatility, particularly in the time of the COVID-19 pandemic, when the coefficient of variation was 70% higher than in the first phase of the global financial crisis. Furthermore, the average VIX levels in the novel coronavirus time were about 50% lower than during the global financial crisis, but almost two times more volatile.

The sequential Bai–Perron test results reveal two structural breaks in the relationship between sugar prices and the VIX Index in the 2000–2020 period. As we suspected, the first breakpoint was linked to the global financial crisis outbreak. The second structural change in that relationship occurred in December 2011. However, surprisingly, the COVID-19 pandemic has not induced the statistically significant structural change in the relationship between sugar prices and the financial market uncertainty. Based on the regression model with Bai–Perron structural changes, we show that from 2000 until the beginning of the global financial crisis, the relationship between the sugar prices and financial market uncertainty was insignificant. Nevertheless, the 2008–2009 crisis substantially changed the situation. It led to structural change and a statistically significant and negative relationship between the S&P GSCI Sugar Index, and the S&P 500 option-implied volatility index changed to become significant and negative. Since 2011, the relationship has still been negative and statistically significant, but weaker. Surprisingly, the COVID-19 pandemic has not increased the strength of dependence. However, during the novel coronavirus pandemic, the enormous increase in uncertainty on financial markets was accompanied by a fall in sugar prices. To verify our analysis's robustness, we supplement the study with a different measure of the financial market uncertainty, i.e. the S&P 500 Realized Volatility Index. The obtained results confirm test results for the VIX Index, and do not reveal COVID-19 driven structural change in the relationship.

The challenge for future research is to explore the investigation of the relationship between sugar price volatility and the financial market uncertainty by applying additional tests, and to investigate the volatility spillover effects between the sugar market and the financial market. It is worth indicating that further studies conducted for longer time series covering the COVID-19 pandemic period might provide different results and verify of our findings' robustness.

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