Safe-Haven Properties of Soft Commodities During Times of Covid-19

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Abstract

We use wavelet coherence analysis on global Covid-19 fear index and soft commodities spot and futures prices to investigate safe-haven properties of soft commodities during the period of novel Corona virus pandemic. The results show that staple food soft commodities (wheat, corn, and cocoa) and the futures on corn, cotton and cocoa possess strong positive co-movement with global Covid-19 fear index and can be used as safe-haven assets due to their price resilience during the times of Covid-19 pandemic. However, the non-staple soft commodities do not exhibit this behavior as their consumption is not persistent and consumers switch to healthy foods during the Covid-19 outbreak to boost their immunity against the Covid19.

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1. Introduction

The Covid-19 pandemic rapidly became the global health crisis when the World Health Organization (WHO) declared it a global pandemic. The effect of Covid-19 outbreak on global economies and financial markets is very different compared to other historical shocks (e.g. droughts, financial crisis and floods) because of its unique feature of restrictions on goods movement at local and international levels (e.g., curfews, lockdowns travel bans, border closures) as preventive measures imposed by governments of more than 200 countries to contain the spread of novel Corona virus. These mobility restrictions triggered demand and supply shocks to the commodities market; however, the impact of these shocks during the Covid-19 pandemic differs across different commodities (Rajput et al., 2020). For instance, the energy and metal commodities are directly linked with economic activities and a slowdown of economic activity during the pandemic reduced the prices of these hard commodities since the Covid-19 outbreak (Erken, 2020; Ozili & Arun, 2020). However, the effect of Covid-19 pandemic on soft commodities (grains, cereals, live stocks etc.) is likely to be different in nature due to their persistent use in essential food items. For instance, the lockdowns and mobility restrictions disrupted the food supply chains and triggered the panic in buying and hoarding behavior among consumers during the initial days of Covid-19 pandemic (Benton, 2020; Hobbs, 2020; Prentice, Chen, & Stantic, 2020). The panic in buying behavior of consumers increased the demand of wheat and its byproducts during the initial days of Covid-19 pandemic (Vercammen, 2020). The persistent demand of essential food commodities, restrictions on mobility of these commodities, and panic in buying and hoarding behavior is likely to trigger a resilience in prices of soft commodities through positive shocks to their prices and can make them safe-haven assets during evolving period of Covid-19. This study uses the wavelet coherence approach on six soft commodities, commodities futures and the global

Covid-19 fear index (GFI) as proxy of Covid-19 to investigate safe-haven properties of soft commodities during Corona virus outbreak.

During the Covid-19 outbreak investors want to invest in alternative asset class such as the commodities to diversify their portfolios, as they perceive that drivers of commodity prices are different from traditional assets. Most of the existing studies (Bodie & Rosansky, 1980; Conover, Jensen, Johnson, & Mercer, 2010; Daskalaki, Skiadopoulos, & Topaloglou, 2017) support the view that investors can achieve diversification benefits by including commodities in their portfolios. These studies compared the portfolio returns of traditional assets using the position of mean-variance efficient frontiers with portfolio returns including commodities and find that inclusion of commodities result in an upward shift of efficient frontier examined using the in-sample analysis.

Some studies (Adams & Glück, 2015; Daskalaki & Skiadopoulos, 2011; Lombardi & Ravazzolo, 2016; Main, Irwin, Sanders, & Smith, 2018; Ohashi & Okimoto, 2016; Silvennoinen & Thorp, 2013) identified that financialization of commodities increased the integration of commodities markets and financial markets which reduced the diversification potential of commodities. For example, Daskalaki and Skiadopoulos (2011) and Skiadopoulos (2012) identified some weaknesses of using Markovitz efficient frontier setting for comparing the portfolio performance as it violates the assumptions of normality of returns and measurement of investors preferences through quadratic utility functions. Further, the use of in-sample approach provides biased results for measuring the diversification benefits as investors evaluate the investment returns using out of the sample approach. Daskalaki and Skiadopoulos (2011) investigate the diversification benefits of commodities by forming the optimal portfolios using higher-order moments of portfolio returns distribution and measure the out-of-sample performance using different proxies. They find that commodities did not provide diversification benefits for commodity investors. Lombardi and

Ravazzolo (2016) also investigated the correlation between the commodity and equity returns using the time-varying Bayesian Dynamic Conditional Correlation approach and find that investors cannot hedge the risks by including the commodities in their investment portfolio. Alternatively, in a recent study, Daskalaki et al. (2017) extended their earlier study by the construction of optimal portfolios in both in-sample and out-of-sample without considering the assumptions regarding the normality and investors preferences using the non-parametric stochastic dominance efficiency approach to point out that adding commodities into portfolios provides the significant diversification benefits specially using the commodity indices.

Although, the impact of Covid-19 pandemic on commodities market is still evolving and a relatively longer data horizon can provide a better picture of the commodity market behavior during Covid-19, many existing studies already explored the effects of uncertainties regarding Covid-19 on commodities market (Bakas & Triantafyllou, 2020; Bouri, Shahzad, Roubaud, Kristoufek, & Lucey, 2020; Ezeaku & Asongu, 2020; Rajput et al., 2020; Salisu, Akanni, & Raheem, 2020; Wang, Shao, & Kim, 2020). These existing studies explored different properties of industrial and soft commodities using different methodological approaches. For instance, Bakas and Triantafyllou (2020) investigated the impact of world pandemic uncertainty index (WPUI) on the volatility of commodity price index (S&P GSCI broad commodity index) and sub-indices of gold and crude oil using vector autoregression (VAR) models. They find that pandemic uncertainty has negative and significant effect on commodity market as a result of lower demand during the pandemic times. Gharib, Mefteh-Wali, and Jabeur (2020) explored the causal relationship between gold spot prices and crude oil during the Covid-19 outbreak using the time-varying granger causality approach. They used the WTI crude oil and gold prices from 4th January 2010 to 4th May 2020 to document a contagion effect of bubbles in gold and oil market during the Covid-19 pandemic. Rajput et al. (2020) discussed the changes in commodities prices during Covid-19 pandemic. They conclude that the oil and metal commodities are mostly affected by Covid-19 due to a reduction in demand and economic activities, while agricultural commodities are least affected as they are indirectly related to economic activities.

Some studies also looked at effect of Covid-19 on soft commodities. For instance, Wang et al. (2020) studied cross-correlations between agricultural futures and crude oil before and after the beginning of Covid-19 pandemic. They applied the multi-fractal detrended cross-correlation method to find that cross-correlations of agricultural futures increased after the beginning of Covid-19 outbreak. Salisu et al. (2020) constructed global Covid-19 fear index (GFI) at the global level to test the prediction power of GFI in commodities market. They used common correlated effects method on the data of 24 commodities, commodity-related volatility indices, and GFI over the period from 11th March 2020 to 18th May 2020. Their results show a positive and significant relationship between commodity price returns and GFI, which supports the view that commodities can be used as a safe-haven asset during the Covid-19 pandemic. In addition, their results also suggest that GFI is a better measure of Covid-19 fear among investors in the commodity market as compared to other proxies. Ezeaku and Asongu (2020) captures only the initial phase of evolving effects of Covid-19 cases to document resilience of soft commodities (grains and cereals) towards uncertainty regarding Covid-19 pandemic. They find that the soft commodities maintained strong and upward trend during the Covid-19 and are more resilient as compared to raw materials, oil, natural gas, precious metals, timber and beverages.

The existing literature examined the safe-haven properties of different commodities using models developed by Baur and Lucey (2010) and Baur and McDermott (2010). However, these existing models by Baur and Lucey (2010) and Baur and McDermott (2010) are used to study the long-term safe-haven properties for commodities and are not suitable to investigate the short-term effects of Covid-19 outbreak because of their inability to capture time and frequency domains simultaneously. Some recent studies show that the safe-haven properties of commodities are time-varying (Dutta, Das, Jana, & Vo, 2020; Shahzad, Bouri, Roubaud, Kristoufek, & Lucey, 2019; Zhang, Hu, & Ji, 2020). As a result, some studies used the rolling-window (Bouri, Lucey, & Roubaud, 2020) , DCC-GARCH approach (Akkoc & Civcir, 2019; Dutta et al., 2020; Li & Lucey, 2017; Lucey & Li, 2015) and bivariate cross-quantilogram approach (Corbet, Katsiampa, & Lau, 2020; Shahzad et al., 2019) to investigate the time-varying safe-haven properties; but, these approaches overlooked the frequency domain to the data. Consequently, some studies (Maghyereh & Abdoh, 2020; Naeem, Hasan, Arif, Balli, & Shahzad, 2020; Rehman & Vo, 2020) proposed the use of quantile cross-spectral coherency approach of Baruník and Kley (2019) to consider the frequency dependencies but this approach fails to capture the time and frequency characteristics simultaneously. Motivated by these findings and usefulness of time and frequency characteristics of wavelet coherency approach to study the safe-haven properties of commodities during shorter horizon leads us to use the wavelet coherency approach to consider both time and frequency characteristics of soft commodities.

Some studies investigated the safe-haven properties of commodities futures as investors wants to minimize risks during the Covid-19 crisis by investing in commodities through futures contracts. The existing studies (Gorton & Rouwenhorst, 2006; Ji, Zhang, & Zhao, 2020; Su, Qin, Tao, & Zhang, 2020) reported the use of commodity futures to hedge risks in trading of both soft and hard commodities. However, the hedging characteristics of commodity futures vary across different investment horizons (Fernandez, 2008; Geppert, 1995). For instance, Bredin, Conlon, and Potì (2015) investigated the safe-haven properties of gold over short and long term horizon using wavelet analysis using gold futures. They find that gold act as a hedge for equity and debt markets for the investment horizons up to one year. Bekiros, Boubaker, Nguyen, and Uddin (2017) investigated the hedging and safe-haven characteristics of gold futures and emerging market stock indices using multi-scale wavelet method and find that the time-scale co-movement patterns in gold and stock markets are more prominent in short to medium investment horizons but they do not find evidence in support of safe-haven characteristics of gold. Ming, Zhang, Liu, and Yang (2020) examined the hedge and safe-haven properties of gold futures and Chinese CSI 300 index and find that gold act as safe haven asset when market returns are low, and this relationship fluctuates with policy changes.

Some recent studies also discussed the safe-haven properties of soft commodities. For instance, Kang, McIver, and Yoon (2017) investigated the return and volatility spillover effects among crude oil, precious metals, and agricultural markets using multivariate GARCH model to find evidence in support of safe-haven characteristics of gold futures. Babirath et al. (2020b) studied the safe-haven properties of sugar futures by comparing it with 2007-2008 global financial crisis and Covid-19 pandemic. They find that sugar futures do not act as the hedge or safe-haven during the Covid-19 pandemic. Further, Ji et al. (2020) investigated the safe-haven characteristics of gold, cryptocurrencies, commodities and foreign exchange futures during the Covid-19 pandemic using cross-quantilogram approach. Their findings support the view that gold and soybean commodity futures act as safe-haven assets during the Covid-19 pandemic. The existing studies shows that inclusion of commodities futures offers diversification benefits for investors because of negative correlation with equities (Conover, Jensen, Johnson, & Mercer, 2009; Conover et al., 2010; Gorton & Rouwenhorst, 2006). To contribute to the ongoing discussion on the behavior of commodities during Covid-19, this study uses the wavelet coherence approach to investigate the safe-haven properties of soft commodities and commodities futures to consider time-varying investment strategies of investors in the commodities market during Covid-19 pandemic.

Our wavelet coherence analysis shows a strong positive co-movement between GFI and soft commodities prices (wheat, corn, cotton and cocoa) during the initial 50 days of Covid-19 outbreak; however, the co-movement turns to negative during the last 20 days of Covid-19 outbreak. Moreover, and corn, cotton and cocoa futures show positive co-movement with Covid-19 pandemic. These findings show that during the initial days agricultural commodities display higher flexibility and prices of these commodities did not fall during the Covid-19 pandemic. This finding suggests that soft commodities can be used as safe-haven assets during the worst times of Covid-19 pandemic using the GFI as proxy of Covid-19. The safe-haven characteristic is particularly prominent in the commodities that are essential and persistent ingredients of staple foods. Our results are important for asset managers in the soft commodities market and suggest that investors can invest in soft commodities during life threating type of global pandemics, as these commodities are resilient to the pandemic due to positive shocks to their prices during the Covid-19 crisis.

The rest of the paper is organized as follows: Section 2 presents the data and research methodology. Section 3 reports the results, and Section 4 concludes the paper.

2. Data and Research Methodology

2.1.The Data

The daily data of the closing prices of soft commodities (wheat, corn, cotton, cocoa, coffee and sugar)[1] and daily settlement prices of commodity futures contracts are downloaded from Datastream database for the period from 27th January 2020 to 3rd September 2020. The data of soft commodities are available for five trading days in a week. The choice of six commodities is motivated by the fact that these commodities and their byproducts, with the exception of cotton which is not a food item but its byproducts are used for extraction of oil, fish feed, livestock and fertilizer, are heavily used as basic ingredient in preparation of food products in most of the countries around the globe and are likely to be widely affected by demand and supply shocks during the Covid-19 pandemic. The data of Covid-19 global new reported cases and global new reported deaths is collected from Covid-19 data repository developed by Roser, Ritchie, Ortiz-Ospina, and Hasell (2020).

Table 1 displays the descriptive statistics of the variables used in this study. The average global Covid-19 fear index is 59.24%, which shows a high fear related to Covid-19 during the times of the study. The kurtosis of global Covid-19 fear index is 3.39, which shows a close normality of the index. The average prices of all commodities (wheat, corn, cotton, cocoa, coffee and sugar) are positive with positive skewness for most of the commodities, while kurtosis values of all commodities are less than three suggesting a non-normal behavior of these commodity prices.

[1] The authors also looked at the daily rice prices to include into the study, but the prices are not available from different databases. Although, monthly prices for rice and other food items are available from world bank and, food and agriculture organization databases but these prices do not suffice to our requirements.

Table 1: Descriptive Statistics					
Variables	**Obs.**	**Mean**	**Std.Dev.**	**Skew.**	**Kurt.**
GFI	159	59.2497	16.9732	0.9925	3.3997
Wheat	159	5.5216	0.3553	0.6325	2.8543
Corn	159	3.2664	0.2896	0.8011	2.2802
Cotton	159	55.9119	4.991	-0.2884	2.5052
Cocoa	159	2339.379	197.0431	0.7541	2.7366
Coffee	159	101.0566	9.9361	0.0316	2.033
Sugar	159	12.2335	1.4451	0.3165	2.2804

Notes: The GFI is global Covid-19 fear index and wheat, corn, cotton, cocoa, coffee and sugar are the prices of soft commodities.

2.2.Construction of global Covid-19 fear index

For measuring the effect of Covid-19 on soft commodities, we follow Salisu and Akanni (2020) and construct the GFI, that is used to study the spread and severity of Covid-19 pandemic. For the construction of GFI, Salisu and Akanni (2020) use reported cases index and reported deaths index after considering the incubation period[2](two weeks duration between catching the infection and appearance of symptoms). The first component of GFI, the reported cases index (RCI), shows how far people's expectations on reported cases in incubation period (14 days) deviate from current cases and is computed as follows:

$$RCI_t = \frac{\sum_i^N c_{i,t}}{\sum_i^N (c_{i,t} + c_{i,t-14})} \times 100 \tag{1}$$

Where i= 1, 2,...,N; t=1,2,…,T; and RCI_t is global Covid-19 reported cases index for time t; $\sum_i^N c_{i,t}$ presents the total global Covid-19 reported cases at time t; $c_{i,t-14}$ is the total global Covid-19 reported cases at the beginning of the incubation period (14^{th} day lag). Finally, the multiplication by 100 provides the RCI index ranging from 0 to 100 in which the higher (lower) values indicate a higher (lower) level of fear.

[2] https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---3-march-2020

The second component of GFI is reported deaths index (RDI), which measures how far the people's expectations from reported deaths in the incubation period (14 days) changes from current deaths. The RDI is computed as follows:

$$RDI_t = \frac{\sum_i^N d_{i,t}}{\sum_i^N (d_{i,t} + d_{i,t-14})} \times 100 \tag{2}$$

Where i= 1, 2,...,N; t=1,2,…,T; and RDI_t is global Covid-19 reported deaths index for time t; $\sum_i^N d_{i,t}$ represents total global Covid-19 reported deaths at time t; $d_{i,t-14}$ is the total global Covid-19 reported deaths at the beginning of the incubation period (14^{th} day lag). Finally, the multiplication by 100 provides the RDI index ranging from 0 to 100, which shows the higher (lower) values indicate higher (lower) level of fear.

The GFI is the composite of new reported cases and deaths on a scale of 0 to 100 and is constructed as follows:

$$GFI_t = [0.5(RCI_t + RDI_t)] \tag{3}$$

Where i= 1, 2,...,N; t=1,2,…,T; RCI_t is global Covid-19 reported cases index for time t; RDI_t is global Covid-19 reported deaths index for time t and GFI_t is global Covid-19 fear index constructed by equally weighting the RCI and RDI indices. The higher value of GFI represents extreme fear, and lower index value shows the absence of fear or panic regarding Covid-19. The GFI uses both the numbers of new reported cases and deaths to make one composite index instead of focusing on both components individually and covers both dimensions that could be related to measuring the severity of fear regarding Covid-19 pandemic.

2.3. Research Methodology

The investors in the commodities markets differs in various aspects (i.e., risk profiles, beleifs, expectations and information sets). For instance, the speculators and market makers are high frequency traders and institutional investors falls in the category of low frequency traders.

The existing studies applied the fourier transform approach to investigate the relationship between variables at different frequencies. But the fourier transformation ignores the time variation which makes it difficult to distinguish the transient relations from structural changes. The consideration of structural changes is important to investigate the macroeconomic variables but fourier transformation did not provide consistent results. Moreover, the the stationarity of the time series is also required for fourier transformation approach which is not fulfilled in most of macroeconomic variables.

To solve the issues in fourier transform, Gabor (1946) introduced the short-term fourier transform approach to consider the time-dimension. In this method, Gabor (1946) divides the time series into sub-samples and apply the fourier transform to each sub-sample. However, the short term fourier transform does not capture the time and frequency variations simultaneously.

The wavelet method was introduced to solve the above issues which considers the change in time series over time and periodic components (frequencies). The wavelet method have several advantages over fourier transformation approach. First, in the wavelet method the widow size adjusts according to longer basis founctions at low frequencies and vice versa. Hence, this new method simultaneously captures the relationship between the soft commodities and GFI across time and frequencies.

Given that wavelet coherency approach is useful to study the short term co-movements of soft commodities and GFI by considering both the time and frequency domains simultaneously, we investigate the save-haven properties of soft commodities using this approach. The next sub-section sheds light on the details of wavelet methodology.

2.3.1. Wavelet Coherence

Torrence and Compo (1998) define the cross-wavelet transform of two time series variables x(t) and y(t) using their cross-wavelet transforms (CWT) W_n^x(u, s) and W_n^y(u, s) as presented below in Equation 4;

$$W_{x,y}(u,s) = W_x(u,s)W_y^*(\mathrm{u, s}) \tag{4}$$

Where $W_x(u,s)$ and W_y^*(u, s) are continuous wavelet transforms of two time series variables x(t) and y(t) respectively. Here 'u' is position index, 's' shows the scale and '*' sign displays the complex conjugate. The wavelet transform captures the local covariance between two time series variables.

The wavelet coherence approach by Torrence and Compo (1998) can calculate the cross-wavelet power to show the areas with higher covariance between time series variables at each scale. The wavelet coherence is used to show the time regions in which co-movement in time series variables is present but may not have high wavelet power. Further, Torrence and Webster (1999) extended the study of Torrence and Compo (1998) by including the the squared wavelet coherence coefficient which is defined in the following Equation 5:

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W_{x,y}(u,s)\right)\right|^2}{S(s^{-1}|W_x(u,s)|^2)S\left(s^{-1}\left|W_y(u,s)\right|^2\right)} \tag{5}$$

Where *'s'* is smoothing operator over time and space and squared wavelet coefficient is in the range of 0≤ *R2(u,* s) ≤ 1 Rua and Nunes (2009). As noted, the definitions closely resemble to the traditional correlation coefficient and without smoothing coherency this is identically 1 at all scales. We further write the smoothing operator 's' in time and frequency space.

$$S(W) = S_{Scale}(S_{time}(w_n(s))) \tag{6}$$

Where S_{Scale} is smoothing along the wavelet scale axis and S_{time} shows the smoothing across time.

The higher wavelet squared coherence values $R^2(u,$ s) means higher the co-movement between the two variables and vice versa. For instance, in our study, the high co-movement between the soft commodities and GFI shows the strong relationship between these variables and vice versa. The wavelet squared coherence is restricted to positive values within the range of 0 to 1 and so, a difference between negative and positive co-movements in two time series cannot be made. To deal with this issue, Torrence and Compo (1998) and Grinsted, Moore, and Jevrejeva (2004) suggest to use the phase difference, which use the difference between positive and negative co-movements between two time series.

The phase difference is defined in the following Equation 7:

$$\phi_{x,y}(u,s) = tan^{-1}\left(\frac{lm\{S(s^{-1}W^{xy}(u,s))\}}{Re\{S(s^{-1}W^{xy}(u,s))\}}\right) \tag{7}$$

Where, *lm* and *Re* are the imaginary and the real parts of smoothed cross-wavelet transform respectively. The black arrows in the wavelet coherence plot display the phase differences. The arrows pointing towards right (left) side shows that time series are in-phase (out-of-phase), where in-phase (out-of-phase) means positive (negative) correlation between two time series variables.

The upward (downward) pointing of arrows shows that the first (second) series leads the second (first) series by π/2. The phase difference of zero means both time series are moving together.

We also used the Monte Carlo simulations to test the statistical significance at each scale by generating the large number of data pairs. The statistical significance at 5% level is indicated by black line in wavelet coherence plots.

3. Empirical Results

We start our empirical analysis with a graph showing co-movements between soft commodities spot prices and global Covid-19 fear index in Figure 1. In the figure, we can observe that prices of the essential food items (wheat, corn, cotton and cocoa) remain stable during the Covid-19 pandemic as compared to non-essential food items (coffee and sugar). Particularly sugar prices are reduced during the Covid-19 crisis.

Figure 1: Soft Commodities Prices and Global Covid-19 Fear Index (GFI)

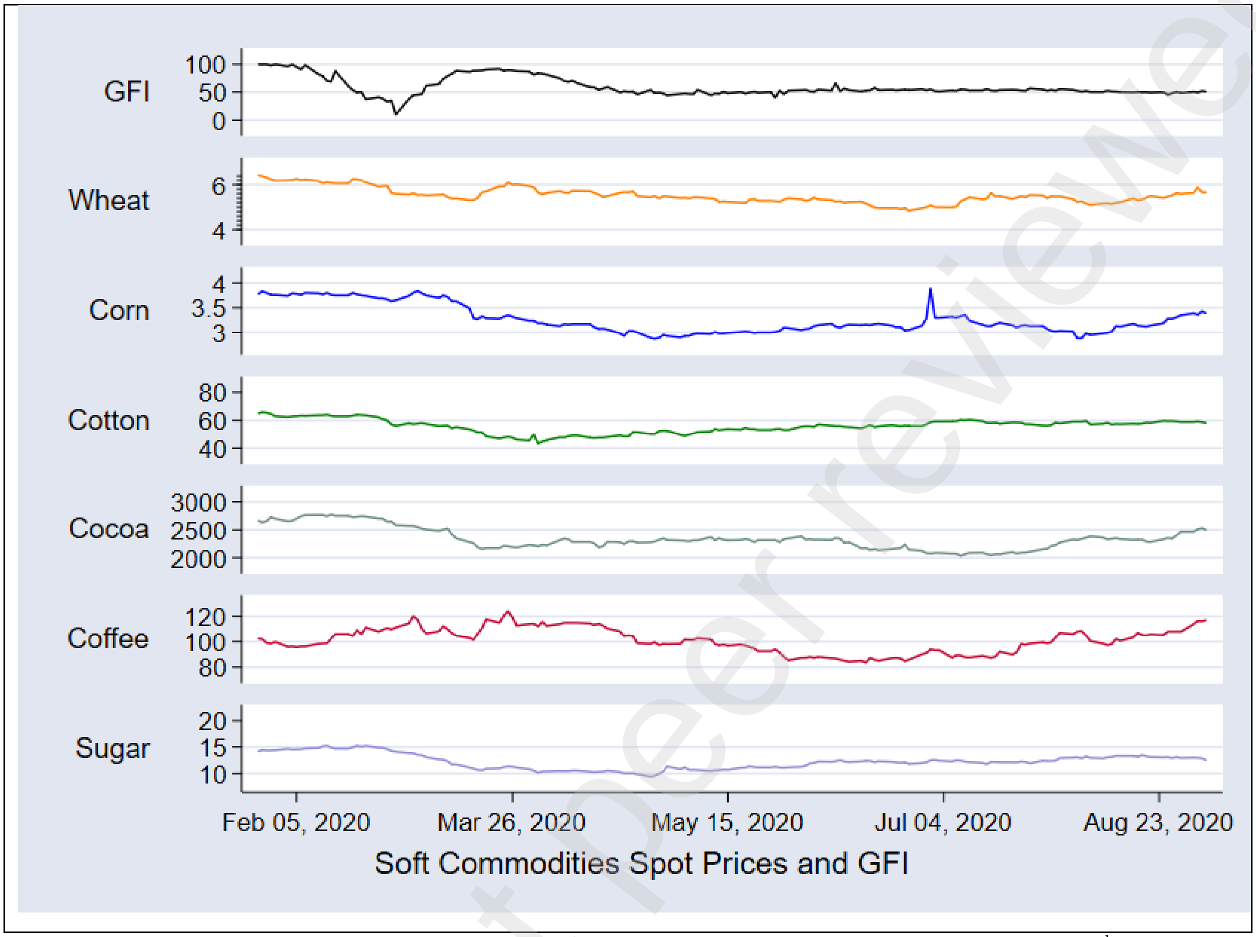


Figure 1: Closing prices of soft commodities and global Covid-19 fear index (GFI) from 27th January to 3rd September, 2020. The closing prices of soft commodities are presented on vertical axis and time period is displayed on horizontal axis of Figure 1.

3.1. Commodities Spot Prices and GFI

This section reports the results of the use of wavelet coherency approach to investigate the co-movement between soft commodities spot prices and GFI as a proxy of Covid-19. Figure 2 displays the wavelet coherency plot of wheat price and GFI. The (↘) direction of arrows in the figure shows the in-phase relationship (positive correlation) between wheat price and GFI during the first 60 days of Covid-19 pandemic, and GFI is leading the wheat prices. The black contours in the figure disclose a positive co-movement significant at 5% level. The comovement is significant at almost all horizons in the figure (at frequencies of 4-days, 4-8 days, 8-16 days and above 32-days). The finding indicates that during the initial days of Covid-19 pandemic the demand of wheat is increased which results in increased wheat price. This finding shows that wheat can be used as a safe-haven asset during the times of Covid-19.

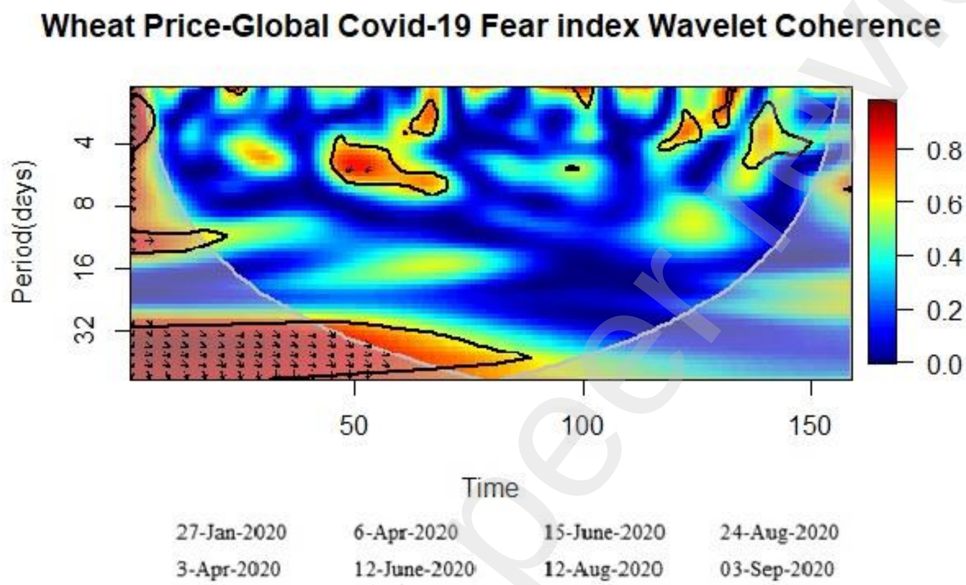


Figure 2 shows the wavelet coherency plots between wheat prices and global Covid-19 fear index, where the horizontal axis shows time in days and the vertical axis displays the period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

Figure 3 displays the wavelet coherency plot between corn price and GFI and reports an in-phase relationship (positive co-movement) during the first 70 days indicated by (↗) direction of arrows. The upward direction of arrows further indicates a leading effect of corn price on GFI. The leading effect of corn shows that the corn prices respond quickly to demand shocks as corn is associated with biofuel production, which is halted during the lockdowns. The black contours show that the co-movement between GFI and corn price is significant at 5% level. These results show that price of corn increased during initial days of the Covid-19 outbreak due to positive shocks to corn prices resulting from increased demand of corn and hoarding behavior of consumers (Hall, Prayag, Fieger, & Dyason, 2020; Vercammen, 2020). Hence, corn prices are resilient to the risk of Covid-19 pandemic and corn can be used as safe-haven asset during the pandemic.

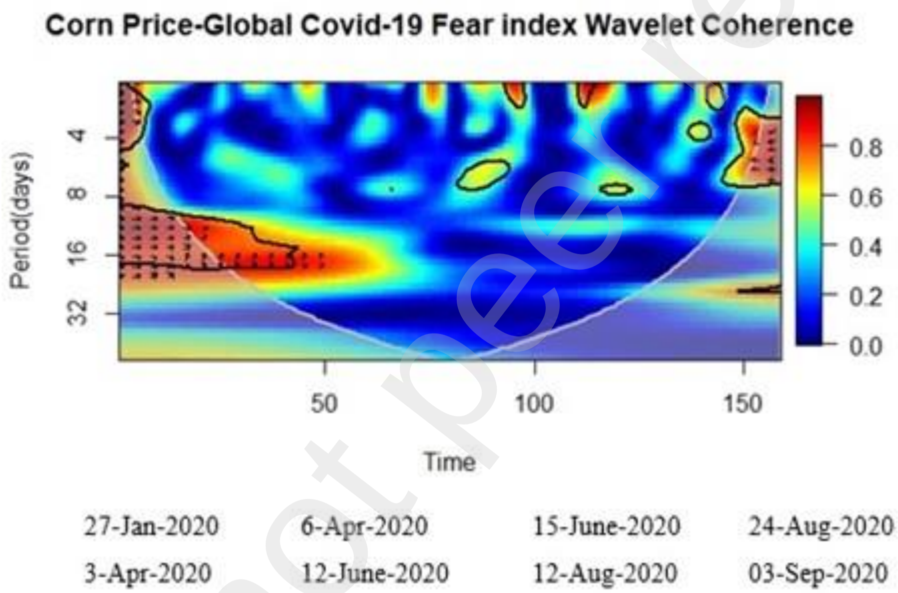


Figure 3 shows the wavelet coherency plots between corn prices and global Covid-19 fear index, where the horizontal axis shows time in days, and the vertical axis shows period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

In Figure 4 we report the wavelet coherency between cotton price and GFI. The black right-directional (↘) arrows at the left bottom of the figure indicate positive co-movement beween cotton price and GFI during the initial 30 days, which turns to negative in the later stage of Covid-

19 pandemic. Further, the downward direction of arrows indicates the leading effect of GFI on cotton price. During the initial days of Covid-19 outbreak the cotton prices decreased due to low global demand but rapidly recovered when restrictions are lifted in China, which is the largest producer of textile products in the world.[3] Our finding suggests that the cotton can be used as a safe-haven asset during the initial days of Covid-19 crisis.

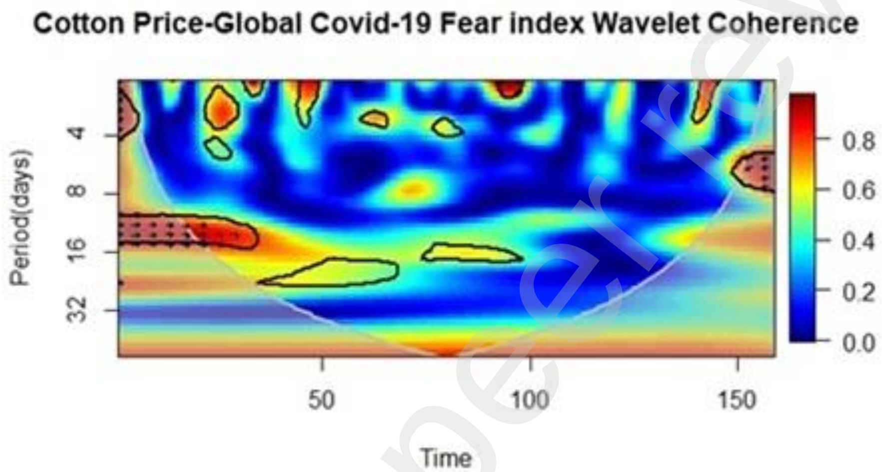


Figure 4 shows the wavelet coherency plots between cotton price and global Covid-19 fear index, where the horizontal axis shows time in days, and the vertical axis displays period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

Figure 5 displays the output plot of the wavelet coherency analysis of the co-movement between cocoa price and GFI. The black contours at the left bottom of the figure show the existence of an in-phase relationship (positive co-movement) between the two variables and the (↘)direction

[3] https://www.iisd.org/system/files/publications/ssi-global-market-report-cotton.pdf

shows the leading effect of GFI on cocoa price. The figure also shows that from 150 days to 169 days, the co-movement turns to negative. Our results show that the stable supply and increase in cocoa demand during the Covid-19 pandemic results in higher price of cocoa. The increased demand is driven by the observation that the consumers use cocoa and its byproduct chocolate for mental well-being and as a result the cocoa market survived during the Covid-19 crisis.[4] The finding supports the view that investors can use the cocoa as safe-haven asset during the Covid-19 pandemic.

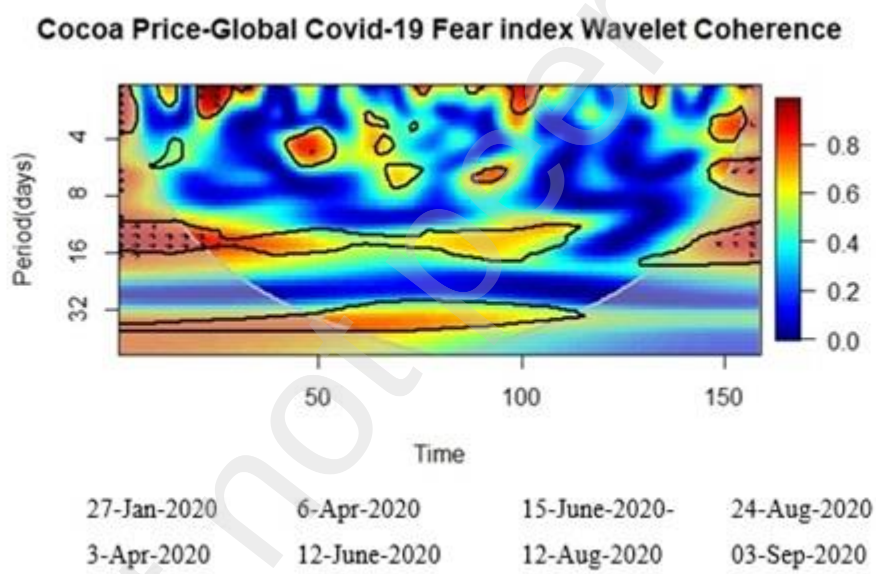


Figure 5 shows the wavelet coherency plots between cocoa prices and global Covid-19 fear index, where the horizontal axis shows time in days and the vertical axis displays period in days. The coherency (correlation) level is displayed by colours on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

[4] https://www.confectioneryproduction.com/news/29630/study-finds-coronavirus-pandemic-has-driven-consumer-drive-for-confectionery-and-snacks/

The wavelet coherency plot of the co-movement between coffee price and GFI is presented in Figure 6. The (↖) direction of arrows displays an out-of-the-phase (negative co-movement) relationship between coffee price and GFI during the initial 30 days of Covid-19, but the co-movement is not strong. The finding is supported by a recent report which indicates that 1% reduction in GDP growth is associated with 0.95% reduction in demand for coffee.[5] The finding is also supported by the fact that coffee is not used as staple food and the lockdowns, and closure of restaurants, hotels and businesses around the globe reduced the demand for coffee and thus the prices of coffee during the Covid-19 pandemic. The result about coffee shows that it cannot act as a safe-haven asset during times of Covid-19.

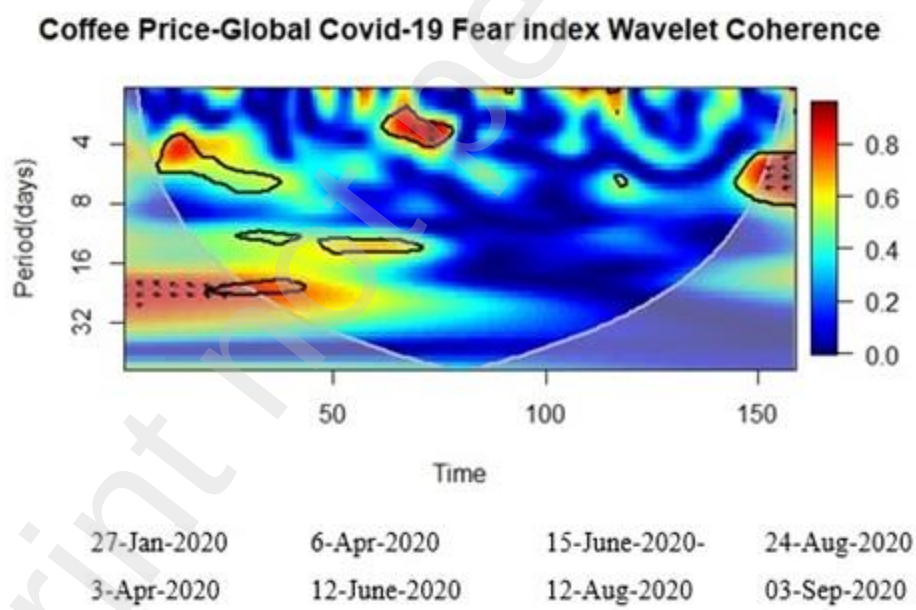
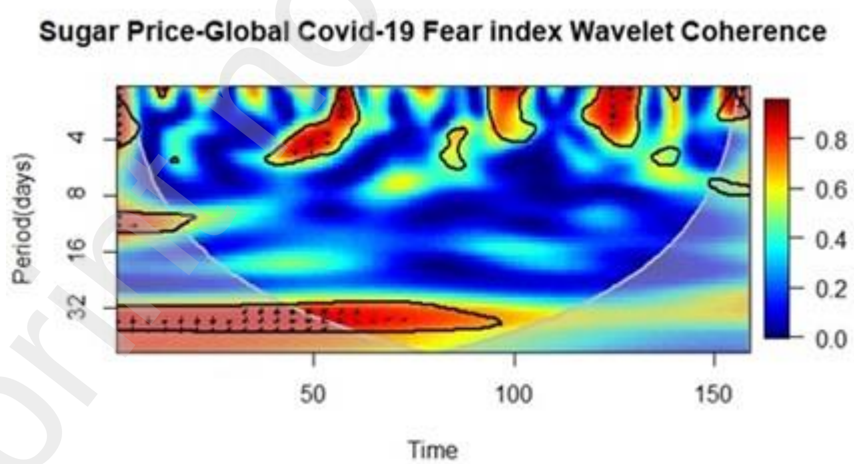


Figure 6 shows the wavelet coherency plots between coffee prices and global Covid-19 fear index, where the horizontal axis shows time in days, and the vertical axis displays period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing

[5] http://www.ico.org/documents/cy2019-20/coffee-break-series-1e.pdf

towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

Figure 7 presents the output plot of the wavelet coherency analysis of the co-movement between sugar price and GFI. The (↖) direction of arrows at the bottom of the figure shows that an out-of-the-phase relationship (negative co-movement) exists between sugar price and GFI and the GFI leads the effect on sugar prices. In addition, the co-movement is strong and consistent across different horizons as clear from different periods on Y-axis. The sugar is used in various food items (i.e. carbonated drinks, confectionaries and dairy products) but this is not staple food. During the Covid-19 pandemic the consumers eating habits changed as they needed an immunity boost against the virus by eating healthy foods (Butler & Barrientos, 2020; Di Renzo et al., 2020) in the absence of Covid-19 vaccine. Hence, during Covid-19 the demand of sugar decreased but the supply didn't change much which resulted in lower sugar prices (Di Renzo et al., 2020). These findings do not support the safe-haven role of sugar during times of Covid-19.



27-Jan-2020	6-Apr-2020	15-June-2020	24-Aug-2020
3-Apr-2020	12-June-2020	12-Aug-2020	03-Sep-2020

Figure 7 shows the wavelet coherency plots between sugar prices and global Covid-19 fear index, where the horizontal axis shows time in days, and the vertical axis displays period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

3.2. Robustness Analysis using Commodity Futures and GFI

For robustness and comparability purposes, we also investigate the co-movement of soft commodities futures with GFI to investigate the safe-haven properties of soft commodities across different investment horizons. Figure 8 shows the wavelet coherency plot of wheat futures and GFI. The (↖) direction of arrows shows the out of the phase relationship (negative correlation) between wheat futures and GFI in different scales with leading effect of wheat futures on GFI. The black contours in the figure disclose a negative co-movement significant at 5% level in different frequency scales. The wheat futures are influenced by uncertainties during the times of Covid-19 hence they cannot be used to diversify the risks regarding the Covid-19 pandemic.

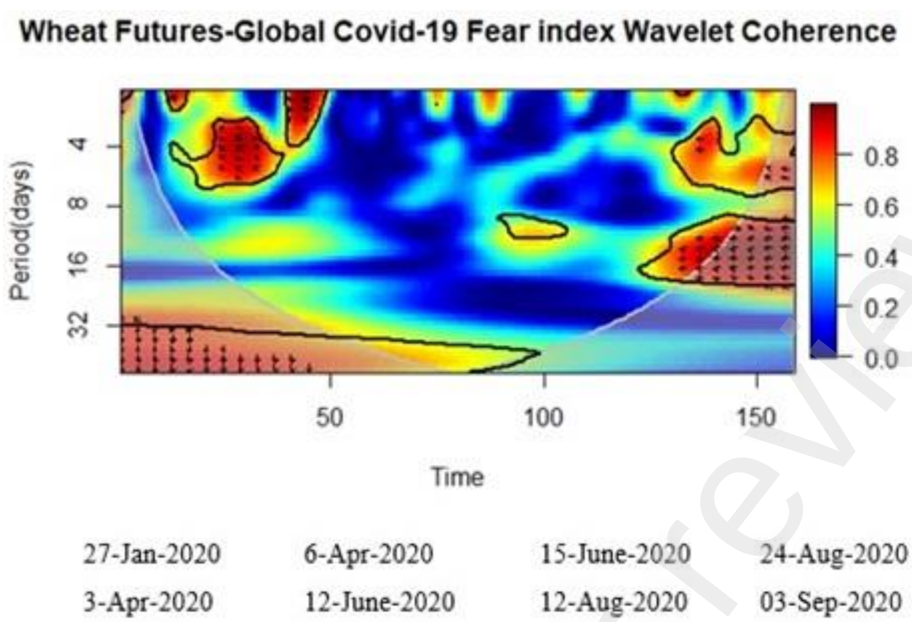


Figure 8 shows the wavelet coherency plots between wheat futures and global Covid-19 fear index, where the horizontal axis shows time in days and the vertical axis displays the period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

Figure 9 displays the wavelet coherency plot between corn futures and GFI and reports an in-phase relationship (positive co-movement) indicated by (↗) direction of arrows in (16-32 days frequency band) with leading effect of corn futures on GFI. However, the co-movement is negative in (8-16 and 40-64 days frequency bands). These results are in line with the results about corn using spot prices suggesting that investors can use corn futures as safe-haven asset during the pandemic.

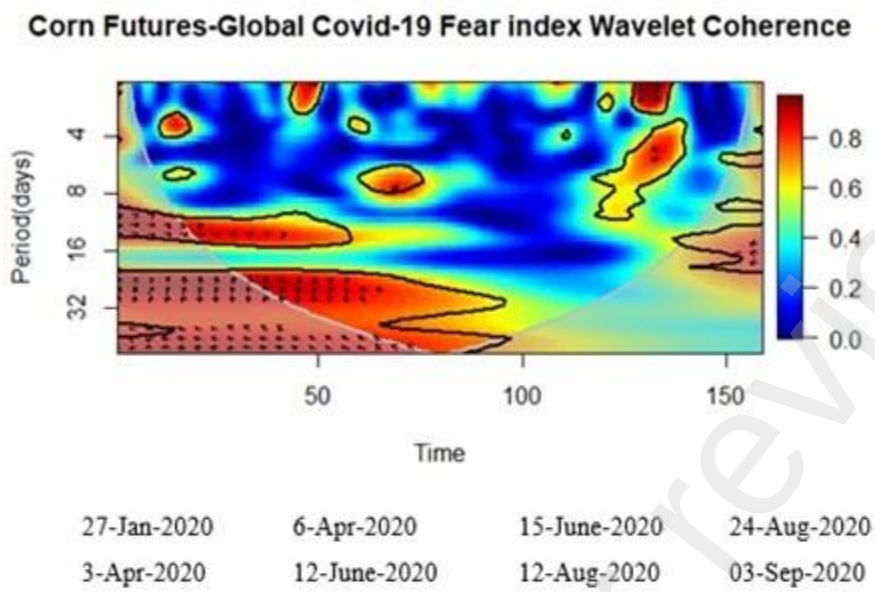
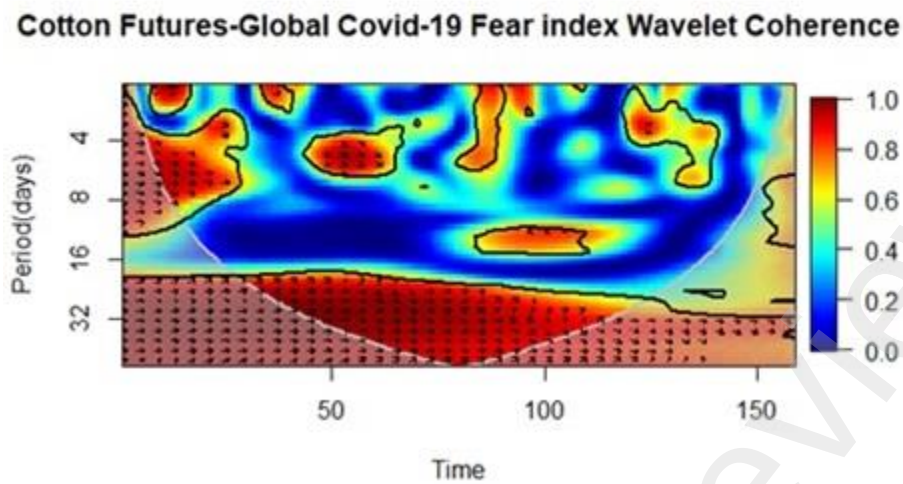


Figure 9 shows the wavelet coherency plots between corn futures and global Covid-19 fear index, where the horizontal axis shows time in days, and the vertical axis shows period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

In Figure 10 we report the wavelet coherency between cotton futures and GFI. The black right-directional (↘) arrows indicate the positive co-movement beween cotton futures and GFI during the Covid-19 pandemic at different frequancies with leading effect of GFI on cotton futures. The positive co-movement shows that investors can use the cotton futures as a safe-haven asset during the Covid-19 pandemic.



27-Jan-2020	6-Apr-2020	15-June-2020	24-Aug-2020
3-Apr-2020	12-June-2020	12-Aug-2020	03-Sep-2020

Figure 10 shows the wavelet coherency plots between cotton futures and global Covid-19 fear index, where the horizontal axis shows time in days, and the vertical axis displays period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

Figure 11 discloses the wavelet coherency output plot for testing the co-movement between cocoa futures and GFI. The black contours at the left bottom of the figure show the presence of an in-phase relationship (positive co-movement) between the two variables and the (↘) direction shows the leading effect of GFI on cocoa price. The finding supports the view that investors can use the cocoa as safe-haven asset during the Covid-19 pandemic.

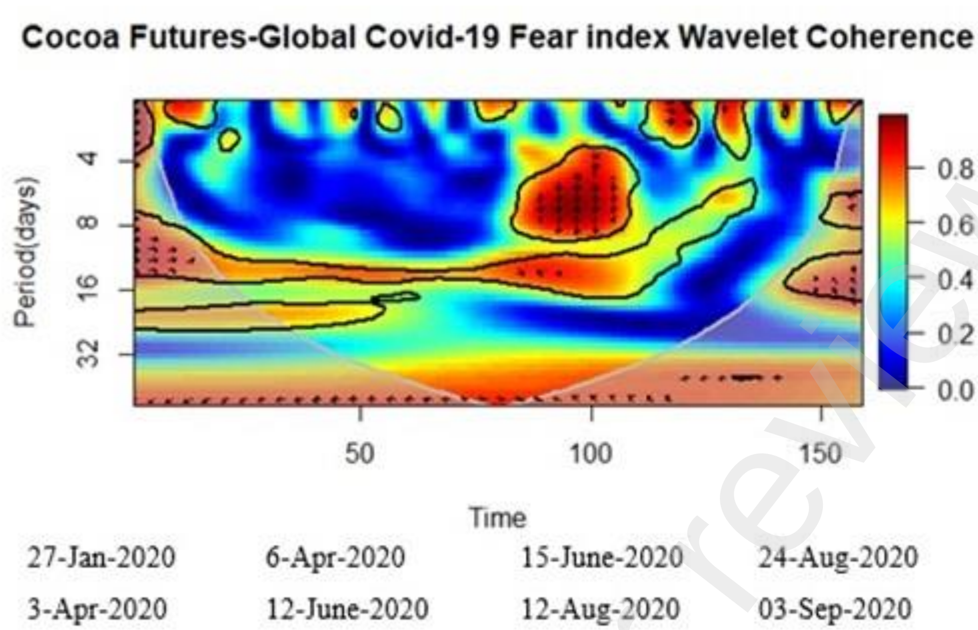


Figure 11 shows the wavelet coherency plots between cocoa futures and global Covid-19 fear index, where the horizontal axis shows time in days and the vertical axis displays period in days. The coherency (correlation) level is displayed by colours on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

The wavelet coherency plot of the co-movement between coffee futures and GFI is presented in Figure 12. The (↘) direction of arrows displays in-phase (positive co-movement) relationship between coffee futures and GFI in 1-4 days investment horizon with leading effect of GFI on commodity futures. However, the co-movement between coffee futures and GFI is not strong in most of the cases. Hence, coffee futures can be used as a safe-haven asset during Covid-19 pandemic.

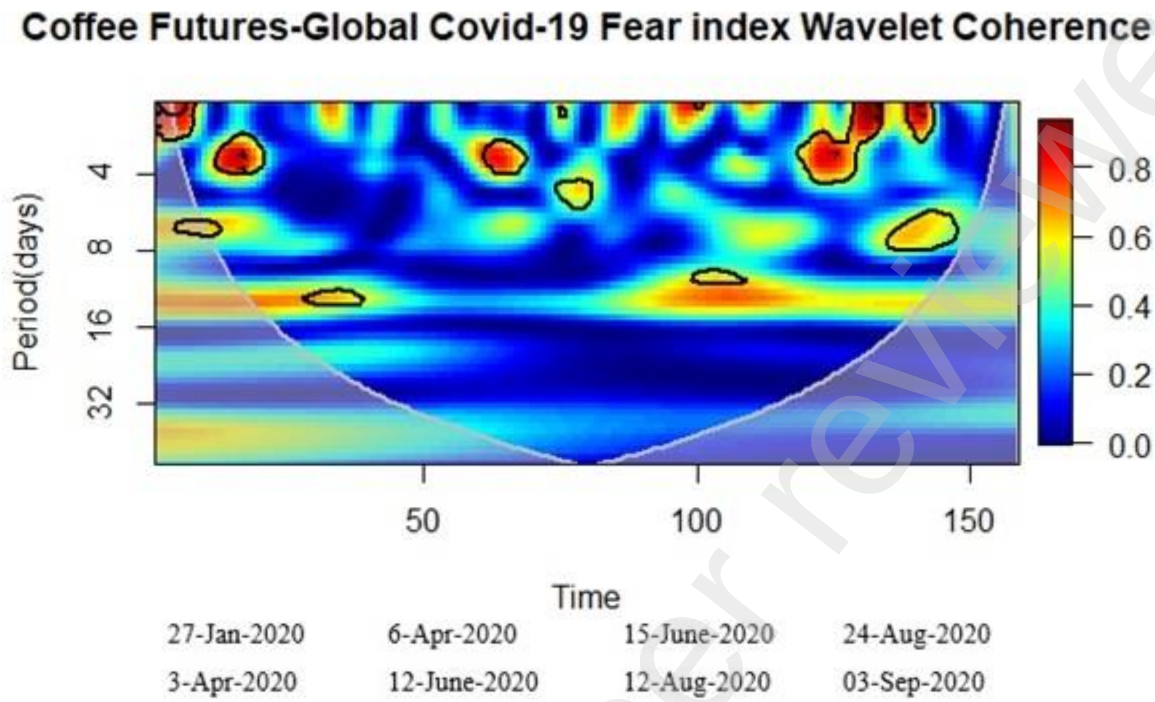


Figure 12 shows the wavelet coherency plots between coffee futures and global Covid-19 fear index, where the horizontal axis shows time in days, and the vertical axis displays period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

Figure 13 presents the output plot of the wavelet coherency analysis of the co-movement between sugar futures and GFI. The (↖) direction of arrows shows that an out-of-the-phase relationship (negative co-movement) exists between sugar futures and GFI and the GFI leads the effect on sugar futures. Moreover, the co-movement is strong and significant in the (8-16 days, 16-32 days and 32-64 days) horizons. The sugar futures did not act as safe-haven asset during the times of Covid-19 which may be due to its higher co-movement with crude oil which affected the sugar futures and our findings are consistent with (Babirath et al., 2020a).

Overall, we find that corn, cotton and cocoa futures act as safe-haven during the Covid-19 pandemic and these results suggest that equity investors can use the soft commodities futures to diversify the risks regarding the Covid-19 pandemic.

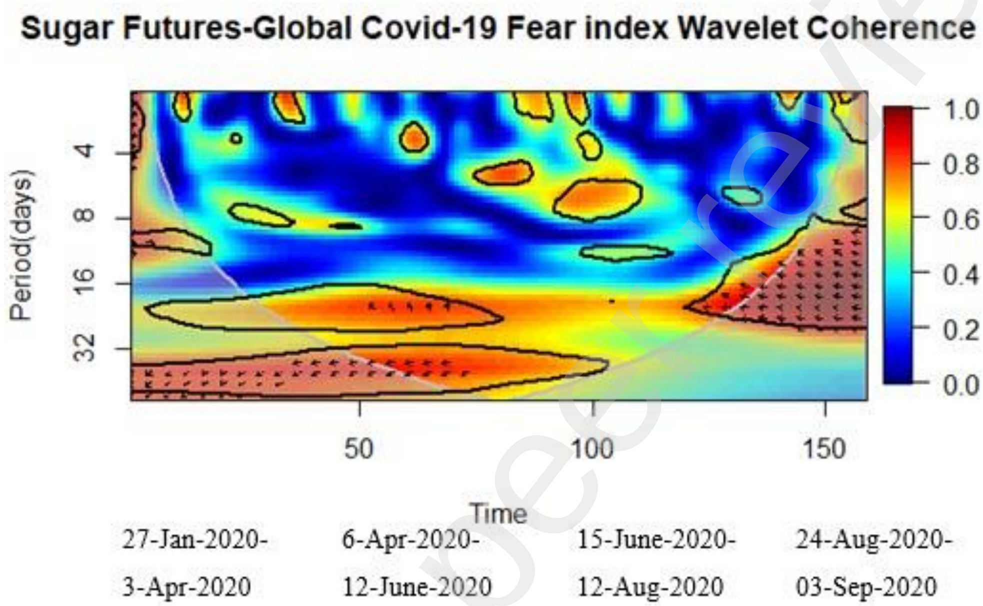


Figure 13 shows the wavelet coherency plots between sugar futures and global Covid-19 fear index, where the horizontal axis shows time in days, and the vertical axis displays period in days. Colours display the coherency (correlation) level on the right side of the main chart; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in coherence plots is the cone of influence, and the black contours in the plots show the regions of significance at 5% level. The phase differences are indicated by arrows, where the arrows pointing towards the right side show an in-phase (positive) relationship and vice versa. The upward(↑) direction of arrows means that the first series leads the second and vice versa.

4. Conclusions

In this study, we explore the co-movement of global Covid-19 fear index, developed by Salisu et al. (2020), and soft commodity prices to trace the safe-haven properties of soft commodities during the Covid-19 pandemic. Our results report a strong positive co-movement between global Covid-19 fear index and soft commodities (wheat, corn, cotton and cocoa) during the initial days of the Covid-19 pandemic when death fear is higher among investors. These results suggest that wheat, corn, cotton and cocoa can be used as safe-haven assets during the Covid-19 as their prices are resilient to the fear of Covid-19 pandemic (Benton, 2020; Rajput et al., 2020; Salisu et al., 2020). Our robustness analysis exhibits that the corn, cotton and cocoa futures can be used as safe-haven assets by investors for different horizons. The risk averse equity investors can diversify by investing in the soft commodities to hedge their portfolios against losses due to Covid-19 crisis.

Overall, our results show that safe-haven properties of soft commodities depend on the nature of the commodities, which is consistent with the view that the intensity of effect of Covid-19 pandemic varies across different commodities due to their link with level of economic activity and consumption patterns (Rajput et al., 2020). The high co-movement between soft commodities spot prices and GFI is present in short-term horizon and co-movement between soft commodities futures is strong in medium- and long-term horizons. Hence, soft commodities are useful for short and long-term investors for diversification of risks regarding the Covid-19 pandemic. Further, these results are sensitive to time-duration of the study as intensity of fear among investors varies over different phases of evolving the Covid-19 pandemic.

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