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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 over the period from January 28, 2020 to April 29, 2021. Our findings show that each of the sampled soft commodities shows safe-haven behavior in one of the spot or futures markets and for one of the short-term or long-term investors during the times of COVID-19. Our results also show that safe-haven properties of soft commodities are contingent upon the nature of the commodity. The findings of our mean-variance portfolio analysis indicate that the portfolios with commodity futures are less risky and efficient compared to the portfolio containing stocks only, thus robustly supporting the safe-haven properties of soft commodities during COVID-19. Our results not only have important implications for individual investors and asset managers in suggesting particular soft commodities to strengthen safe-haven and diversification features of their portfolios but also can assist the policy makers to understand and disentangle health fear dimension of several interlocking dynamics affecting the spot and futures prices of soft commodities during COVID-19.

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., 2021). 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 and 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 et al., 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 the novel Corona virus outbreak.

During the initial days of the COVID-19 pandemic the stock markets around the world tumbled to their lowest levels and resulted in significant losses for traditional investors. For instance, Dow Jones Industrial average plunged 7.79% on March 9, 2020 and lost 9.9% again on March 12, 2020, a worst drop in the history of the US. The circuit breakers of S&P 500 triggered four times in March 2020 due to unprecedented heavy losses to equity investors (Shahzad et al., 2021a,b). In addition, the global average impact of COVID-19 on economies has been estimated to be a 4.4% decline in global GDP growth. The heavy losses in equity markets and an uncertain gloomy outlook of the global economies triggered traditional equity investors to look for the alternative safe-haven assets to protect their portfolios or generate positive returns (Hong et al., 2021; Shahzad et al., 2021).

The most discussed safe-haven assets in the extant literature include gold (Baur and Lucy, 2010; Shahzad et al., 2020) and cryptocurrencies (D. G. Baur and Hoang, 2021; Dwita Mariana, Ekapatra and Husodo, 2021; Goodell and Goutte, 2020; Rubbiani et al., 2021a,b,c; Xie et al., 2021). Some existing studies (Bodie and Rosansky, 1980; Conover et al., 2009; Daskalaki and Skiadopoulos, 2011; Daskalaki et al., 2017; Ji et al., 2020) support the view that equity investors can achieve diversification benefits by including commodities in their portfolios. Prior literature also reports that commodities futures offer diversification benefits to the risk averse equity investors because of their negative correlation with equities (Cai et al., 2020; Conover et al., 2010; Gagnon et al., 2020; Gorton and Rouwenhorst, 2006). The commodity is the class of assets that provide positive returns to equity investors during crisis and can offset their accumulated losses from investments in the equity markets. Investors may consider the commodities as safe-haven assets during COVID-19 to offset their market risks and protect their portfolios, as they perceive that drivers of commodity prices are different from traditional assets (Dubey and Shankar, 2020; Graham et al., 2013; Yamori, 2010). For instance, Cunningham and Smith (2021) document that commodity prices are having low correlation with the equity markets and the prices of commodities depend upon the demand and supply factors.

Thus far the empirical studies to support the safe-haven properties of soft commodities during COVID-19 are scant and cover only the initial phase of evolving COVID-19 pandemic. For instance, Salisu et al. (2020) use a composite global COVID-19 fear index to test the prediction power of commodities market over the period from March 11, 2020 to May 18, 2020. Their results show a positive and significant relationship between commodity returns and GFI pointing to the safe-haven characteristics of commodities during the initial days of COVID-19 pandemic. Ezeaku and Asongu (2020) capture only the beginning phase of the evolving effects of COVID-19 cases to document that the soft commodities’ prices maintain a strong and upward trend during the COVID-19 pandemic and are more resilient as compared to hard commodities. Babirath et al. (2020) studied the safe-haven properties of sugar futures to document that sugar futures do not act as the hedging or safe-haven asset during the COVID-19 pandemic. Ji et al. (2020) used cross-quantilogram approach to investigate the safe-haven characteristics of gold, cryptocurrencies, commodities, and foreign exchange futures during the COVID-19 pandemic. Their findings support the view that gold and soybean commodity futures act as safe-haven assets during the COVID-19 pandemic. All these studies provide a limited insight about the safe-haven properties of soft commodities; and they are restricted only to the beginning period of evolving COVID-19 pandemic.

The statistical models used in existing empirical literature to examine the safe-haven properties of assets include – but not limited to - quantile regression approach (Baur and Lucy, 2010; Baur and McDermott, 2010; Bianchi et al., 2020; Smeich and Papiez, 2017), bivariate cross-quantilogram framework (Manohar and Guntur, 2021; Shahzad et al., 2019; Uddin et al., 2019), time-varying Joe–Clayton copula method (Nguyen and Liu, 2017; Tiwari et al., 2020), DCC GARCH approach (Akhtaruzzaman et al., 2020; Akkoc and Civcir, 2019; Kinateder et al., 2021), rolling window approach (Bouri et al., 2021; Bouri et al., 2020), and quantile cross-spectral coherency framework (Le et al., 2021; Maghrebeh and Abdoh, 2020; Naeem et al., 2020). However, these approaches can capture only one of the time or frequency dimensions of the data and fail to cover both the time and frequency characteristics of the co-moving time series simultaneously.

The wavelet coherence method considers both time and frequency dimensions of the two-time series at the same time to identify the specific points at which the assets act as safe-haven at different investment horizons. In particular, our use of wavelet method is advantageous over the other methods for at least three reasons. First, an essential characteristic of the wavelet method is to capture latent processes with varying cycle trends, patterns, lead-lag interactions, and stationarity issues inherited by the underlying time series (Fakhfekh et al., 2021; Sherif, 2020). The wavelet coherence approach is particularly useful to analyze soft commodity markets because of non-stationary time series signals of soft commodities during the COVID-19 pandemic (Aguirar-Conraria and Soares, 2011; Bilgili et al., 2020; Bilgili et al., 2021; Shehzad et al., 2021). Second, Fetzer et al. (2020) document that not only the COVID-19 spread but also its contagious effects on mortality rates are significantly non-linear. Since, wavelet framework is a suitable technique in presence of nonlinear lead-lag relationship between the time series, the use of wavelet coherence suits to our data analysis because of the involvement of COVID-19 related data in our analysis. Finally, the statistical inference of the relationship between our study variables may be affected by the time span of the available data; however, the wavelet coherence framework is not affected by the size of the data.

In summary, our aforementioned gap analysis of extant literature concludes a need to investigate the safe-haven properties of soft commodities during COVID-19 pandemic. Our discussion also discloses the apparent advantages of wavelet coherence framework over the other methods used to investigate the safe-haven properties of assets. We therefore attempt to bridge this gap in the existing
literature and investigate safe-haven properties of soft commodities using wavelet coherence approach on spot and futures prices of commodities, and the global COVID-19 fear index (GFI) as proxy of the COVID-19.

Overall, our results about the safe-haven properties of soft commodities are mixed across different investment horizons and across spot and futures markets of soft commodities. We find that wheat, cotton, and sugar can be safe-haven asset for long-term investors in both the spot and futures markets but may not show safe-have properties for the short-term investors during the times of COVID-19. On the other hand, cocoa can be safe-haven assets for short-term investors in both spot and futures markets during the outbreak of novel Corona virus but may not be safe-haven commodity for the long-term investors in both markets in the duration of COVID-19 pandemic. We find opposite behavior of corn across spot and futures markets by observing that corn shows safe-haven property for the long-term investors in futures market but exhibits the opposite behavior for short-term investors in spot market. However, coffee possesses safe-haven properties for short-term investors in spot market but shows opposite behavior in the futures market. In general, our findings show that every soft commodity shows safe-haven behavior either in spot or futures market and either for short-term or long-term investors during the times of COVID-19. Our results also show that safe-haven properties of soft commodities depend on the nature of the commodity. The finding is consistent with the view that the intensity of the effect of COVID-19 pandemic varies across different commodities due to their link with the level of economic activity and consumption patterns (Rajput et al., 2021). Our mean-variance portfolio robustness analysis indicates that among all combinations of risky traditional assets and non-traditional assets, the portfolio with stock market indices and commodity futures is least risky and efficient compared to the portfolio containing stocks only; and the portfolio with stock market indices, cryptos and commodity futures is most efficient if three asset classes are considered in the portfolio construction. Hence, equity investors can hedge the risks in their portfolios by including the commodity futures in their portfolios.

We contribute to the existing literature in a few ways. First, compared to existing studies (Babirath et al., 2021; Ezeaku and Asongu, 2020; Ji et al., 2020; Salisu et al., 2020), our longer data span covers almost all existing waves of evolving COVID-19, and provides more insights about safe-haven properties of soft commodities for both long- and short-term portfolio investors. Second, our results have important implications for asset managers in suggesting particular soft commodity (ies) to strengthen safe-haven and diversification features of their long- or short-term equity portfolios during life threatening type of global (local) health crisis. Finally, the study of co-movement between COVID-19 crisis and spot (futures) prices of soft commodities can assist the policy makers to understand and disentangle health fear dimension of several interlocking dynamics affecting the prices of commodities and commodity futures.

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 January 28, 2020 to April 29, 2021.\(^2\) The data of soft commodities are available for five trading days in a week, which is aligned with indicators of COVID-19 fear. 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 ingredients in preparing 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 et al. (2020).

2.2. Construction of global COVID-19 fear index

For construction of global COVID-19 fear index (GFI), we follow Salisu and Akanni (2020) who used it to study the spread and severity of COVID-19 pandemic. In the construction of GFI, Salisu and Akanni (2020) used reported cases index (RCI) and reported deaths index (RDI) after considering the incubation period (two weeks duration between catching the infection and appearance of symptoms).\(^3\) The first component of GFI, RCI, shows how far are the peoples’ expectations on reported cases in incubation period (14 days) deviated from new cases and is computed as follows:

\[
RCI = \frac{\sum c_i}{\sum (c_i + c_{i-14})} \times 100
\]

\(^1\) The authors also looked at the daily demand and supply data of commodities to include into the study, but the demand and supply data is not available from different databases. Although, monthly demand and supply statistics are available from world bank and, food and agriculture organization databases but monthly data is not useful to study the short-term price movements.

\(^2\) Our use of spot prices of soft commodities instead of returns in the wavelet coherence analysis is based on existing mainstream studies (Abid et al., 2020; Aloui et al., 2018; Cai et al., 2020; Kang et al., 2019; Pal and Mitra, 2017; Z. Umar, Gubareva and Teplova, 2021) that use wavelet coherence and other approaches to investigate safe-haven properties of agricultural commodities, industrial commodities and cryptocurrencies.

\(^3\) https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—3-march-2020.
where \( i = 1, 2, \ldots, N; t = 1, 2, \ldots, T; \) and \( RCI_i \) is global COVID-19 new reported cases index at time \( t \); \( \sum_{i=1}^{N} c_{i,t} \) presents the new global COVID-19 reported cases at time \( t \); \( c_{i,t-14} \) is the new global COVID-19 reported cases at the beginning of the incubation period (14th day lag). Finally, the multiplication by 100 provides the RCI index ranging from 0 to 100, where the higher (lower) values indicate a higher (lower) level of COVID-19 fear due to new reported cases.

The second component of GFI is RDI, which measures how far are the peoples’ expectations from reported deaths in the incubation period (14 days) changed from current deaths. The RDI is computed as follows:

\[
RDI_i = \frac{\sum_{i=1}^{N} d_{i,t}}{\sum_{i=1}^{N} (d_{i,t} + d_{i,t-14})} \times 100
\]

where \( i = 1, 2, \ldots, N; t = 1, 2, \ldots, T; \) and \( RDI_i \) is new global COVID-19 reported deaths index at time \( t \); \( \sum_{i=1}^{N} d_{i,t} \) represents new global COVID-19 reported deaths at time \( t \); \( d_{i,t-14} \) is the number of new global COVID-19 reported deaths at the beginning of the incubation period (14th day lag). Finally, the multiplication by 100 provides the RDI index ranging from 0 to 100, where the higher (lower) values indicate a higher (lower) level of COVID-19 fear due to new reported deaths.

The GFI is the composite index of RCI and RDI, spans on a scale of 0–100, and is constructed as follows:

\[
GFI = 0.5(RCI + RDI)
\]

where \( i = 1, 2, \ldots, N; t = 1, 2, \ldots, T; \) \( RCI_i \) is global COVID-19 reported cases index at time \( t \); \( RDI_i \) is global COVID-19 reported deaths index at time \( t \); and \( GFI \) is global COVID-19 fear index constructed by equally weighting the \( RCI_i \) and \( RDI_i \) indices at time \( t \). 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 thus covers both dimensions that could be related to gauging the severity of fear regarding COVID-19 pandemic.

### 2.3. Research methodology

Existing studies use several statistical techniques to investigate the relationship between two-time series variables. Some of the techniques to study the time-varying relationship between two time series are the bivariate cross-quantilogram approach (Corbet et al., 2020; J. A. Hernandez, Shahzad et al., 2019; Uddin et al., 2019), DCC-GARCH approach (Abid et al., 2020; Akhtaruzzaman et al., 2021; Burdekin and Tao, 2021; Kinateder et al., 2021) and rolling window approach (Bouri et al., 2020, 2021). These methods ignore the frequency dependencies of the data in empirical estimations. Consequently, some studies (Baumohl, 2019; Conlon et al., 2021; Maghyereh and Abdoh, 2021) use the quantile cross-spectral coherence method of Barunik and Kley (2019) to study the dependencies in tails of joint distribution of each pair of assets by considering the frequency domain. This approach is useful for investors as dependencies between assets tend to increase during the period of market stress (Akhtaruzzaman et al., 2021). However, the method fails to capture the time and frequency characteristics simultaneously.

The issues regarding the simultaneous capturing of time and frequency dimensions are solved with the introduction of wavelet coherence approach. The wavelet coherence framework allows the adjustment of the window size of time series according to extended functions at low and high frequencies. Although many existing studies have used the wavelet coherence approach in empirical analysis (Rubbaniy et al., 2021; Rubbaniy et al., 2021; Sharif et al., 2020; Umar et al., 2021a,b), our use of wavelet coherence approach is motivated by the following reasons. First, an essential characteristic of the wavelet method is to capture latent processes with time varying cycle trends, lead-lag interactions, and patterns in the underlying time series (Fakhfekh et al., 2021; Sherif, 2020). Second, a major advantage of wavelet coherence approach relates with its flexibility in dealing with non-stationary signals which are prevalent in the prices of soft commodities (Aguiar-Conraria and Soares, 2011; Demir et al., 2020; Jiang and Yoon, 2020; León and Soto, 1997; Oglend and Asche, 2016; Shehzad et al., 2021). In addition, the wavelet coherence framework is also useful to study the co-movements between time series variables with frequent structural changes (Fruehwirt et al., 2021; Kristoufek et al., 2016), and the variables that face sudden fluctuations in their structure. Third, the wavelet framework is a suitable technique when the underlying time series exhibits a nonlinear lead-lag relationship. Fetzer et al. (2020) observe the significant non-linearity in COVID-19 spread and its contagious effects on mortality rates. Since, our measure of COVID-19 spread also involves new cases and deaths in its computation, we therefore expect a nonlinear relationship in our time series variables. Finally, the statistical inference of the relationship between our study variables may require longer spans of the data; however, the wavelet coherence framework is not affected by the length of the time series variables.

Given the advantages of the wavelet coherence approach over other methods to simultaneously capture the time and frequency domains in investigating the relationship between two time series, we apply this framework to investigate the co-movement of global COVID-19 fear index with soft commodity spot and futures prices. The following section provides a detailed description of our wavelet coherence approach.

### 2.4. Wavelet coherence

The cross-wavelet transform of two-time series variables \( x(t) \) and \( y(t) \) is defined by Torrence and Compo (1998), where the
cross-wavelet transformations (CWT) \( W_{x}^{s}(u, s) \) and \( W_{y}^{s}(u, s) \) are specified in Equation (4):
\[
W_{x,y}(u, s) = W_{x}(u, s)W_{y}^{*}(u, s)
\]  
(4)
where \( W_{x}(u, s) \) and \( W_{y}^{*}(u, s) \) are continuous wavelet transforms of time series variables \( x(t) \) and \( y(t) \); \( u \) is the position index, \( s \) shows the scale and \( * \) sign displays the complex conjugate. The wavelet transform assumes the local covariance between two-time series variables.

The wavelet coherence approach by Torrence and Compo (1998) remains robust to measure the cross-wavelet power to display the areas of significant covariance at each scale between time series variables. Torrence and Webster (1999) extended the work of Torrence and Compo (1998) to include the squared wavelet coherence coefficient defined in the equation below:
\[
R^{2}(u, s) = \frac{|S(s^{-1}W_{x}(u, s))|^{2}}{S^{2}(s^{-1}|W_{x}(u, s)|^{2})S^{2}(s^{-1}|W_{y}(u, s)|^{2})}
\]  
(5)
where \( s \) represents operator over time and space, and squared wavelet coefficient falls in the range of \( 0 \leq R^{2}(u, s) \leq 1 \) (Rua and Nunes, 2009). This definition is associated with the traditional correlation coefficient, and without smoothing coherency, it is identical to 1 at all scales. We further write the smoothing operator \( s \) including time and frequency dimensions in the following equation:
\[
S(W) = S_{\text{Scale}}(S_{\text{Time}}(W_{x}(s)))
\]  
(6)
where \( S_{\text{Scale}} \) is smoothing along the wavelet scale axis and \( S_{\text{Time}} \) shows the smoothing across time. The higher values of wavelet squared coherence \( R^{2}(u, s) \) show a higher co-movement between two-time series variables and vice versa.

The wavelet squared coherence is constrained to positive values within the range of \( 0–1 \) and in this case the difference between positive and negative co-movements between two-time series variables cannot be observed. To address the issue, Torrence and Compo (1998), and Grinsted et al. (2004) suggested the inclusion of phase difference to capture the difference between positive and negative co-movements between two-time series. The phase difference equation of Torrence and Compo (1998), and Grinsted et al. (2004) is defined as:
\[
\varphi_{x,y}(u, s) = \tan^{-1}\left(\frac{\text{Im}\{S(s^{-1}W_{y}(u, s))\}}{\text{Re}\{S(s^{-1}W_{y}(u, s))\}}\right)
\]  
(7)
where \( \text{Im} \) and \( \text{Re} \) are the imaginary and the real components of smoothed cross-wavelet transform, respectively. The result of a cross-wavelet coherence analysis is generally a plot or figure, which has five significant parts: the black arrows with eight directions (\( \rightarrow , \rightarrow , \downarrow , \downarrow , \downarrow , \downarrow , \uparrow , \uparrow \)), warm and cold colours, black contours, two axes, and the cone of influence (see Figs. 2–7). The \( \rightarrow (\rightarrow) \) black arrows display an in-phase (out-of-phase) relationship or positive (negative) correlation, while \( \downarrow (\uparrow) \) directed arrows exhibit the leading effect of the first (second) series. For instance, the black arrows with direction \( \downarrow \) in the wavelet coherence plots show an in-phase relationship or positive co-movement between two-time series where the second series leads the first series by \( \pi/2 \). The black arrows with direction \( \uparrow \) in the wavelet coherence plots show an out-of-phase relationship or negative co-movement between two-time series where the first series leads the second series by \( \pi/2 \). The zero-phase difference means both time series variables are moving together with weak correlation. The black curves in the plots show the regions with coherence significance at a 5% level, and the solid white bell-shaped line in wavelet coherence plots is the cone of influence.

3. Empirical results

We start our empirical analysis by presenting the descriptive statistics of the variables of our study in Table 1. The average value of global COVID-19 fear index is 55.08%, which shows a high fear related to COVID-19 during the times of our study. The kurtosis value of global COVID-19 fear index is 7.33, which indicates a leptokurtic distribution 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 the commodities are less than three, except Cocoa, suggesting a non-normal, platykurtic and heavy tail behavior of the distributions of these commodity prices over the sample period.

Table 1
Descriptive statistics.

| Variables | Obs. | Mean   | Std.Dev. | Skew. | Kurt. |
|-----------|------|--------|----------|-------|-------|
| GFI       | 328  | 55.08  | 12.48    | 1.90  | 7.33  |
| Wheat     | 328  | 6.01   | 0.63     | 0.29  | 2.11  |
| Corn      | 328  | 4.11   | 0.93     | 0.88  | 2.62  |
| Cotton    | 328  | 64.64  | 11.088   | 0.43  | 2.25  |
| Cocoa     | 328  | 2365.44| 151.45   | 0.40  | 3.49  |
| Coffee    | 328  | 110.14 | 11.31    | -0.09 | 2.13  |
| Sugar     | 328  | 13.51  | 1.82     | -0.09 | 2.27  |

Notes: The GFI is global COVID-19 fear index and wheat, corn, cotton, cocoa, coffee, and sugar are the prices of soft commodities.
Fig. 1 displays the graphical co-movements between soft commodities’ spot prices and global COVID-19 fear index. In the figure, we can observe that prices of the essential food items (wheat, corn, cotton, and cocoa) are increasing during the COVID-19 pandemic as compared to non-essential food items (coffee and sugar) due to lack of mobility. For example, the COVID-19 resulted in more than 15% increase in the prices of staples from the pre-COVID-19 crisis levels (Elleby et al., 2020; M. Hernandez, Kim, Rice and Vos, 2020).

Fig. 1 shows closing spot prices of soft commodities and global COVID-19 fear index (GFI) from January 28, 2020 to April 29, 2021. The closing prices of soft commodities are presented on vertical axis and the time in days is displayed on horizontal axis. The horizontal scale also shows the time span of three waves of COVID-19.

3.1. Commodities spot and futures prices and GFI

After looking at basic statistics and the graphical variations in the GFI and commodity prices, we next apply wavelet coherence approach to investigate the safe-haven properties of soft commodities. Panel-A of Fig. 2 displays the wavelet coherency plot of wheat prices and GFI. The (\(\ bentarrow\)) direction of arrows in the figure shows the in-phase relationship (positive correlation) between wheat prices and GFI during the first 60 days of COVID-19 pandemic, where GFI is leading the wheat prices. The black contours in the figure disclose a positive co-movement significant at 5% level. The co-movement is significant at almost all horizons in the figure (at frequencies of 1-4 days, 4-8 days and 32-64 days). The finding indicates that demand of wheat increases during the initial days of COVID-19 pandemic which results in increased wheat prices. This finding shows that wheat can be used as a safe-haven asset during the times of COVID-19.

For robustness and comparability purposes, we also investigate the co-movement of GFI and wheat futures and present the wavelet coherency plot of wheat futures and GFI in Panel-B of Fig. 2. The (\(\ bentarrow\)) direction of arrows shows the in-phase relationship (positive correlation) between wheat futures and GFI at 32-64 days frequency band with leading effect of GFI on wheat futures. The wheat futures are not influenced by uncertainties during the times of COVID-19 and can be used to diversify the risks regarding the COVID-19 pandemic. However, the co-movement between wheat futures and GFI is not strong in most of the cases.

Fig. 2 shows the wavelet coherency plots of the co-movement of wheat spot and futures prices with global COVID-19 fear index, where the horizontal axis shows time in days and the vertical axis displays the period in days (investment horizon). The colours displayed on the right side of the main plots indicate the coherency (correlation) level; moving from blue to red colour shows the higher absolute correlation value concerning \(R^2(u, s)\). The solid white curved line in the 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 (\(\ bentarrow\)) direction of arrows means that the first time series leads the second and vice versa.

Panel-A of Fig. 3 displays the wavelet coherency plot between corn prices and GFI and reports an out-of-the-phase relationship (negative co-movement) during the first 50 days indicated by (\(\ bnotext\)) direction of arrows. The upward direction of arrows further indicates a leading effect of corn prices on GFI. The leading effect of corn shows that the corn spot 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 prices is significant at 5% level, which could be due to lower demand of agricultural commodities used in the production of biofuels (Rajput et al., 2021).

The wavelet coherency plot between corn futures and GFI in Panel-B of Fig. 3 reports an in-phase relationship (positive co-movement) indicated by (\(\ bentarrow\)) direction of arrows (at 32-64 days frequency band) with leading effect of GFI on corn futures. These results show that futures price of corn increased during initial days of the COVID-19 outbreak, which is due to positive shocks to corn futures prices resulting from increased demand of corn futures for investment purpose of equity investors. Hence, corn futures prices are resilient to the risk of COVID-19 pandemic and corn can be used as safe-haven asset during the pandemic.

A comparison of our results in Panel-A and Panel-B of Fig. 3 supports the view that long-term investors can use the corn as safe-haven asset in futures market by shifting their investments from the turbulent equity markets to soft commodity futures during the times of COVID-19 pandemic or similar health crisis.4

Fig. 3 shows the wavelet coherency plots of the co-movement of corn spot and futures prices with global COVID-19 fear index, where the horizontal axis shows time in days and the vertical axis displays the period in days (investment horizon). The colours displayed on the right side of the main plots indicate the coherency (correlation) level; moving from blue to red colour shows the higher absolute correlation value concerning \(R^2(u, s)\). The solid white curved line in the 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 (\(\ bentarrow\)) direction of arrows means that the first time series leads the second and vice versa.

In Panel-A of Fig. 4, we report the wavelet coherency between cotton prices and GFI. The black right-directional (\(\ bentarrow\)) arrows at the left bottom of the figure indicate positive co-movement between cotton prices and GFI from 100 to 180 days, which turns to negative in the later stage of COVID-19 pandemic. Further, the upward direction of arrows indicates the leading effect of cotton price on GFI. The positive co-movement between cotton prices and GFI at 100–180 days frequency band shows that long-term investors used cotton as a safe-haven asset during the COVID-19 pandemic. This finding suggests that the cotton can be used as a safe-haven asset during the spread of COVID-19 crisis. We also display the wavelet coherency between cotton futures and GFI in Panel-B of Fig. 4. The black right-directional (\(\ bentarrow\)) arrows indicate a positive co-movement between cotton futures and GFI during the COVID-19 pandemic at different

4 [https://www.allaboutfeed.net/animal-feed/raw-materials/corn-sugar-and-soybeans-resistant-to-covid-19/](https://www.allaboutfeed.net/animal-feed/raw-materials/corn-sugar-and-soybeans-resistant-to-covid-19/)
frequency bands with leading effect of cotton futures on GFI. The positive co-movement at 64–70 days frequency band shows that long-term investors used the cotton futures as a safe-haven asset during the COVID-19 pandemic. A comparison of our results in Panel-A and Panel-B of Fig. 4 supports the view that long-term investors can use the cotton as a safe-haven asset in both spot and futures market during the COVID-19 pandemic as cotton remained resilient to COVID-19 due to the pandemic timing. For instance, during the first wave of COVID-19 the crop was already harvested in most of the countries and also had little impact on new plantings. Due to these reasons cotton prices are not influenced by supply shocks due to lockdowns.\footnote{https://www.graincentral.com/cropping/cotton/covid-19-impacts-global-cotton-sector-usda/}

Fig. 4 shows the wavelet coherency plots of the co-movement of cotton spot and futures prices with global COVID-19 fear index, where the horizontal axis shows time in days and the vertical axis displays the period in days (investment horizon). The colours displayed on the right side of the main plots indicate the coherency (correlation) level; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in the 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 time series leads the second and vice versa.

Fig. 3. Wavelet coherence analysis of corn spot and futures prices.

Fig. 4. Wavelet coherence analysis of cotton spot and futures prices.

Fig. 5. Wavelet Coherence Analysis of Cocoa Spot and Futures prices.
Fig. 5 displays the plots of the wavelet coherency analysis of the co-movement of GFI with cocoa spot and futures prices. The black contours around (↘) directional arrows at the left upper Panel-A of the figure reveal the existence of a significant in-phase relationship (positive co-movement) between the two variables; and the (↘) direction of arrows shows the leading effect of GFI on cocoa price at the frequency band of 1–16 days. The figure also shows that in the second wave of COVID-19 from 220 days to 250 days, the co-movement is strong and positive at 2–8 days frequency band. These findings support the safe-haven properties of cocoa for short-term investors. We argue that the stable supply and increase in cocoa demand during COVID-19 pandemic results in higher prices 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. Panel-B of Fig. 5 shows the wavelet coherency output plot of the co-movement between cocoa futures and the GFI. The black contours around (↘) directional arrows at the left upper Panel-B of the figure show the existence of a significant in-phase relationship (positive co-movement) between the two variables; and the (↘) direction of arrows shows the leading effect of GFI on cocoa price at the frequency band of 1–16 days. In addition, in both panels (∧) direction of arrows in the frequency band of 32–64 suggests an out-of-phase (negative co-movement) relationship of GFI with cocoa spot and futures prices.

A comparison of our results in Panel-A and Panel-B of Fig. 5 supports the view that short-term investors can use the cocoa as safe-haven asset in both spot and futures market during the COVID-19 pandemic. However, long-term investors may not consider cocoa as safe-haven asset in both spot and futures market during the COVID-19 pandemic due to the absence of co-movement of GFI with cocoa spot and futures prices.

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

Fig. 6. Wavelet coherence analysis coffee spot and futures.

Fig. 7. Wavelet coherence analysis sugar spot and futures.
Fig. 5 shows the wavelet coherency plots of the co-movement of cocoa spot and futures prices with global COVID-19 fear index, where the horizontal axis shows time in days and the vertical axis displays the period in days (investment horizon). The colours displayed on the right side of the main plots indicate the coherency (correlation) level; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in the 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 (\u2191) direction of arrows means that the first time series leads the second and vice versa.

The wavelet coherency plot of the co-movement between coffee prices and GFI is presented in Panel-A of Fig. 6. A general (\u2197) direction of arrows in Panel-A, surrounded by black contours, displays an in-phase (positive co-movement) relationship between coffee prices and GFI during the initial 50 days of COVID-19, and in the 2–16 days frequency band. Here GFI is leading the two series. However, the co-movement turns to negative in 32–64 days frequency band. The findings show that coffee can be considered a safe-haven asset for the short-term investors, but long-term investors take coffee not to be a safe-haven asset. We also present the wavelet coherency plot of the co-movement between coffee futures and GFI in Panel-B of Fig. 6. A general (\u2197) direction of arrows displays an out-of-the-phase (negative co-movement) relationship between coffee futures and GFI in 16–32 and 66-70 days investment horizon with leading effect of GFI. This finding suggest that coffee futures do not possess safe-haven characteristics during COVID-19.

A comparison of our results in Panel-A and Panel-B of Fig. 6 shows that coffee can be used as a safe-haven asset in spot market during COVID-19 pandemic for the short-term investors but cannot be considered a safe-haven asset by short- or long-term investors in futures market. The upward pressure on coffee prices during the initial days of COVID-19 was due to restrictions related to COVID-19 in major coffee producing countries.

Fig. 6 shows the wavelet coherency plots of the co-movement of coffee spot and futures prices with global COVID-19 fear index, where the horizontal axis shows time in days and the vertical axis displays the period in days (investment horizon). The colours displayed on the right side of the main plots indicate the coherency (correlation) level; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in the 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 (\u2191) direction of arrows means that the first time series leads the second and vice versa.

Panel-A of Fig. 7 presents the output plot of the wavelet coherency analysis of co-movement between sugar spot prices and GFI. We observe that the co-movement vary across different horizons and frequency bands in the wavelet coherency plot in Panel-A. For instance, (\u2197) arrows show a negative co-movement between sugar spot prices and GFI in 32–40 days frequency band. 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 and Barrientos, 2020; Di Renzo et al., 2020) in the absence of COVID-19 vaccine. Hence, during the beginning of 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 for short-term investors during times of COVID-19. However, the (\u2197) direction of arrows at the bottom of the figure in Panel-A shows that an in-phase relationship (positive co-movement) exists between sugar spot prices and GFI with leading effect of sugar prices in above 64 days frequency band. This finding suggests a safe-haven role of sugar for long-term investors in the spot market. We also present the output plot of the wavelet coherency analysis of the co-movement between sugar futures and GFI in Panel-B of Fig. 7. We again observe that the co-movement between sugar futures and GFI vary across different frequency bands in the wavelet coherency plot. The (\u2197) direction of arrows shows that an out-of-the-phase relationship (negative co-movement) exists between sugar futures and GFI in 16–20 days frequency band and the sugar futures lead the two-time series. Similarly, at 32–40 days frequency band an out-of-the-phase relationship (negative co-movement) exists between sugar futures and GFI, where GFI is leading the effect. The co-movement turns to positive and significant in more than 64 days investment horizon.

A comparison of our results in Panel-A and Panel-B of Fig. 7 shows that sugar may not act as safe-haven asset for short-term investors in both spot and futures market but acts as safe-haven asset for the long-term investors in both spot and futures markets as during the second half of 2020 the institutional fund managers became optimistic and started to rebuild the long-term positions in sugar futures (Kotzyza et al., 2021).

Fig. 7 shows the wavelet coherency plots of the co-movement of sugar spot and futures prices with global COVID-19 fear index, where the horizontal axis shows time in days and the vertical axis displays the period in days (investment horizon). The colours displayed on the right side of the main plots indicate the coherency (correlation) level; moving from blue to red colour shows the higher absolute correlation value concerning $R^2(u, s)$. The solid white curved line in the 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 (\u2191) direction of arrows means that the first time series leads the second and vice versa.

Overall, our results about the safe-haven properties of soft commodities are mixed across different investment horizons and across spot and futures markets. For instance, wheat, cotton, and sugar can be safe-haven asset for long-term investors in both the spot and futures markets but may not show safe-haven properties for the short-term investors during the times of COVID-19. The findings may be supported by the physical properties of some of these assets. For instance, wheat together with corn and sugar is often used for preparation of the staple food recipes and for production of processed foods. A global supply chain disruption of these staple food commodities may result in demand-pull inflation in their prices resulting from consumers’ panic buying for the staple food at the start of COVID-19 and during lockdowns. The increased demand of staple food commodities attracted the equity market investors towards the soft commodities market which resulted in the increased futures prices of these commodities during the initial days of the COVID-19 pandemic.
19 pandemic. However, the price inflation varies across commodities and over time during the COVID-19 pandemic and in case of wheat the harvesting of wheat might have offset the demand-pull price inflation effect of the wheat (Spencer et al., 2018) resulting in no safe-haven property in wheat in the short-run. Nevertheless, the commodity shows safe-haven property in the longer investment horizon being an essential ingredient of the staple food across the world.

We find that cocoa act as safe-haven asset for short-term investors in both spot and futures markets during the outbreak of novel Corona virus but is not a safe-haven commodity for the long-term investors in both markets during COVID-19 outbreak. The reason of short-term safe-haven property of cocoa is due to its use in boosting the immunity during COVID-19 times as it has been documented immunity booster against influenza (Kamei et al., 2016). Another explanation of the short-term safe-haven property of cocoa is the demand-pull price inflation resulting from disruption in its supply chain (Cadby, 2021; Clapp and Moseley, 2020). The safe-haven property of corn futures market during the initial days of COVID-19 can be argued by its active trading and liquidity even during the turbulent times as corn futures market has been providing better returns during the times of uncertainty in the past and during the times of COVID-19 (He et al., 2021).

We also observe opposite behavior of some commodities across spot and futures markets during the times of COVID-19. For instance, corn shows safe-haven property for the long-term investors in futures market but exhibits the opposite behavior for short-term investors in spot market. However, coffee possesses safe-haven properties for short-term investors in spot market but shows opposite behavior in the futures market. In general, our findings show that every sampled soft commodity shows safe-haven behavior either in spot or futures market and either for short-term or long-term investors during the times of COVID-19. Overall, our results show that safe-haven properties of soft commodities depend on the nature of the commodity, which is consistent with the view that the intensity of effect of COVID-19 pandemic varies across different commodities due to their link with the level of economic activity and consumption patterns (Rajput et al., 2021).

3.2. Portfolio analysis using commodity futures, cryptocurrencies and stock indices

Although our wavelet coherence analysis concludes the existence of safe-haven properties in soft commodities based on the wavelet coherence analysis on pairs of time-series, a diversified portfolio analysis with soft commodities as an asset may further be required for the robustness purposes. In this section, we analyze whether inclusion of commodity futures in the market portfolio of stocks provides the safe-haven or portfolio diversification benefits to the investors. For this purpose, we construct random portfolios with the four scenarios: (i) Scenario 1 includes set of risky traditional assets, (ii) Scenario 2 comprises of risky traditional assets and cryptocurrencies, (iii) Scenario 3 has asset mix of stocks and commodity futures, and (iv) Scenario 4 contains risky traditional assets, cryptocurrencies, and commodity futures. The details about the selected stock market indices, cryptocurrencies and soft commodity futures are given in Table 2.

| Panel-A: Stock Market Indices |
|-------------------------------|
| Ticker | Index | Country |
| GSPC | S&P 500 | US |
| FTSE | FTSE 100 | UK |
| GSPTSE | S&P/TSX Composite | Canada |
| GDAXI | DAX Performance Index | Germany |
| HSCC | Hang Seng China Enterprises | China |
| BSESN | BSE Sensex | India |
| BVSP | Ibovespa | Brazil |
| BFX | Belgium 20 index | Belgium |
| KSE | PSX 100 index | Pakistan |
| NZ50 | S&P/NZX 50 | New Zealand |
| MERV | Merval | Argentina |
| DJU | Dow Jones Utility Average | US |
| AXJO | S&P/ASX 200 | Australia |

| Panel-B: Soft Commodity Futures |
|-------------------------------|
| Ticker | Futures |
| ZW%3DF | Wheat Futures |
| ZC%3DF | Corn Futures |
| CT%3DF | Cotton Futures |
| CC%3DF | Cocoa Futures |
| SB%3DF | Sugar Futures |

| Panel-C: Cryptocurrencies |
|----------------------------|
| Ticker | Currency |
| BTC-USD | Bitcoin |
| ETH-USD | Ethereum |
| XRP-USD | Ripple |
| LTC-USD | Litecoin |

Notes: Table 2 shows the stock indices, commodity futures and cryptocurrencies selected to examine the diversification potential of different assets in a diversified portfolio during COVID-19. The selection of the indices is based on the countries hit hard by spread of the COVID-19 pandemic and being the biggest producers of soft commodities. The choice of the commodities futures is driven by the notion that they add to the market efficiency and investors are more interested in them as compared to the spot market. The set of cryptocurrencies is selected based on highest capitalization and liquidity.
futures are provided in Table 2.

We start our portfolio analysis of diversification and safe-haven features of soft commodities by plotting the heatmap of correlations between stock indices, cryptocurrencies and soft commodities in Fig. 8. In the figure, the blue colour shows a lower correlation and red colour indicates a higher correlation between the variables. As clear from Fig. 8, the correlations between different stock market indices are higher than their correlations with the cryptocurrencies and commodity futures. The low correlation between stock market indices and commodity futures indicates the diversification benefits of construction of multi-asset portfolios including the soft commodities. This finding shows that investors can get a higher portfolio risk diversification by investing in the basket of stocks and soft commodities.

Fig. 8 shows the heatmap of the correlations between stock market indices, cryptos and soft commodity futures during the COVID-19 pandemic. Moving from blue to red colour shows a lower to higher correlation between the variables.

After analyzing at the correlations between different assets, we next construct the mean-variance efficient portfolios of all four scenarios mentioned above and post the results in Table 3. Panel-A of Table 3 presents global mean-variance optimal portfolios for all four scenarios, where portfolio risk and mean returns are presented on X-axis and Y-axis, respectively. As we can see in Scenario 4 of Panel-A, the basket of stocks, cryptocurrencies and soft commodity futures provides better investment allocation relative to other three scenarios suggesting that adding soft commodities and cryptocurrencies in traditional equity portfolios can increase the expected returns for a given level of risk or vice versa. Our findings are consistent with findings of Belousova and Dorfleitner (2012), Cai et al. (2020) and Lombardi and Ravazzolo (2016) by stating that inclusion of soft commodities in a well-diversified portfolio reduces the portfolio risk and provides diversification benefits to equity investors.

Panel-B of Table 3 shows the mean returns, standard deviations and Sharpe ratios for the multi-asset optimal portfolios constructed for all the four scenarios mentioned above. As clear from Panel-B, the portfolio in Scenario 3 (portfolio of market indices and commodity futures) possesses least level of risk (SD = 4.42%) and provides better risk-adjusted returns (Sharpe ratio = 15.03%) compared to Scenario 1 (portfolio of market indices) suggesting that a stock portfolio with commodity futures provides lower risk and highest risk-adjusted return compared to a stock portfolio without commodity futures. The risk-return characteristics of a portfolio can further be enhanced by including the cryptos in the portfolio of stocks and commodity futures indicated by the highest Sharpe ratio for Scenario 4 (market indices, cryptocurrencies, and commodity futures).

Overall, our findings indicate that among all four combinations of stocks, cryptos and soft commodities, the portfolios with commodity futures are least risky and efficient compared to the portfolio with stock market indices only. Hence, equity investors can hedge the risks in their portfolios by including the commodity futures in their portfolios. The analysis further provides the robust evidence that soft commodity futures can be used as safe-haven assets by the equity investors, and the risk averse equity investors can invest in the soft commodities to hedge their portfolios against losses due to COVID-19 crisis.

4. Conclusions

This study aims to explore the co-movement of global COVID-19 fear index, developed by Salisu et al. (2020), with the spot and futures prices of soft commodities to trace the safe-haven properties of soft commodities during the COVID-19 pandemic.

Overall, our results about the safe-haven properties of soft commodities based on wavelet coherence analysis are mixed across spot and futures markets of soft commodities, and across different investment horizons. We find that wheat, cotton, and sugar can be safe-haven asset for long-term investors in both the spot and futures markets but may not show safe-haven properties for the short-term investors during the times of COVID-19. On the other hand, cocoa can be safe-haven assets for short-term investors in both spot and futures markets during the outbreak of the novel Corona virus but may not be safe-haven commodity for the long-term investors in both markets during the COVID-19 outbreak. We find opposite behavior of corn across spot and futures markets by observing that corn shows safe-haven property for the long-term investors in futures market but exhibits the opposite behavior for short-term investors in spot market. However, coffee possesses safe-haven properties for short-term investors in spot market but shows opposite behavior in the futures market. In general, our findings show that each soft commodity shows safe-haven behavior at least in one of the spot or futures markets and for one of the short-term or long-term investors during the times of COVID-19. Our results also show that safe-haven properties of soft commodities depend on the nature of the commodity. The finding is consistent with the view that the intensity of the effect of COVID-19 pandemic varies across different commodities due to their link with the level of economic activity and consumption patterns (Rajput et al., 2021).

Our mean-variance portfolio robustness analysis indicates that among all four combinations of stocks with cryptos and soft commodities, the portfolios with commodity futures are least risky and efficient compared to the portfolio containing stocks only; and, the portfolio with stock market indices, cryptos and commodity futures is most efficient. Hence, equity investors can hedge their portfolio risks by including the commodity futures in their portfolios during times of COVID-19. The analysis provides the robust evidence that soft commodity futures can be used as safe-haven assets by the equity investors, and the risk averse equity investors can invest in the soft commodities to hedge their portfolios against losses due to COVID-19 crisis.

Since, the institutional and individual investors in the equity market have displayed a renewed interest for alternative investments during the COVID-19 pandemic, our results have important implications for individual investors and asset managers in suggesting particular soft commodities to strengthen safe-haven and diversification features of their long- or short-term equity portfolios during life threatening type of global (local) health crisis. The findings of our study can assist the policy makers to understand and disentangle health fear dimension of several interlocking dynamics affecting the prices of commodities and commodity futures.

Finally, our results are sensitive to time-duration of the study as intensity of fear among investors varies over different phases of the evolving COVID-19 pandemic.
Table 3
Global mean variance Optimal Portfolios with Stock Indices, Commodity Futures and Major Cryptocurrencies During the COVID-19.

Panel-A: Mean-Variance efficient frontier of all 4 constructed portfolios

| Scenario 1 (stock market indices) | Scenario 2 (stock market indices with cryptocurrencies) | Scenario 3 (stock market indices with commodity futures) | Scenario 4 (stock market indices, cryptocurrencies and commodity futures) |
|----------------------------------|-------------------------------------------------------|--------------------------------------------------------|---------------------------------------------------------------|
| E(R)                             | 0.0172                                                | 0.0306                                                 | 0.0066                                                        | 0.0105                                                        |
| SD                               | 0.1453                                                | 0.1890                                                 | 0.0442                                                        | 0.0579                                                        |
| Sharpe Ratio                     | 0.1185                                                | 0.1621                                                 | 0.1503                                                        | 0.1814                                                        |

Notes: Panel-A of Table 3 plots figures of all four global mean-variance optimal portfolios of stocks with cryptos and soft commodities on given level of portfolio risk (without short sales). In all four figures, mean portfolio returns are presented on Y-axis and standard deviation (risk) is presented on X-axis for all four different scenarios. Panel-B of Table 3 presents mean portfolio returns, risk and Sharpe ratios of all four different scenarios.

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