The impact of Covid-19 on commodity markets volatility: Analyzing time-frequency relations between commodity prices and coronavirus panic levels

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ARTICLE INFO

ABSTRACT

We apply wavelet analyses to study how the Covid pandemic influenced the volatility of commodity prices, covering various classes of commodities. We document the intervals of low, medium, and high coherence between the coronavirus panic index and the moves of the commodity prices. The low coherence intervals indicate the diversification potential of commodity investments during a systemic pandemic such as Covid-19. We document differences in the observed patterns per commodity category and evidence their potential role for designing cross-assets hedge strategies based on investments in commodities.

1. Introduction

During the first half of 2020, Covid-19 pandemic has severely damaged the global economy and disrupted the smooth functioning of financial and commodity markets. The massive impact of the pandemic on the planetary scale has led to a rapid increase in the literature on the Covid-19 fueled economic crisis; see Al-Awadi et al. (2020); Umar and Gubaeva (2021); Dutta et al. (2020); Sharif et al. (2020); Zhang et al. (2020); Umar et al. (2021); and the references therein. In particular, the global pandemic of Covid-19 has severely affected worldwide financial markets (Godel, 2020; and Zhang et al., 2020; Umar and Gubaeva, 2021a), including commodity trading and investments (Wang et al., 2020; Umar et al., 2020a,b and the references therein).

Although the apogee of the pandemic-fueled panic observed in late

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March is now a way behind us, the further dynamic of the disease and its economic consequences still remains highly uncertain. Due to this elevated uncertainty, policymakers worldwide experience difficulties in both formulating sustainable recovery policies, including resources policy, and prioritizing issues to be addressed in the first place. On the other hand, in their response to the Covid-19 caused uncertainty, investors and portfolio managers have commenced an active search for safe havens (see, e.g., Gubareva and Umar, 2020; Zaremba et al., 2021) targeting the protection of their investments through diversification of their portfolios.

In addition to several rather common diversification opportunities such as gold (Corbet et al., 2020), cryptocurrencies (Conlon and McGee, 2020, Umar et al., 2020a,b; Conlon et al., 2020; Demir et al., 2020; Umar and Gubareva, 2020; Iqbal et al., 2021), Islamic and ethical equitiesUmar et al., 2020, 2020a (Umar et al., 2020, 2020a; Umar and Gubareva, 2021), international financial assets (Riaz et al., 2019, 2020, 2020; Umar et al., 2019; Kenourgios et al., 2020; Umar and Spierdijk, 2017) derivative products (Naeem et al., 2020; Bouri et al., 2020; Go and Lau, 2020; Shahzad et al., 2020; Tvedt, 2020), etc., many market players opt for diverse types of commodities, namely; energy, agricultural, livestock, precious and non-precious metals (see, for instance, Sharif et al., 2020; Sifat et al., 2021; Umar et al., 2021a; and the references therein). Hence, it is particularly important to study the relationship between the level of the Covid-19 provoked panic and the volatility of commodities' prices.

Covid-19 pandemic is profoundly challenging global society and economy. To withstand and mitigate the rapid penetration and economic consequences of the virulent disease, the vast majority of countries have implemented social distancing and severely restricted travel facilities. These contingency measures have adversely affected many industries and corporations, triggering a worldwide upsurge in unemployment. Because of the changing macroeconomic conditions, commodity prices have fallen. Due to the tremendous impact of the pandemic on the planetary scale, the literature on the Covid-19 fueled economic crisis has grown at a rapid pace; see Zhang et al. (2020); and the references therein. In particular, the global pandemic of Covid-19 has severely affected worldwide commodity markets (Godel, 2020; Sharif et al., 2020; and Wang et al., 2020). It is worth mentioning that the impact of the global financial crisis on commodity markets has been duly addressed in the literature (see, for instance, Go and Lau, 2020, and the references therein). However, the impact of the Covid-19 triggered crisis on the commodity market has not yet been duly addressed in the literature, with some exceptions; see, Dutta et al. (2020); Ker and Cardwell (2020); Wang et al. (2020); Borgards et al. (2021); Sifat et al. (2021); Umar et al. (2021a); and the references therein. Our research fills this gap contributing to the respective strand of the literature.

Amidst the Covid-19 negative news and impacts, there has been a growing consensus among many investors that the mainstream investment paradigm must evolve, advancing from the sole focus on profit maximization to a more balanced vision based on the concept of resources sustainability. In parallel, the Covid-19 crisis has attracted a new wave of attention to the role of commodity investments as portfolio diversifying factors, capable of spreading risk across different commodity categories. The pandemic has highlighted their attractiveness as a potentially viable hedge strategy among other reasons due to the fact that certain commodities have exhibited lower price volatility in comparison to variations in stock prices during the Covid-19 strongly bearish conditions and initial recovery from them. Such circumstances make investors to search for alternative investments capable of providing attractive returns and still offering the required hedging attributes.

Hence, we believe that studying the dynamics of commodities through the Covid-19 bear market and the initial recovery from it provides a unique way to study the economic impact of the pandemic on the prices of important resources, which are crucial for the overall stability of the worldwide financial system and the global economy. Although the price dynamics of diverse commodities, such as energy, agricultural,

livestock, precious metals, and non-precious metals had been explored in the recent past (see, e.g., Zaremba et al., 2019; Umar et al., 2021b, Cerin et al., 2020), the impact of Covid-19 panic on commodity markets still remains to be duly addressed by the academy. Moreover, it is very desirable to analyze the behavior of commodities compared to the level of Covid-19 fueled panic in order to assess the potential capacity of commodities to be used as a hedge for more volatile equity and fixed-income assets in the periods of systemic global crises, such as Covid-19 pandemic turmoil. Inspired by other studies based on wavelet analysis (Sun and Xu, 2018; Zaremba et al., 2019; and Goodell and Goutte, 2020; Jawadi et al., 2020; Khalfaoui et al., 2020), we employ the wavelet coherence and wavelet phase difference techniques to investigate the impact of Covid-19 fueled panic on the volatility of the commodity prices.

Our motivation to explore the comparative behavior of the Covid-19 panic levels and the prices of commodities is related to the fact that they have been heavily affected by market expectations and speculations, which are always amplified by herd behavior in the periods of crisis. Our research contributes to the incipient and, hence, insufficient literature on commodity market reaction to the Covid-19 provoked crisis. Our findings are important for commodity market players and regulators in their attempts to comprehend and forecast the behavior of commodity prices during the periods of global economic and financial distress, as we discuss the unique dynamics of the Covid-19 crisis.

The contribution of our research to the current state of the art is three-fold. First, we fill in the existing gap related to the lack of academic research on the dynamic interdependence maps of mood variables, such as panic levels, and prices in the main commodity markets in the time-frequency perspective. Second, our paper adds to the current literature on commodity markets' response to the Covid-19 economic impact. As our sample period covers the most recent global crisis caused by the pandemic, our findings can provide useful insights for investors, traders, risk managers, regulators of commodity markets, and resources policy makers. Third, we document the intervals of low, medium, and high coherence between the PI and the commodities. Our results may be useful for designing cross-asset commodity-based hedging strategies in line with earlier research on this subject (e.g., Rehman et al., 2019), as we evidence that commodities offer attractive hedging attributes, effective in the periods of systemic global crises.

The rest of the paper is organized as follows. Section 2 provides the literature review. Section 3 discusses the data and methodologies employed. Section 4 presents the results and provides their interpretation. Section 5 concludes.

2. Literature review

In this section, we provide a literature survey aimed at highlighting the most relevant research aligned with the scope of our paper. Thus, our overview covers the following two topics: (i) pre-Covid commodity markets since the Global Financial Crisis and (ii) Covid-19 influence on commodity markets.

2.1. Commodity markets since the global financial crisis

It is worth mentioning that the Global Financial Crisis (GFC) has led to a substantial increase in the interest of academic community and market players in the commodity market, in general, and has triggered a strand in the literature dedicated to the impact of the global financial crisis on various sectors of the commodity market, in particular. It is also worth noting that commodity markets also have been thoroughly investigated prior to Covid-19 pandemic. Herein, we consider a selected set of relevant studies, aligned with the topic of our research. It is also worth mentioning that the GFC has caused a phenomenal upsurge in interest towards resources policies, and investing in commodities.

We start our survey addressing a seminal paper by Vacha and Barunik (2012), investigating the co-movement of energy commodities, by

studying their dynamics in the time-frequency domain. This is one of the pioneering studies applying wavelet tools to commodity market data, while previously a major part of economic time series analysis was performed in the time or frequency domain separately. Authors, using the wavelet framework, propose a new, model-free way of estimating time-varying correlations and apply it to crude oil, gasoline, heating oil, and natural gas, analyzing the period 1993–2010. They uncover interesting dynamics of correlations between energy commodities in the time-frequency space.

Another seminal study of commodity markets is represented by the research performed by Fernandez-Perez et al. (2017). Their findings demonstrate that commodity portfolios, which capture the backwardation and contango phases exhibit in-sample and out-of-sample predictive power for the first two moments of the distribution of long-horizon aggregate equity market returns, and for the business cycle. Backwardation and contango our found to represent plausible investment opportunities, aligned with the intertemporal capital asset pricing model.

In parallel, a survey on the financial economics of white precious metals is undertaken by Vigne et al. (2017). Awareness for precious metals as an investment vehicle has increased especially after the GFC of 2008–2009 as a result of increased financialization in the commodity markets following a 'flight-to-quality' concept (Gubareva and Borges, 2016). In this context, Vigne et al. (2017), provide a thorough review of the academic literature on the financial economics of silver, platinum, and palladium. The survey covers the findings on a wide variety of topics in relation to white precious metals, including market efficiency, forecastability, behavioral findings, diversification benefits, volatility catalyzers, macroeconomic drivers, and their relationships with other assets.

In the more recent work of Rehman et al. (2018), a time-varying connectedness approach is applied to study the interrelations between precious metal returns and oil shocks. This paper examines the impact of oil shocks on precious metal returns using a structural vector auto-regression model (Kilian and Park, 2009) capable of capturing variability in the effects through rolling window impulse response functions. In addition, the extended dynamic connectedness approach of Diebold and Yilmaz (2014) based on structural forecast error variance decomposition is applied. Rehman et al. (2018), report time-varying effect of disintegrated structural oil shocks on precious metal returns with a significant increase during the GFC of 2008–2009. Their results also indicate that the aggregate demand shocks have the most significant spillover effect on the precious metals except gold. Additionally, they report that oil specific demand shocks during the GFC have the highest impact on gold and palladium, hence, offering possible hedging opportunities against the oil price movement. Their findings have important investment implications for individual and institutional investors.

The study by Rehman et al. (2019), is already focused on the post-GFC period. Authors investigate the presence of short- and long-run asymmetric relationships between energy and non-energy commodities for weekly data from January 2010 to June 2018. Using the nonlinear ARDL methodology, they demonstrate that oil prices have significant long-run negative effects on the prices of gold and silver, indicating that for both metal commodities, oil price increases lead to more decrease than the subsequent oil prices decrease. Crude oil, among other energy commodities, is found to offer more diversification benefits when combined with gold or silver; however, minimal diversification benefits can result from combining crude oil with wheat or platinum. Gas futures, among other energy markets, offer more diversification opportunities when combined with copper, wheat, platinum, or palladium, while coal offers maximum diversification benefits when combined with gold, silver, or wheat.

Now we would like to highlight a very interesting research by Zaremba et al. (2019), testing the inflation hedge properties of commodities with the longest data series ever used; for the years 1265–2017. A wavelet analysis is applied to commodity prices and inflation data from the United Kingdom to detect co-movement across different times and frequencies. Authors demonstrate robust inflation hedging properties of agricultural, energy, and industrial commodities for the 4- to 8-year horizon throughout almost the entire seven-century-long period.

Adhikari and Putnam (2020), study comovement in commodity futures markets, analyzing the energy, grains, and livestock sectors. In particular, they focus on the excess comovement of commodity futures returns. Their results show that measures of excess comovement "within-sectors" are much higher relative to "across-sector" measures. In addition, they test the relevance of two new "cross-market" factors related to changes in inventory and open interest as determinants of commodity futures returns. Authors find a strong positive relationship between changes in cross-market open interest and futures returns in the energy and livestock markets. In contrast, the impact of changes in cross-market inventory on futures returns in the energy and grains sectors is very minor.

Chen and Mu (2020), investigate asymmetric volatility in commodity markets. Their paper studies the return–volatility relationship in a range of commodities. Authors show that the volatility of price changes can be positively or negatively related to demand shocks. An "inverse leverage effect" - the volatility is higher following positive price shocks - is found in more than half of the daily spot prices. The effect is weaker in the three-month futures market, the period after mid-2000s, and monthly historical volatility measures. Only crude oil exhibits a "leverage effect" - higher volatility follows a negative shock - and the reason is explored in the context of its special market structure.

Ciner et al. (2020), address spillovers, integration, and causality in non-ferrous metal markets. Authors investigate the interrelationships in the global base metal markets along the years 1994–2016 using a variety of econometric methods, including wavelet analysis. The results demonstrate the high intensity of both return and volatility spillovers across the selected markets. Furthermore, the degree of co-movements varies among time and frequencies. The findings show that the behaviour of the non-ferrous metals is similar to other conventional asset classes, like equities and bonds, justifying the position that metals have become an investment class.

Assessing volatility in the energy market during the period covering the GFC, Elsayed et al. (2020), study time-varying co-movements between the energy market and global financial markets, being interested in the implications for portfolio diversification and hedging strategies. Their study explores the time patterns of volatility spillovers between the energy market and stock prices of seven major global financial markets including clean energy, energy, information technology corporations, equity markets, and United States economic policy index over the period from December 28, 2000 to December 31, 2018. Authors show that the impact of energy market becomes strong in the global financial market when the data is divided into pre-, during, and post-GFC periods. Finally, the hedge ratios are volatile over time and their maximum value is observed during the financial crisis period of 2008–2009.

Khalfaoui et al. (2020), investigate the time-frequency dynamics of money demand, oil prices, and macroeconomic variables, considering as an example the case of India. They also consider the period encompassing the GFC, namely, the years 1994–2017. The paper uses the wavelet coherency and the partial wavelet coherency techniques. Authors conclude that causal interplays between variables are more pronounced in the long run. In particular, they highlight the elevated efficiency of the wavelet partial coherency technique.

Addressing volatility spillover effects among commodities and other asset classes, Mandaci et al. (2020), study dynamic connectedness and portfolio strategies between energy and metal markets. Authors consider a wide historical data on daily futures data from 1992 to 2019. The study finds that the dynamic connectedness of the asset volatilities increases during the GFC. Moreover, this paper evidences that the cross-asset-classes hedge strategies are more effective than those based on assets within the same asset classes.

Considering the period from 2000 to 2017, Saif-Alyousfi et al.

(2020), analyze the impact of oil and gas price shocks on bank performance in the major oil and gas exporting countries. Results indicate that oil and gas price rises have a direct bearing on bank performance through the channel of price-induced bank deposits and related lending to business activities. The negative impact on bank performance due to a drop in oil and gas prices is greater than the positive effect of a rise in prices. Findings suggest that oil and gas price volatility has an asymmetric effect on conventional and Islamic banks. Conventional banks reap more benefit from the increased cash flow created by oil and gas prices, compared to Islamic banks. While Islamic banks are generally vulnerable to adverse oil and gas price shocks, conventional banks tend to benefit more from positive oil and gas price shocks. However, the authors find that the association between oil and gas price shocks and bank performance has been distorted by the GFC, the Arab Spring, and the Yemen War. Their findings are potentially useful for the central banks and governments in oil and gas exporting countries.

Tvedt (2020), studies the interlinkages between commodity market flexibility and financial derivatives. Real flexibility is modelled as an instantaneous adjustment of production in response to demand-driven changes in commodity prices and by gradual entry or exit of production units. Increased real flexibility typically reduces the market price of financial flexibility. The paper includes an insightful empirical section on oil and gas markets.

West (2020), investigates extractable global resources and the future availability of metal stocks. The primary purpose of this article is to suggest that estimates of extractable global resources of metals made using current methodologies are inherently uncertain. This uncertainty renders them generally unfit for guiding policy regarding resource depletion and governance. The author concludes that maintaining metal supplies for future generations will be better served by continuing to improve our understanding of the impacts of ever-increasing mining activity on natural systems, and states that such impacts may be reduced by improved mining practices.

However, the uncertainty of future availability estimates becomes much more elevated due to unexpected events such as the Covid-19 pandemic. The next subsection is, hence, dedicated to uncovering the nexus of the ongoing pandemic outbreak on several sectors of the commodity market.

2.2. Covid-19 influence on commodity markets

The recent Covid-19 pandemic has presented a unique challenge and inspired a new stream of literature focused on the impact of the global virulent disease on financial markets, in general, and commodity markets, in particular. However, the impact of the Covid-19 triggered crisis on the latter has not yet duly addressed in the literature. We acknowledge an each time augmenting number of welcome exceptions and review here a selected set of the most recent contributions from the academy to the field of commodity trading and resources governance.

The Covid-19 pandemic is providing a stress test throughout every aspect of the economy, not just agriculture and food. Nonetheless, Ker and Cardwell (2020) are vying for attention to the Canadian agriculture and food sectors under the impacts of the ongoing coronavirus outbreak. Based on years of a consumer-driven food system, Canadians have come to expect any food in the form, time, and location desired, always available at a reasonable price. However, Covid-19 has caused immediate and pronounced changes in consumer food demand. Nonetheless, Canadians are still consuming a vast array of foods at reasonable prices despite a few short-lived stockouts. To date, this situation represents an affirmation of the global food supply system. Moreover, authors highlighting the importance of short-run emergency policies and the economic stimulus packages, conclude that governments should tread carefully in making structural policy changes at this time.

Wang et al. (2020), undertake an analysis of the impact of Covid-19 on the correlations between crude oil and agricultural futures, such as London Sugar, London Wheat, USA Cotton #2, and USA Orange Juice

futures. Authors use a multifractal detrended cross-correlation analysis approach to study the cross-correlations. They are focused on the influence of Covid-19 on the cross-correlations of multifractality between crude oil and agricultural futures. Authors find that the multifractal cross-correlations of all agricultural futures have increased after the emergence of Covid-19 except the orange juice futures market.

Commodity futures markets are also scrutinized by Borgards et al. (2021), who perform an intraday analysis of price overreaction in the twenty considered commodity futures based on intraday data from November 20, 2019 to June 3, 2020, with a focus on the impact of the Covid-19 pandemic. Authors find that the price overreactions are higher during the Covid-19 outbreak. They observe significant differences between soft and hard commodities and conclude that crude oil represents a special commodity with a different price overreaction behavior. Authors also find that extreme overreactions during the Covid-19 pandemic provide a great potential for profitable trading returns, which can be exploited by traders.

In their turn, Sifat et al. (2021), address the Covid-19 pandemic influence on speculations in energy, precious metals, and agricultural futures. They report new evidence that speculation in energy and precious metal futures are more prevalent in crisis periods and even more so during the Covid-19 pandemic. In contrast, agricultural futures attract more hedging pressure. Post-GFC patterns mirror the 1980s' recessions. Using quantile regression on a long-horizon sample, the authors also find that speculative pressure generally coincides with abnormal returns in normal circumstances but not in the current pandemic. They also conclude that volatility is strongly and often non-linearly associated with speculation across instruments.

Return and volatility transmission between oil price shocks and agricultural commodities has been recently investigated by Umar et al. (2021a). This paper studies the connectedness between oil price shocks and agricultural commodities for the sample period from January 2002 to July 2020 and, hence, covers three global crises: the GFC, the European sovereign debt crisis and the Covid-19 pandemic crisis. Authors employ Granger causality tests and the static and dynamic connectedness spillover index methodology. They find that the shocks in oil prices are Granger-caused mainly by price changes of grains, live cattle, and wheat, while supply shock Granger-causes variations mostly in grain prices. Umar et al. (2021a) find that, from the point of view of static connectedness, for both price and volatility spillovers, the livestock is the largest transmitter, while the lean hogs are the major receiver. Their dynamic analysis evidences that connectedness increases during the financial crisis period, turning their results are potentially useful for investors, portfolios managers, and policy makers.

As we have seen above, the recent Covid-19 pandemic has presented a unique challenge and inspired a new stream of literature focused on the impact of the global virulent disease on financial markets. Our research fills this gap contributing to this strand of academic research. We add to this yet incipient and, hence, insufficient literature by documenting the reaction of various commodity prices to the Covid-19 induced crisis. Our findings are important for investors, pursuing diversification with investments in commodities, as we discuss their unique performance during the Covid-19 crisis.

3. Data and methods

This study applies the squared wavelet coherence (SWC) and wavelet coherence phase difference (WCPD) techniques following Torrence and Compo (1998), Torrence and Webster (1999), and more recent works by Sun and Xu (2018), and Zaremba et al. (2019). Our approach is applied to daily data of the Coronavirus Worldwide Panic Index (PI) and commodity prices. The time span of our analysis covers the first seven months of 2020. We analyze the interdependencies between the pandemic-fueled panic, measured by the PI, and the volatility of diverse commodity prices, encompassing various categories of commodity products.

3.1. Data and descriptive statistics

We employ the Ravenpack Coronavirus Panic Index (PI) and gauge its interdependence with the volatility observed during the first seven months of 2020 in various sectors of the commodity market. The Ravenpack PI is an index that is commonly used as a proxy for the level of news chatter that refers to panic or hysteria and coronavirus. The PI historical time series are obtained from Ravenpack. The Ravenpack Coronavirus PI measures the pandemic panic level as a share of news referring to panic and coronavirus in the total volume of news. Hence, it reflects the extension and impact of the pandemic on public mood influencing investment decisions because of the level of coronavirus awareness of investors. The PI value lies between 0 and 100. For instance, the value of 6.5 indicates that 6.5 percent of all news globally is talking about panic and Covid-19.

Apart from the PI, our dataset includes the time series of prices for the five following commodity aggregates: energy commodities, agricultural products, livestock commodities, precious metals, and non-precious metals. We use the volatility of the S&P GSCI spot commodity indices. The data is obtained from Thomson Reuters DataStream. Table 1 reports the summary statistics for the volatility in commodity prices for the selected categories of commodity products from the January 21, 2020, (the date World Health Organization announced that Covid-19 is transferable from human to human) to the end of July 2020.

3.2. Econometric framework

Inspired by several studies based on wavelet analysis (Sun and Xu, 2018; Zaremba et al., 2019; and Goodell and Goutte, 2020; Jawadi et al., 2020; Khalfaoui et al., 2020), we employ the wavelet coherence and wavelet phase difference techniques to investigate the impact of Covid-19 fueled panic on the volatility of the commodity prices. The wavelet techniques allow us to obtain the results in the form of time-frequency heat-maps containing information on both coherence and time difference of the studied pairs of indices. Specifically, the wavelet coherence analysis is capable of providing insights on the joint behavior of indices, not only along the sole dimension of time, but also over different investment time-scales, thus enabling us to study various patterns of commodities' price movements and co-movements. In addition, we employ the phase difference technique to obtain further information on the direction of indices co-movements and investigate the causality relationships between the variations in the levels of Covid-19 panic and the prices of the analyzed commodities.

Among the diverse approaches employed in the field of econometrics to study the interdependencies between the level of news chatter that refers to coronavirus panic or hysteria and the dynamics of various commodity markets, we choose the wavelet technique allowing for analyses in the time-frequency space. Following existing in literature examples of this methodology, in our investigation we further advance the state of the art developed in several previous studies based on wavelet

analysis (Zaremba et al., 2019; Umar and Gubareva, 2020, 2021, 2021; Long et al., 2021; and Umar et al., 2021b).

The wavelet-based framework allows obtaining results in a format of heatmaps in the time-frequency domain, which contain information, simultaneously, about pair-wise coherence and coherence time-difference of the considered pairs of variables. Because of this peculiarity, such method of analysis facilitates a joint consideration of information coming from the frequency and time perspectives. The wavelet transformation is widely applied in many areas of scientific research. It is also worth mentioning a few recent applications of wavelet technique to study the pandemic impacts upon capital markets: Demir et al. (2020); Gubareva and Umar, 2020; Umar and Gubareva (2020), 2021; Umar et al. (2021b), and the references therein.

We acknowledge the existence of a wide range of diverse econometric frameworks applicable for studying coherence and contagion patterns. However, among many other techniques, we stay with the wavelet-based approach because of the rationale discussed below. As the first argument, we highlight that the wavelet coherence technique is an appropriate toolkit for obtaining valuable knowledge regarding a simultaneous dynamics of a pair of data-series, as its outputs provide information in both, time and frequency dimensions. It turns to be especially suitable for studying lead-lag patterns and co-movements between indices. Taking into consideration the relevance of considering distinct investment horizons, i.e., frequency ranges, in the context of our research, our natural choice is the wavelet-based analysis. The second point is that for the wavelet method to be employed, no hardly restricting assumptions, e.g., process stationarity, etc., are needed. Hence, this technique is appropriate to investigate both linear and non-linear phenomena. The third attractive feature of the employed herein approach is related to the capacity of the wavelet methodology to provide relevant findings even if only relatively short data histories are available. This peculiarity is especially important in the case of limited Covid-19-concerned time-spans of data. Wrapping-up, the above addressed characteristics of the wavelet technique certify it as a robust scientific method, widely used to study coherence patterns brought about by jointly analyzed diverse arrays of data; see, Vacha and Barunik (2012); Zaremba et al. (2019); Gubareva and Umar, 2020; and Umar and Gubareva (2021a). Herein, we follow the wavelet-based approach to investigate the lead and lag interrelations of the variations in the levels of coronavirus panic and financial performance in various sectors of the commodity market.

The above-mentioned studies prove the capacity of the wavelet-based approach to be a powerful tool in producing valuable knowledge on interrelation causality in the behavior of diverse pairs of variables, simultaneously analyzing them in a time-frequency space. This potentially enables us to study various patterns of the interdependency relationship between the pairs of variables comprising the coronavirus panic index, on the one hand, and on the other hand, one of the sectors of commodity markets. Further on, the phase-difference technique is used in our research to generate valuable knowledge regarding the direction

Table 1

Descriptive statistics for the PI and commodity price indices for the selected aggregates.

	Agriculture	Energy	Livestock	Precious Metal	Non-Precious Metal	Panic Index
Average	0.14	0.71	0.27	0.21	0.39	3.32
Standard deviation	0.05	0.53	0.16	0.12	0.25	1.79
Skewness	0.40	0.95	1.18	1.14	0.87	0.72
Kurtosis	0.04	(0.21)	0.07	0.74	(0.50)	0.66
Minimum	0.04	0.15	0.10	0.06	0.10	–
1st quartile	0.10	0.28	0.16	0.12	0.20	2.37
Median	0.14	0.48	0.22	0.17	0.30	3.08
3rd quartile	0.17	1.13	0.33	0.29	0.56	4.21
Maximum	1.00	2.14	1.00	1.00	1.00	9.24
Observations	134	134	134	134	134	134

Note. The table reports daily changes in the PI and the prices of commodities, Jan–Jul 2020.

of the comovements and, hence, to study the causal interrelations of the variations in the level of coronavirus panic and returns and volatility of commodity markets.

The squared wavelet coherence (SWC) technique is based on a bivariate framework established with a continuous wavelet transform, able of providing a variety of scaled localizations (Rua and Nunes, 2009). To perform the time-frequency wavelet-based analyses of the co-movement between time-series, we use the wavelet coherence approach consisting of both the cross-wavelet transform (CWT) and coherence.

The CWT of two time-series $x(t)$ and $y(t)$, in line with Torrence and Compo (1998), is expressed through their individual CWTs: $W_n^x(u,s)$ and $W_n^y(u,s)$ as:

$$W_n^{xy}(u,s) = W_n^x(u,s)^* \, W_n^y(u,s) \tag{1}$$

where u indicates the location, s represents the scale, and the asterisk $*$ designates the complex conjugate. The CWT puts in evidence those areas in the time-frequency domain where the considered time-series co-move, even if they do not show a common high power. In other words, it captures the local covariance between the two time series $x(t)$ and $y(t)$ at each scale. For instance, a CWT value close to one signifies a high degree of synchronization between the time-series. On the other hand, a CWT figure in proximity to zero signals an absence of relationship.

We follow the framework of Torrence and Webster (1999), and define the squared wavelet coherence (SWC), which captures the co-movements between the two time-series as:

$$R^2(u,s) = \frac{|S(s^{-1}W^{xy}(u,s))|^2}{S\left(s^{-1}|W^x(u,s)|^2\right)S\left(s^{-1}|W^y(u,s)|^2\right)} \tag{2}$$

where S is a smoothing operator over time as well as frequency scale. The SWC is but a correlation coefficient in the time-frequency domain. The SWC value for any day at any frequency from high (daily) to low (32-day period) is bounded by 0 (depicting zero correlation) and 1 (depicting perfect correlation between the two time-series).

It is worth mentioning that differently from the common Pearson correlation coefficient of the two time-series, the SWC assumes only positive values. Hence, such an approach is unable to distinguish co-movements of opposite signs, i.e., cannot differentiate between positive and negative correlations.

To get a deeper insight into the correlations analyses and lead-lag relations among the two time series, we employ the WCPD technique (Torrence and Compo, 1998), which allows for distinguishing between the two possible co-movements: positive and negative.

The WCPD is expressed as:

$$\Phi_{xy}(u,s) = tan^{-1}\left(\frac{Im\{S(s^{-1}W^{xy}(u,s))\}}{Re\{S(s^{-1}W^{xy}(u,s))\}}\right) \tag{3}$$

where Im and Re are, respectively, the imaginary and real parts of the smoothed CWT. For both the PI and commodities, the daily moves are gauged by calculating the changes between the two consecutive index prices.

It is worth noting that the employed graphical presentation of the WSC provides us with the causal relationships between the two time-series. For instance, we employ black arrows on the SWC panels to indicate phase-differences. A phase-difference equal to zero corresponds to perfect co-movements of the two time-series. Arrows pointing to the right (left) indicate time series which are in-phase (out of phase), i.e., are positively (negatively) correlated. An arrow pointing upward indicates that the first time series leads the second by $\pi/2$. By analogy, an arrow with downward direction signifies that, in this case, the second time series leads the first by $\pi/2$. Bearing these rules in mind, one could intuitively decipher the meaning of an arrow pointing in any other imaginable direction.

The next section is dedicated to the results and their discussion.

4. Results

Following several previous researches (Baffes, 2009; Dutta and Noor, 2017; Rehman et al., 2019), our results are structured according to the topological classification of the traditional commodities in the two following classes: energy commodities and non-energy commodities, being in our case agricultural commodity products, livestock commodities, precious metals, and non-precious metals. Due to their different nature and bearing in mind the fundamental importance of energy resources for the production of non-energy commodities, the energy and non-energy commodities are expected to be affected by the pandemic in different ways.

4.1. Coronavirus panic index (PI) and energy commodity prices

We begin our analysis by examining the SWC results between the PI and the aggregate price index of energy commodities. The term 'energy commodities' refers to a variety of coal, oil, gas, and gasoline derived products. These include such energy resources as coal, oil, gasoline, heating oil, and natural gas, among others.

Fig. 1 displays the results for the SWC measure and WCPD based lead-lag relationship between the PI and the energy commodity prices. The legends on the right-hand side of the panels in Fig. 1 show the keys for reading the heatmaps. Time is displayed on the horizontal axis and the frequency, or the length of the period of analysis in days, is shown on the vertical axis. The interpretation of the left-hand graph of Fig. 1 is based on the color displayed for any day and frequency. In general, the warmer the color (yellow to red), the greater the coherence or interdependence between the indices. The cooler colors (green to blue) imply less coherence.

For the PI–Energy pair, we document a varying level of coherence ranging from low to medium and high coherence over the entire time scale. It is worth noting that for the 2-weeks-plus low-frequency band on the top of the left-hand-side panel in Fig. 1 above the heatmap appears to be predominantly red, signifying a high coherence during the analyzed period.

The initial period shows high overall coherence, although by the end of the month within the 1-week frequency band we observe a set of blue spots with green aureoles implying lower levels of coherence during that time interval. We associate this pattern to the pre-Covid-19 period, when markets still predominantly continued exhibiting growth trends and a rather smooth functioning, preceding the panic-leads-market phase, provoked by the pandemic in February 2020. Over the frequency scale, coherence is high across most frequencies, but more specifically, it changes from high to medium-low for higher frequencies, with the lowest coherence observed for the 3-day's frequency horizon. This result represents a certain interest from the point of view of energy commodity trading, as the above phenomenon of diminishing coherence for a set of frequencies exhibits not constant but alternating patterns along the time scale. A further research of this phenomenon is desirable.

The predominantly red-colored intervals imply that the volatility of the energy commodity prices is highly correlated with the Covid-19 induced panic, leaving less room for diversification through investments in energy commodities. However, the intervals of green regions imply that the energy commodities exhibit also some diversification attributes despite the drastic effects of the pandemic contingency measures implemented in February–March 2020, in the vast majority of countries worldwide.

We also identify the causality and phase differences between the PI and the energy commodity moves. As already briefly mentioned in the methodology section, arrows on the SWC plot indicate the phase differences between the PI and the energy commodity index moves. For example, → and ← indicate that both the PI and the energy commodities are in phase and out of phase, respectively. ↗ and ↙ indicate that the PI
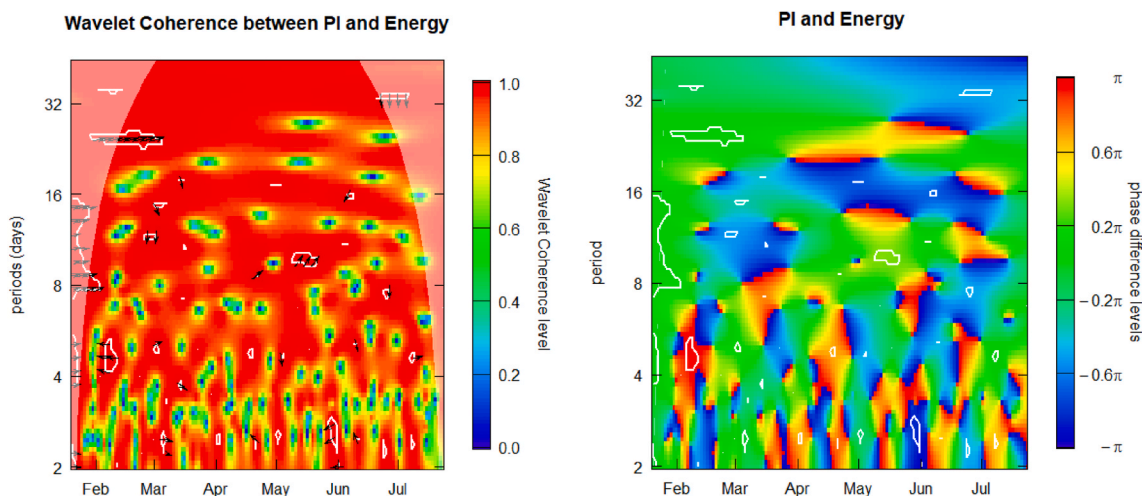
Fig. 1. Wavelet analysis: the Panic Index (PI) versus the Energy commodity prices.

moves are leading those of the energy commodities, while ↘ and ↖ indicate that the PI moves are lagging behind those of energy commodity prices. In particular, the left-hand heatmap of Fig. 1 exhibits for the second half of January, the "→" arrows, signifying an in-phase relationship in the 2-day to 2-weeks band, and indicating the positive correlation between the PI and the energy commodity index. We ascribe this period to the early phase of the pandemic, when Covid-19 begins to spread on a global scale.

To gain further insight into the interdependency relationship, the right-hand heatmap of Fig. 1 identifies the lead-lag relationship between the PI and the energy commodity prices. We notice two important features here. First, we observe several regions of anti-phase, since February 2020 onwards, where a lead by the energy commodity prices over the coronavirus panic level is especially evident by the blue color. It signifies that the price movements of the energy commodities as a whole precede the movements in the level of panic coronavirus panic, which reflects the advances of the pandemic on the planetary scale. Second, interestingly enough, within the 1-week frequency band we observe alternating patterns suggesting an unsynchronized behavior of the two indices, although over the larger investment horizons in the 1-week-plus band, these asynchronies are self-cancelled as evidenced by the green tonality. However, the overall average tonality of the upper half of the phase-difference heatmap could be characterized as cooler than green, as the blue zones clearly predominate over the residual reddish-yellow

regions, evidencing the overall leadership of the energy commodities movements in the 2-week-plus frequency band. Such results may be considered broadly consistent with the fact that energy resources prove to be essential in daily life. This makes consumers and traders most aware of changes in the pricing of energy commodities, preceding the overall general sentiment regarding the advancement/backtrack of the pandemic.

Our findings regarding the lead role of energy commodity prices could be of use for investors prospecting investments in energy resources as possessing some attractive hedging attributes, whose potential for portfolio diversification does not disappear, as evidenced herein, even within the periods of acute global crises.

4.2. Coronavirus panic index (PI) and non-energy commodity prices

Now we extend our analysis and report the results for a set of selected traditional non-energy commodities.

4.2.1. Agricultural commodity products
Fig. 2 displays the results for the SWC measure and WCPD between the coronavirus Panic Index (PI) and the agricultural commodity index. The overall coherence pattern in the left heatmap is similar to the respective panel of Fig. 1 and the respective findings regarding the impact of the PI on the volatility of the energy commodity index.
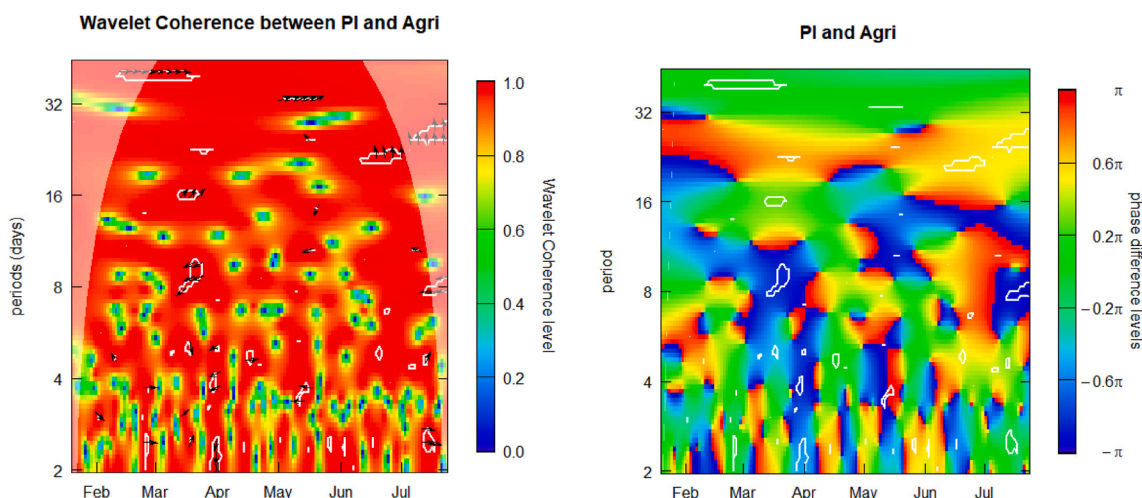

Fig. 2. Wavelet analysis: the Panic Index (PI) versus the Agricultural commodity prices (Agri).

However, in the phase-difference graph, we observe that the hot - yellow and red - regions are more visible along the whole studied period, especially for the 2-week-plus investment horizons and in June and July also for 1-to-2-week frequency band, being these zones representative of agricultural commodity price movements lagging behind those of the PI. These warm colored regions indicate that the pricing of the agricultural commodity products follows the overall advancements/retrocessions in the general panic sentiment geared by the Covid-19 pandemic.

Nonetheless, it is worth mentioning that the borders between the deep blue regions, on the one hand, and the green and intense red zones, on the other hand, are quite neat, serving as an indication of lead-lag regime switching. This observed feature represents a valuable attribute for creating elaborated dynamic hedge strategies based on investments in agricultural commodities.

4.2.2. Livestock commodities

Fig. 3 presents the results for the SWC measure and WCPD between the PI and the livestock commodity index. As with the other two indices analyzed above, we observe an alternating pattern of high and low coherence across time and frequency scales. Over the frequency scale, similarly to the previous cases, we also observe that coherence is high for the investment horizons superior to 1 week, diminishing for the panel's bottom 2-to-4-day's band. However, the overall phase difference tonality is predominantly green, and, hence, situated somewhere between the cooler-than-green panel of energy commodities and the warmer-than-green agricultural commodities heatmap. Still, we see several anti-phase and in-phase periods along the whole observation period. In addition, at the top of the phase difference heatmap, we observe a green/greenish blue belt of the 2-to-4-weeks frequency band, becoming a yellowish lane for the 1-month-plus investment horizons, meaning that the livestock commodity prices lag behind the coronavirus panic levels dynamics, especially for the investments horizons superior to one month.

In addition, we notice that the borders between the in-phase and anti-phase regions, differently from the agricultural commodities, are not so neat appearing rather blurry – no evidences of well-defined regime switching, – indicating that the livestock commodity products do not represent a good candidate either for static, or for dynamic hedge strategies, not exhibiting an attractive diversification potential along the Covid-19 pandemic.

4.2.3. Precious metals

Fig. 4 presents the results for the SWC measure and WCPD based lead-lag relationship between the coronavirus Panic Index (PI) and the precious metals index. The SWC analysis results in an alternating pattern

of high and low coherence across time and frequency scales, similarly to the previously considered indices of energy, agricultural, and livestock commodities. As in the case of the energy commodities, we observe that the initial period, corresponding to the second half of January, exhibits high overall coherence. We ascribe this pattern to the pre-Covid-19 period, when still the markets predominantly exhibited growth trends and a rather smooth functioning, preceding the panic-leads-market phase, provoked by the pandemic in February 2020. Over the frequency scale, coherence is high across most frequencies, especially for the 2-weeks-plus investment horizons. At the bottom of the SWC panel, i. e., for higher frequencies, the coherence changes from high to medium-low, with the lowest coherence observed for the 3-day's frequency horizon. This result represents a certain interest from the point of view of precious metals trading, as the above phenomenon of diminishing coherence for a set of frequencies exhibits not constant but alternating patterns along the time scale. A further research of this phenomenon is desirable.

However, differently from the previously addressed cases, for the precious metals we see a cloud of the arrows ↘ in March–April in the lower part of the 2-week-plus frequency band. According to the previously discussed legend: arrows pointing to the left indicate time series, which are out of phase, i.e., are negatively correlated, while an arrow pointing upward indicates that the first time series leads the second by π/2. Therefore, the observed cloud of the arrows ↘ indicates that in March and April the price movements of the precious metals are partially out of phase with the PI, and that precious metals partly play a leadership role vis-à-vis the coronavirus panic, leading the PI time series approximately by π/4. Such results may be considered broadly consistent with the fact that precious metals prove to play an essential role as safe haven assets. This makes consumers and traders most aware of changes in their pricing, thereby preceding the overall general sentiment regarding the advancement/backtrack of the pandemic. This is comprehensible that such a role becomes more statistically significant in the region indicated by the borders of the cloud covering the most rapid pace of economic and financial changes around the apogee of the pandemic, when general sentiments were lagging to adequately reflect the overwhelming disruption of normality due to the Covid-19 impacts. We attribute this period to the effects of full-swing social distancing, and once again demonstrate that the wavelet analysis correctly reflects the underlying Covid-19 reality.

Moreover, we report a few interesting findings of the phase difference analysis. Herein, similarly to the case of agricultural commodities, it is worth mentioning that the borders between the deep blue regions, on the one hand, and the green and intense red zones, on the other hand, are quite neat, serving as an indication of well-defined lead-lag regime
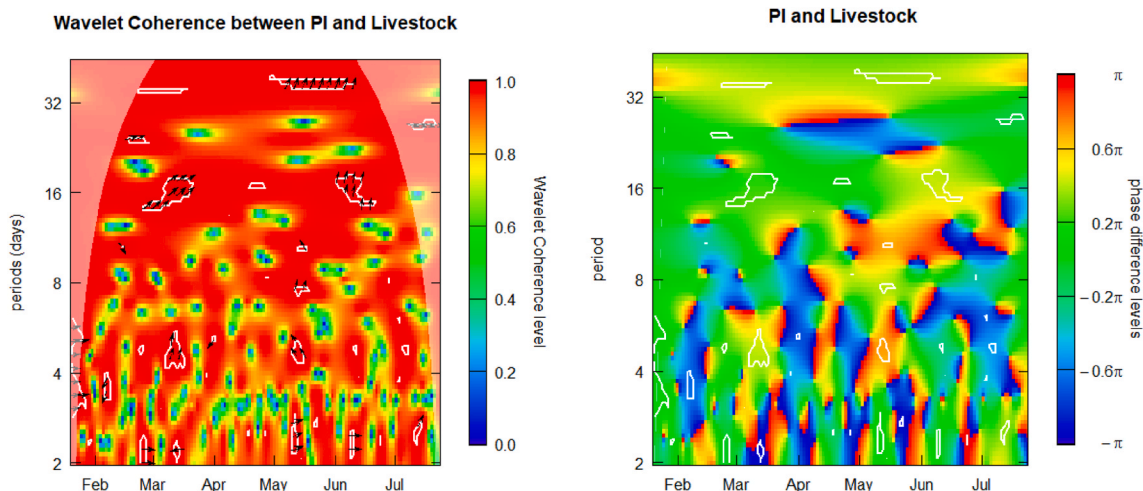

Fig. 3. Wavelet analysis: the Panic Index (PI) versus the Livestock commodity prices.
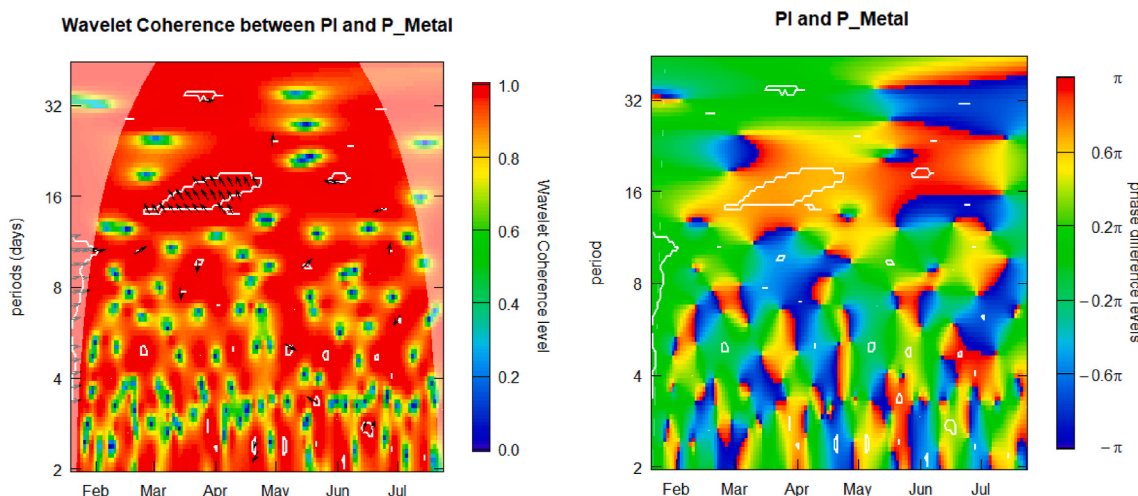
Fig. 4. Wavelet analysis: the Panic Index (PI) versus precious metal prices (P_Metal).

switching. This observed feature represents a valuable attribute for designing dynamic hedge strategies based on investments in precious metals. In this manner, they are attractive candidates for hedging purposes.

4.2.4. Non-precious metals

Fig. 5 visualizes the results for the SWC measure and WCPD based lead-lag relationship between the PI and the non-precious metal index. Similarly to the previous cases, here again, the red predominant tonality corresponds to a high coherence. However, there are intervals of low coherence (green) across the time-frequency scale. In particular, for higher frequencies (1–8 days), we observe recurrent intervals of low coherence, especially for the 1-to-4-days band. A further research of this feature is needed, especially as in the case of non-precious metals, the short mini-cycles of average duration about 10 days are particularly well noticeable; see several small blue spots with greenish turquoise aureoles along the entire analyzed period.

To gain further insight into the interdependency relationship, we also identify the causality and phase differences between the PI and the non-precious metals index. In the right-hand panel of Fig. 4, we observe that for the 2-week-plus frequency band the predominant tonality is blue. The left-hand upper corner is also blue/sky blue colored. In general, the observed phase-difference pattern is similar to that of the phase diagram for energy commodities. These two panels, energy and non-

precious metals, are the coolest panels in comparison to the other phase difference heatmaps. A pronounced well-defined blue cloud in the central part of the panel indicates that the PI lags behind the price moves of the non-precious metals index, certifying that non-precious metals perform the leadership role, especially evident in April–June 2020, i.e., in times of recovery from the Covid-19 crisis lows experienced in late March. This finding makes non-precious metals the most attractive investment targets during the initial recovery period, capable of providing hedging attributes for those thinking to pursue a diversification of their assets by means of investing in traditional non-energy commodities. From this analysis, we conclude that non-precious metal resources play a role of the main causality driver in the periods of recovery from recessions and global crises.

4.3. Economic implications of the results

In this final subsection dedicated to the achieved results, we provide more comments about economic implications of our findings, putting them in perspective vis-à-vis previous studies on the similar subjects.

On the one hand, our results corroborate the conclusion of earlier studies dedicated to the impact of Covid-19 on cross-correlations between crude oil and agricultural futures (Wang et al., 2020), on commodity price overreactions (Borgards et al., 2021) and on the connectedness between oil price and agricultural commodities (Umar
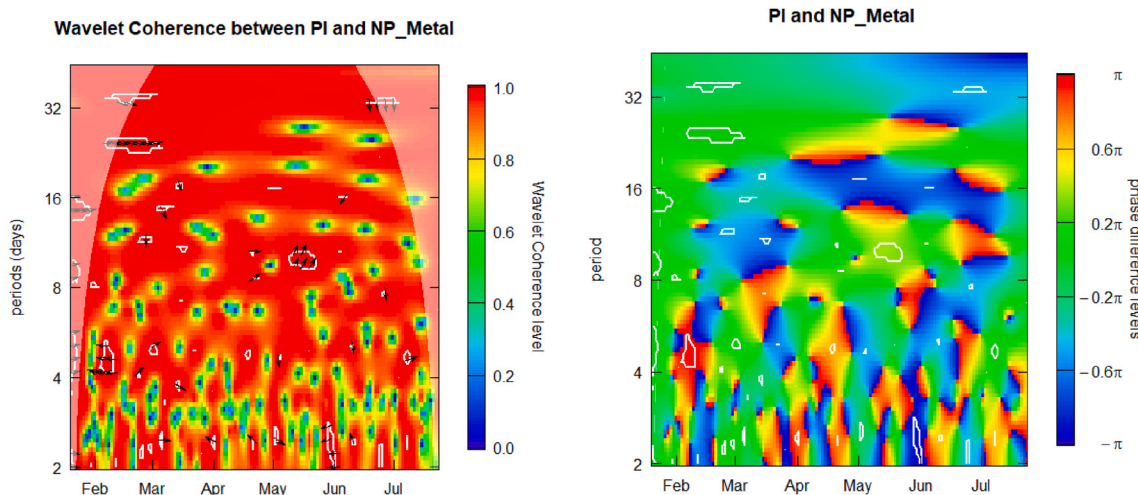

Fig. 5. Wavelet analysis: the Panic Index (PI) versus non-precious metal prices (NP_Metal).

et al., 2021a). The above-mentioned studies come to the conclusion that either oil-agricultural cross-correlations, or overreactions of soft and hard commodity prices, or oil-agricultural interconnectedness increases during the apogee of the pandemic-triggered crisis. Our research is supportive in respect of these findings, as we observe and document the predominant regions of high coherence in the time-frequency domain between the Covid-19 panic level and performance of the considered commodity categories.

On the other hand, based on our wavelet-based multi-scale analysis, we are able to detect well-defined zones of low coherence, which indicate that certain commodity asset classes may be successfully used for designing downside risk hedging strategies and allowing for appropriating diversification benefits. This our conclusion is aligned with the findings of Borgards et al., 2021), who, studying several commodity futures, state that extreme price overreactions during the Covid-19 pandemic provide a great potential for profitable trading returns, which can be exploited by traders. However, our research provides a deeper dive in the five most important sectors of the commodity market rather than in the commodity futures.

Hence, the economic implications of our results reside in their potential for a smoother operation of commodity markets, in particular, and financial markets, in general. Note that the capital markets under normal conditions, i.e., without turmoil and stress, are a necessary condition for the sustainable economic development without extremal lows and highs, representing inherent features of business cycle. Avoiding their exacerbations requires reducing the uncertainty and instability of financial markets, and our research represents one of the needed steps in this direction.

5. Conclusion

This study examines the interdependence between the Coronavirus Panic Index (PI) and the volatility of five traditional categories of commodities, covering energy and non-energy resources. We employ wavelet coherence and wavelet phase difference methodologies, which allow studying the influence of public sentiment on the main sectors of the commodity market.

Our research contributes to the literature along three perspectives. First, the present work fills in the existing void related to the insufficiency of the academic coverage of dynamic interdependences between mood variables, such as panic levels and prices of the main commodities. Second, our paper adds to the current literature on the commodity markets' response to the Covid-19-triggered economic crisis. Therefore, our findings are potentially useful insights for investors, traders, risk managers, regulators of commodity markets, and resources-policy makers. Third, we document the intervals of low, medium, and high coherence between the PI and the commodities in the time-frequency space. Hence, our results provide relevant insights for designing cross-asset commodity-based hedging strategies in line with earlier researches on this subject as we evidence that commodities offer attractive hedging attributes, effective in the periods of systemic global crises.

In particular, our results show alternating zones of high, medium, and low coherence between various commodity indexes and the PI. The predominant high coherence implies the high correlation between a systemic event such as the Covid-19 pandemic and the commodity market volatility, emphasizing the importance of alternative assets for hedging. However, there are intervals of low coherence across various time and frequency scales for these indices. The low coherence intervals show that several commodities offer attractive attributes, which allow harvesting diversification benefits. For instance, precious metals can serve as a potential safe haven even during a global catastrophe such as the Covid-19, while no-precious metals exhibit a superior diversification potential during the recovery from recessions and global crises. We also observe several differences in the patterns of coherence exhibited by various commodities encompassing energy and non-energy resources. We report that appealing hedging attributes are less pronounced in

livestock commodity exposures.

Thus, our findings corroborate the usage of commodity investments by investors pursuing diversification and downside risk hedge strategies, based on market segmentation across various sectors of economic activity, and most importantly, differentiating between various categories of commodities. The results of this study have important implications for portfolio managers, private and institutional investors, resources policy makers, and future research. The results can be useful for portfolio managers and investors for designing cross-sector and cross-asset hedge strategies, which could work in the periods of global crisis, as evidenced by the Covid-19 pandemic. Thus, banks and hedge funds could use our findings for better delineating accurate risk profiles of traditional commodities. On the other hand, policymakers can use the results of this research for designing policies to reduce market volatility during such highly uncertain times and optimize the usage of available energy and non-energy resources. Lastly yet importantly, future research can focus on extending our results by using alternative techniques and measuring the portfolio implications of including such investments in a portfolio choice framework.

Authors statement

Zaghum Umar: Conceptualization, Methodology, Investigation, Formal analysis, Data Curation, Validation, Visualization, Writing - Review & Editing, Resources.

Mariya Gubareva: Conceptualization, Methodology, Investigation, Resources, Writing - Original Draft, Writing - Review & Editing, Validation, Project administration, Funding acquisition.

Tamara Teplova: Conceptualization, Methodology, Investigation, Writing - Review & Editing, Validation, Resources.

Acknowledgments

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