Energy Commodity Price Response to COVID-19: Impact of Epidemic Status, Government Policy, and Stock Market Volatility

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ABSTRACT

The outbreak of the COVID-19 pandemic has hit the global financial markets, including energy commodities. The aim of the paper is to examine the reaction of the energy commodity market to the COVID-19 pandemic, particularly the epidemic status, the stringency of the government anti-COVID-19 policy, and the stock market volatility. We use daily data on the S&P GSCI Energy index, the number of new confirmed COVID-19 global cases, the self-developed Global Stringency Index, and the VIX index. The research covers the period from January 2 to September 30, 2020, i.e. the first phase of the COVID-19 pandemic. Based on a structural vector autoregressive model we observe a significant and negative energy commodity market's reaction to the changes in the stock market volatility. Moreover, the results imply that the increase in the Global Stringency Index leads to the decline in the S&P GSCI Energy index but the reaction is significant only on the third day after the shock. We reveal no significant impact of global epidemic status on energy commodity prices.

Keywords: Energy Commodities, COVID-19 Pandemic, Stock Market Volatility, Global Stringency Index, Government Anti-COVID-19 Policy, Structural Vector Autoregressive Model
JEL Classifications: G01, G12, G15, H12, Q41

1. INTRODUCTION

The spread of the COVID-19, an infectious disease caused by the severe acute respiratory syndrome coronavirus 2 – SARS-CoV-2, moved the World Health Organization to officially classify it as a global pandemic on March 11, 2020 (Andersen et al., 2020; Maier and Brockmann, 2020). Since the beginning of the pandemic till 30 September 2020, about 35 million cases of COVID-19 have been reported worldwide, causing more than one million deaths. The adverse global COVID-19 scenario states that the pandemic will potentially infect 7.0 billion people, causing 40 million deaths (Walker et al., 2020). The novel coronavirus has shaken the global economy and societies on an unprecedented scale since the global financial crisis (2008-2009) or the Great depression (1929-1933), and is epidemically compared to the Spanish flu

pandemic of the 1918 (Baker et al., 2020; Barro et al., 2020; Boot et al., 2020; McKibbin and Fernando, 2020; Nicola et al., 2020). The novel coronavirus represents the fear of the unknown and should be treated as the father of all fears that have overtaken global financial and economic systems. As a consequence, this fear has led to the national governments' reactions worldwide (Phan and Narayan, 2020).

The outbreak of the COVID-19 pandemic has affected significantly the global financial markets (Al-Awadhi et al., 2020; Czech et al., 2020; Goodell, 2020; He et al., 2020; Okorie and Lin, 2020). There are numerous studies on the COVID-19 pandemic impact on stock markets (Ashraf, 2020b; Zhang et al., 2020) and foreign exchange markets (Benzid and Chebbi, 2020; Gunay, 2020). March 2020 witnessed one of the most dramatic stock market

crashes in history (Mazur et al., 2020), a substantially sharper fall than the stock market decline during the global financial crisis of 2008-2009, which reflected the bursting of the asset price bubble (Anand et al., 2013).

The COVID-19 outbreak has led to extensive declines in international commodity prices (Rajput et al., 2020). Wagner (2020) claims that the COVID-19 represents a fearsome and novel risk that has stirred feverish behaviour among investors. However, reasonable economic expectations have also underlain movements in the stock prices despite the existence of the volatility and panic on stock markets. The COVID-19 outbreak as well as government measures to contain it have affected global supply chains and commodity prices. The novel coronavirus pandemic has linked to unprecedented shock that has disrupted both supply and demand of commodities (Ezeaku and Asongu, 2020). Rajput et al. (2020) observe a sudden drop in supply and demand of all classes of commodities including energy ones, as a consequence of the novel coronavirus outbreak.

As we showed above, there are numerous and profound studies on the COVID-19 pandemic impact on the stock market. However, the energy commodities reaction to the novel epidemic crisis has not been thoroughly investigated yet, although energy commodities, particularly crude oil, belong to the most commonly traded commodities (Perifanis and Dagoumas, 2018). Our study focuses on the energy commodity prices reaction to key factors linked to the COVID-19 pandemic, i.e. the epidemic status, the stringency of governmental anti-COVID-19 policy, and the financial market volatility. We are aware that the above-mentioned important factors do not form a complete catalogue and we share the opinion of Baker et al. (2020) that the extraordinary financial market reaction to the COVID-19 is painted with a broad brush. However, we would like to show how the energy commodity market responds to variables directly related to the COVID-19.

Majority of studies report that the number of lab-confirmed COVID-19 cases has a negative impact on financial market behaviour. According to Liu et al. (2020), the outbreak of the novel coronavirus had a significant negative impact on stock market returns across all affected countries, and the numbers of confirmed COVID-19 cases significantly hit the major stock indices performances, particularly in Asia, where they suffered a greater decline. Ashraf (2020b), using daily data on confirmed COVID-19 cases and deaths and stock market returns from 64 countries from around the world from January to April 2020, finds that stock markets quickly responded to the novel coronavirus pandemic and the response varied over time. The stock markets reacted more proactively to the increase of the confirmed COVID-19 cases as compared to the increase in the number of deaths. Baig et al. (2020) indicate that the growing number of confirmed cases and deaths due to COVID-19 are linked to a significant increase in market volatility and illiquidity. Bouri et al. (2020) observe a positive relationship between EMVID – a daily newspaper-based index of uncertainty linked to infectious diseases and realized oil volatility. However, Onali (2020), based on the U.S. and six other countries majorly affected by the first phase of the pandemic, shows that changes in the number of COVID-19

cases and deaths do not affect the stock market returns. Energy commodity market reaction to epidemic status has been hardly investigated. Moreover, the studies focus mainly on oil prices, and their results are inconsistent and vary due to the length of the adopted research period. Narayan (2020), based on a threshold regression model over the period between December 31, 2019, and May 5, 2020, observes the significant impact of the number of COVID-19 infections on oil prices. Moreover, he indicates that there is a threshold value of around 85 thousand coronavirus infections after which COVID-19 has had a bigger effect on oil prices in the first phase of the pandemic. However, Sharif et al. (2020), using the wavelet approach over the period between January 1 and March 30, 2020, show no significant effect of the number of COVID-19 infections on oil prices.

The second factor assumed to affect the energy commodity market in the time of the COVID-19 pandemic is the stringency of government anti-COVID-19 policy. The severity level of the observed government reactions is unprecedented but its impact on the financial market is not deeply investigated and proven. Baker et al. (2020), based on the U.S. stock market, indicate that government restrictions on commercial activity and voluntary social distancing are the key factors affecting stock markets in the first phase of the novel coronavirus pandemic. Eleftheriou and Patsoulis (2020), based on 45 stock market indices, observe the existence of negative direct and spillover effects of governments' anti-COVID-19 social distancing measures, including lockdowns, in the initial period of the pandemic. Ashraf (2020a), using daily panel data from 77 countries, finds that the implementation of government anti-COVID-19 measures negatively affected stock market returns in the first phase of the pandemic, while government announcements regarding public awareness programs, testing and quarantining policies, and income support packages largely resulted in positive market returns. Baig et al. (2020) suggest that implementations of anti-COVID restrictions and lockdowns significantly contribute to increased market illiquidity and volatility. Zaremba et al. (2020) demonstrate that government anti-COVID-19 responses, i.e. information campaigns and public event cancellations trigger the increase in international stock market volatility. We do not find any study focusing on the impact of government anti-COVID-19 responses on the energy commodity market.

The third factor considered to influence the energy commodity prices during the novel coronavirus pandemic is the stock market volatility. Kamdem et al. (2020) observe that the commodity markets, characterised by large price changes, react strongly to unexpected events, and involve many players who anticipate each other's actions, particularly in times of high volatility. Yin and Han (2014), using a new macroeconomic uncertainty index developed by Baker et al. (2016), showed that increased volatility in uncertainty leads to an increase in commodity prices and their volatility, whereas increased volatility in commodity markets boosts the macroeconomic policy uncertainty. Moreover, they indicated that the relationship between uncertainty and commodity prices varies significantly over time, particularly before and after the global financial crisis. However, Wang et al. (2015) reveal the significant predictability of the relationship between the economic

policy uncertainty and commodity prices regardless of the time period. Sari et al. (2011) prove that shocks in risk perceptions have a negative but short-term impact on oil prices, implying that the growing market volatility over the economic recovery is hitting the global energy demand and causes the oil prices to decline. Silvennoinen and Thorp (2013) observe that the higher stock market uncertainty increases commodity returns correlation with equity returns. Li et al. (2016) find that in the crisis and post-crisis periods fluctuations in oil markets are significantly associated with fluctuations in stock market volatility. Moreover, exogenous shocks can escalate information transmission between oil prices and volatility. We indicate the COVID-19 pandemic as an example of such a shock. In the study, we focus on the financial and not the general economic uncertainty. To measure the stock market volatility, we use the VIX index in the study. The VIX, implied at the Chicago Board Options Exchanges (CBOE), is recognized as the most popular proxy for the global financial market uncertainty (Fernandes et al., 2014) and widely acknowledged as a broad-based investor "fear gauge" (Mele et al., 2015). Cheng et al. (2015), studying the commodity market reactions to changes of VIX index before and after the global financial crisis, showed that traders reduced their net long positions in the times of crisis in response to market distress, while hedgers eased this task by reducing their net short positions as commodity prices went down. Nazlioglu et al. (2015), investigating a volatility transmission between oil prices and financial stress (measured by Cleveland financial stress index) in pre-crisis, in-crisis, and post-crisis periods, revealed that oil prices spill on financial stress before the crisis, but the reversed spillover effect was observed after the crisis. Moreover, they found no changes in volatility transmission pattern dynamics before and after the crisis. Reboredo and Uddin (2016), based on energy and metal commodity markets, indicate that the stock market volatility, measured by the VIX index, is not so crucial in determining commodity futures prices. Salisu et al. (2020) show the existence of a positive relationship between commodity price returns and the COVID-19 global fear index, confirming that commodity returns increase as COVID-19 related fear rises. Ji et al. (2018) indicate the existence of a negative dependence between energy commodity prices and changes in uncertainty. Moreover, energy price returns are more sensitive to uncertainty increases than to uncertainty declines.

The paper aims to investigate the reaction of the energy commodity market to the COVID-19 pandemic, particularly the number of the new confirmed COVID-19 global cases, the stock market volatility, and the global stringency of government anti-COVID-19 policy.

Our contribution is that applying a structural vector autoregressive model (SVAR) we assess the reaction of energy commodity markets to rapidly growing stock market volatility and the stringency of global anti-COVID-19 policy. To the best of our knowledge, there are no other studies investigating the commodity, particularly energy, market reaction to stringency levels of government anti-COVID-19 responses. It should be stressed that we are the first who develop the Global Stringency index based on country-level data.

The outline of our paper proceeds as follows. Section 2 presents the aim of the study, research hypotheses, and a description of the material and research methods used. Section 3 reports the empirical findings and provides the discussion. Finally, Section 4 offers our conclusions.

2. MATERIALS AND METHODS

The aim of the paper is to investigate the reaction of the energy commodity market to the COVID-19 pandemic, particularly the number of the new confirmed COVID-19 global cases, the global stringency of government anti-COVID-19 policy, and the stock market volatility. In order to achieve the main aim of the study, we have formulated three research hypotheses:

- H1: The number of the new confirmed COVID-19 global cases does not affect energy commodity prices
- H2: The global stringency of government anti-COVID-19 policy has a significant and negative impact on energy commodity prices
- H3: Energy commodity prices are significantly and negatively affected by the stock market volatility in the time of COVID-19.

Our research covers the period between January 2 and September 30, 2020, i.e. the first phase of the COVID-19 pandemic.

Energy commodity prices are represented by the S&P GSCI Energy index and S&P Dow Jones subindex which measures the energy commodity market performance. The index includes crude oil (and supporting contracts) and natural gas. The index is calculated primarily on a world production-weighted basis and comprises two principal energy commodities that are the subject of the active, liquid future market. The primary source for production data constitutes the United Nations. The S&P GSCI Energy index is considered a reliable and publicly available benchmark for investment in energy commodities and is designed to be a tradable index accessible to financial market participants. Moreover, the index reflects general levels of price movements and inflation in the global economy, which enhances its suitability as a benchmark (S&P Global, 2020). The S&P GSCI Indices has been providing index-based performance measures of real assets since 2007, as the S&P acquired the GSCI from Goldman Sachs (Wiederhold and Boal, 2019). The data on energy commodity prices come from Refinitiv Datastream.

We assume that the epidemic status, the stringency of government anti-COVID-19 policy, and the stock market volatility belong to the key indicators affecting the energy commodity prices during the novel coronavirus pandemic. We use the data on the number of new confirmed cases of COVID-19 to measure the epidemic status from the world perspective. The number of confirmed COVID-19 cases belongs to the three key indicators of the novel coronavirus pandemic, apart from the number of COVID-19 deaths and the total number of tests (Brodeur et al., 2020). The data are taken from Worldometer Coronavirus Update.

To measure the stringency of government anti-COVID-19 policy we apply the Stringency Index developed by the Blavatnik School of Government from Oxford University. The Stringency Index provides a systematic measure of tracking the severity level of government responses to the COVID-19 pandemic in time

across more than 170 countries. The Stringency Index consists of eight individual government response measures, including school closing, workplace closing, public events cancellations, restrictions on gathering size, public transport closing, stay-at-home requirements, restrictions on internal movements, restrictions on international travel, and public information campaign. The index ranges from 0 to 100 (Hale et al., 2020).

As the pandemic is global in nature, the stringency of government policy from a worldwide, not a single-country perspective must be considered. Due to this fact, we have developed the Global Stringency Index (GSI). To our knowledge, we are the first to apply this approach, while other studies focusing on a country-level or regional perspective.

$$\text{Global Stringency Index } (GSI)_t = \frac{SI_{1t} \cdot GDP_{1\omega} + SI_{2t} \cdot GDP_{2\omega} + \ldots + SI_{nt} \cdot GDP_{n\omega}}{GDP_{1\omega} + GDP_{2\omega} + \ldots + GDP_{n\omega}} \quad (1)$$

where SI_t is a single-country Stringency Index at time t, where $t \in [1,2,3,\ldots,T]$, GDP_ω is a single-country annual gross domestic product in constant prices at time ω, and n is the number of countries. In the study we assume that $t=1$ reflects the date – January 2, 2020, and $t=T$ represents September 30, 2020. Overall, our time series equals 189 observations. We use data on annual 2019 GDP values at constant 2010 USD. The index is based on 171 country-level Stringency Indices and GDPs which covers all the countries included both in World Bank statistics and the Oxford COVID-19 Government Response Tracker data.

In our study, we use the option-implied stock market volatility measured by the VIX index. The VIX was introduced by Whaley (2009) and has been computing on a real-time basis throughout each trading day since 1993 at the Chicago Board Options Exchange (CBOE). The VIX is a forward-looking index of the expected return volatility of the S&P 500 index over the next 30 days and is implied from the prices of the S&P 500 index options, which are predominantly used by the market as a means of ensuring the value of stock portfolios (Fernandes et al., 2014; Whaley, 2009). The VIX is widely used as a barometer for market uncertainty, providing market participants and observers with a measure of the U.S. stock market's expected volatility. The VIX index is not directly tradable, but the VIX methodology provides a script for replicating volatility with a portfolio of SPX options, a key innovation that led to the creation of tradable VIX futures and options (CBOE, 2020). The data on the VIX index come from the Chicago Board Options Exchange (CBOE).

The paper applies a structural vector autoregressive model (SVAR) model to examine the relationship between energy commodity prices and the selected variables linked to the COVID-19 pandemic, i.e. epidemic statutes measured by the new COVID-19 case, the stringency of anti-COVID-19 governmental policy, and the stock market volatility. Application of the structural vector autoregressive models (SVAR) into energy commodity prices analysis is widely observed in recent studies (Antonakakis et al., 2014; Chen et al., 2016; Degiannakis et al., 2018; Ji et al., 2018; Kilian and Murphy, 2014; Kamdem et al., 2020; Śmiech et al., 2015).

An equation (2) presents the general form of the SVAR model:

$$AX_t = \delta_1 X_{t-1} + \delta_2 X_{t-2} + \ldots + \delta_p X_{t-p} + \mathsf{C}u_t \quad (2)$$

where X_t represents a vector of endogenous variables, A, δ, C and u_t are serially uncorrelated error terms. Equations (3) and (4) present the reduced form of SVAR (1) model, obtained by multiplying with A^{-1}:

$$X_t = A^{-1} \delta_1 X_{t-1} + A^{-1} \delta_2 X_{t-2} + \cdots + A^{-1} \delta_p X_{t-p} + A^{-1} \mathsf{C}u_t \quad (3)$$

$$X_t = D_1 X_{t-1} + D_2 X_{t-2} + \cdots + D_p X_{t-p} + \varepsilon_t \quad (4)$$

where $D_i = A^{-1} \delta_i$, $i=1,\ldots,p$, and $\varepsilon_t = A^{-1} \mathsf{C}u_t = \gamma u_t$. In order to identify the structural form parameters, the restrictions must be placed on the parameter matrices. It is assumed that the shocks may affect a subset of variables directly within the current time period, whereas another subset of variables is affected with a time lag only. A well-known example of such an identification scheme is the recursive (triangular) identification suggested by Sims (1980). It means that the shocks enter the equations successively so that the additional shocks of the equation do not affect the variable explained by the first equation at the same time (Lütkepohl and Krätzig, 2004). In the model, the order of endogenous variables is important because it implicitly determines the connection between innovations. It is common to place the variable by the timeline of their occurrence. The variable that is considered to occur first is placed first in the vector of endogenous variables. The paper assumes that the first endogenous variable is the number of global COVID-19 cases (COVID). Then we assume that the global stringency of anti-COVID-19 policy (GSI) is affected by the epidemic status. The third variable is a stock market volatility (VIX) that, during the new coronavirus pandemic, is highly driven by both epidemic status and the stringency of global anti-COVID-19 restrictions. Energy commodity prices (Energy) are assumed to be affected both by the epidemic status, the stringency of government anti-COVID-19 restrictions, and the stock market volatility. The order of variables in the model has been set based on the broad literature review (Aloui et al., 2016; Cheng et al., 2020; Devpura and Narayan, 2020; Gil-Alana and Monge, 2020; Sari et al., 2011). Above assumptions are depicted in equation (5) that link the reduced-form errors to the structural shocks:

$$\begin{bmatrix} \varepsilon_{COVID} \\ \varepsilon_{GSI} \\ \varepsilon_{VIX} \\ \varepsilon_{Energy} \end{bmatrix} = $$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ \gamma(GSI,COVID) & 1 & 0 & 0 \\ \gamma(VIX,COVID) & \gamma(VIX,GSI) & 1 & 0 \\ \gamma(Energy,COVID) & \gamma(Energy,GSI) & \gamma(Energy,VIX) & 1 \end{bmatrix}$$

$$\begin{pmatrix} u_{COVID} \\ u_{GSI} \\ u_{VIX} \\ u_{Energy} \end{pmatrix} \quad (5)$$

The study is based on the impulse response functions, forecast error variance decompositions. An impulse response function traces the effect of a shock to one endogenous variable on the other variables in SVAR model. The shocks underlying the impulse responses are based on Cholesky decomposition with the ordering COVID, GSI, VIX, Energy. The forecast error variance decomposition analysis provides information about the relative importance of each random shock to one endogenous variable in affecting the other variable. It tells us about the proportion of the movements in a sequence due to its own shocks versus shocks to the other variable.

The series stationarity is checked based on the augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979; 1981) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) tests. The ADF test verifies the null hypothesis that a time series is I(1), which means that the process contains a unit root and therefore is non-stationary, against the alternative hypothesis that the process is stationary. On the other hand, KPSS test verifies the null hypothesis that a time series is stationary (I(0)) against the hypothesis that the process is non-stationary.

3. RESULTS AND DISCUSSION

Since the oil crisis in 1973, oil prices have proven to be more volatile than the prices of most other commodities (Fleming and Ostdiek, 1999; Regnier, 2007). Major, unexpected episodes, such as the Gulf War, the Asian crisis, and the 9/11 attack, significantly affected oil price volatility (Dey et al., 2020; Li et al., 2020; Olowe, 2010; Zhang et al., 2009). Moreover, energy commodity prices have started to be extremely volatile since the 2008-2009 global financial crisis when a decline of almost two-thirds of Brent price in half a year was observed (a drop from the historical high of $132.72 in July 2008 down to $43.32 per barrel in February 2009) (Zhang, 2017). Thus, we suspect that the energy commodity prices reaction to the COVID-19 is the most substantial among all groups of commodities. Figure 1, that presents the existence of high and growing volatility on the energy commodity market since the global financial crisis, corresponds to the above-mentioned research studies.

Aloui et al. (2020) find that energy commodity index reaction to the novel coronavirus has been varying over time due to fundamentals factors as well as behavioural and psychological ones. In the consequence of the oil price war and dampened oil demand, the energy sector was the most hit with a 15% average, monthly decline in energy indices between December 2019 and April 2020. The largest 1-month crude oil plunge in history was recorded in March 2020 (Ezeaku and Asongu, 2020). During the first phase of the COVID-19 pandemic, crude oil prices plunged to a historic low since the beginning of the XXI century. An unprecedented event was observed on April 20, 2020, when crude oil futures for the US oil benchmark (WTI – West Texas Intermediate) closed at –$37.63 per barrel (Ji et al., 2020). It should be stressed that the energy market is currently going through one of the most volatile times in its history. Crude price volatility is affected, apart from the COVID-19 pandemic, not only by macroeconomic and microeconomic factors but also by the speculative activities and non-economic variables, including the conflict between Russia and Saudi Arabia (Bildirici et al., 2020).

Figure 2 indicates a substantial and persistent increase in the number of new confirmed COVID-19 global cases from less than 20 thousand in mid-March to more than 300 thousand at the end of the analysed period. The visible daily seasonality in the number of new infections depends on the day-of-week link to the total number of COVID-19 tests. A decline of energy commodity prices observed before the official pandemic announcement on March 11, 2020, seems to be not associated with changes in global epidemic status. Moreover, over the period from June 1 to September 30, 2020, the S&P GSCI Energy index was stable and ranged from 124 to 147, while the number of global new infections was more than tripled in the same time. It might suggest no significant relationship between these two examined variables.

The first several shock waves in financial markets linked to the COVID-19 uncertainty were recorded in the second half of February 2020, when the financial volatility rapidly increased (Albulescu, 2020). Figure 3 shows both a substantial decrease in energy commodity prices and high average levels of uncertainty measured by the VIX index over the period from February 20 to April 21, 2020. At this time the VIX index represented high uncertainty levels. The index reached its maximum of 83 points on March 16, the level higher than during the global financial crisis. i.e. the collapse of Lehman Brothers Bank. Moreover, over the same

Figure 1: The volatility of the S&P GSCI Energy index over the period from January 1, 1983, to September 30, 2020
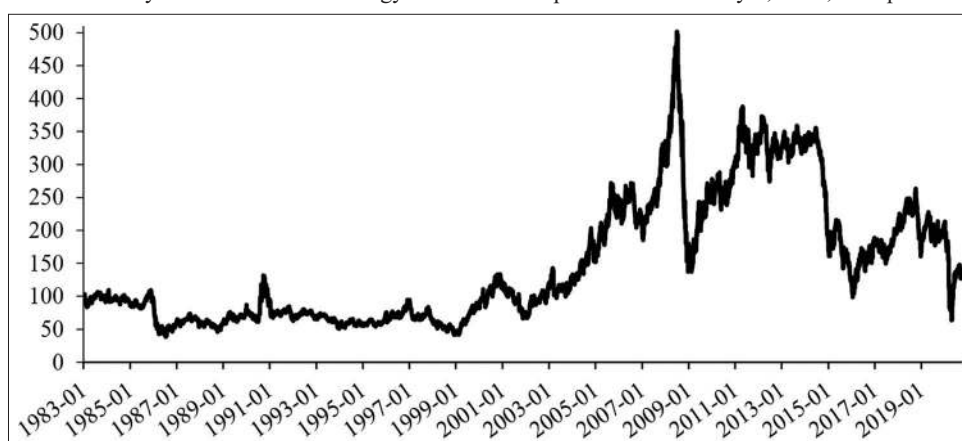
period the S&P GSCI Energy plunged from 184 to 64 points. From May to the end of September 2020 both variables were less volatile. The energy commodity market has been growing more than 30% but has not recovered from the pre-COVID-19 period. Furthermore, the average level of the VIX index was around 30, i.e. still above the pre-pandemic values. It might imply the existence of a linkage between energy commodity prices and the stock market uncertainty.

Figure 4 depicts the self-developed global stringency index calculated on the basis of formula (1). As first confirmed cases of novel coronavirus infections were recorded in the U.S. and Europe, subsequent government restrictions started to be implemented worldwide, which is reflected in the GSI values. Starting from the second half of February to the end of March 2020, a rapid increase in severity of national governments anti-COVID-19 policy, including entire economies' lockdown, was observed. From early April to mid-September the GSI levels remained high, however slight easing of government regulations was introduced. Figure 4 indicates a substantial fall of GSI in the last 2 weeks of the analysed

period (the second half of September 2020) that might reflect the end of the first phase of the COVID-19 pandemic. Figure 4 might imply the existence of a significant correlation between energy commodity prices and the stringency of government anti-COVID-19 policy.

The paper applies a structural vector autoregressive model (SVAR) to study the relationship between energy commodity prices and the variables that characterised the situation on the financial markets and global economy during the COVID-19 pandemic i.e. new COVID-19 cases, stringency of anti-COVID-19 policy, and option-implied volatility of the stock market (VIX). In order to avoid any spurious inferences, the variables are tested for stationarity. Table 1 presents the calculated t-statistic for ADF unit root test and Kwiatkowski-Phillips-Schmidt-Shin test statistic for KPSS stationarity test.

The combination of ADF and KPSS tests suggests that the analysed time series are integrated of order 1 (I(1)). We obtain the stationary

Figure 2: The S&P GSCI Energy index and the number of new confirmed COVID-19 global cases over the period from January 2 to September 30, 2020
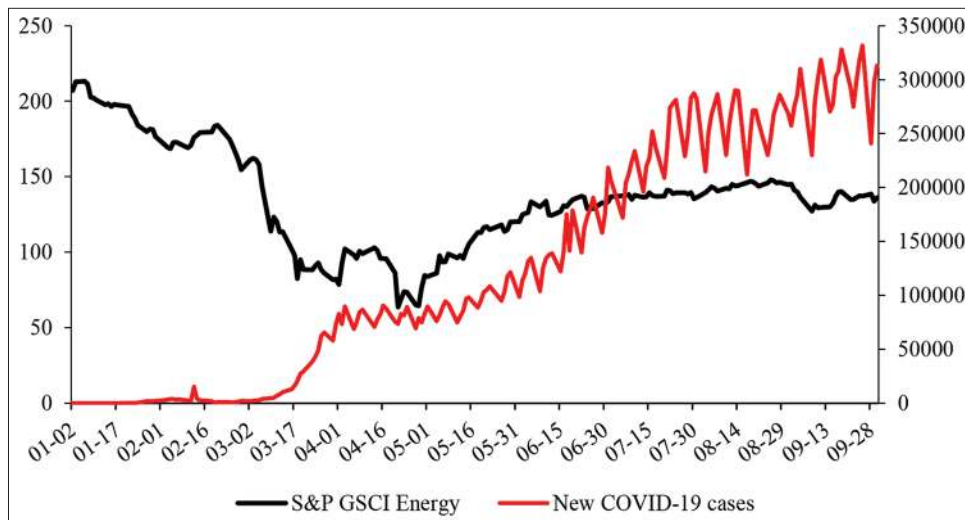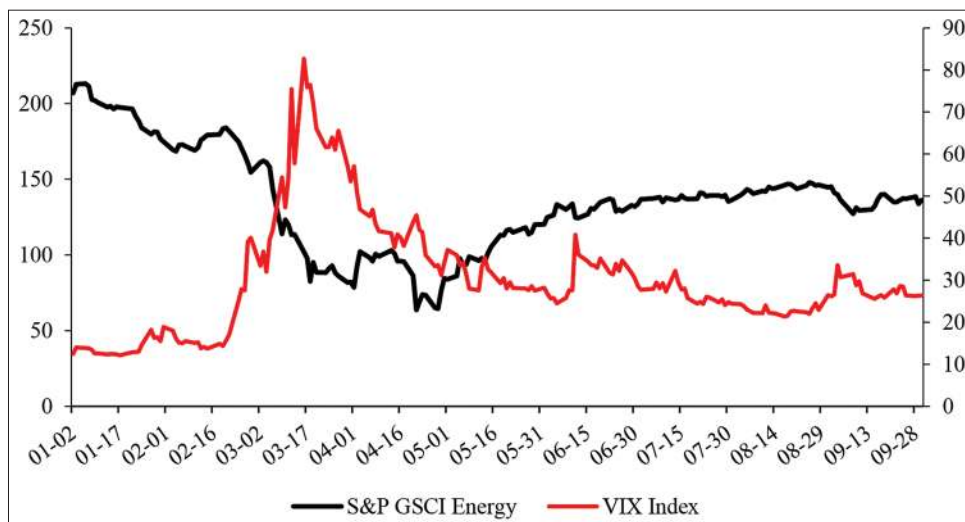

Figure 3: The S&P GSCI Energy index and the VIX index over the period from January 2 to September 30, 2020

processes by applying the first differences of the log values of the original series.

The optimal lag length of the VAR model is selected based on Akaike Information Criterion (AIC). The lowest value of AIC was obtained for 3 lags (AIC = –0.583). The Lagrange Multiplier test result implies that the residuals are not serially correlated. LM test statistics for 3 lag equals 16.12 with the corresponding

Table 1: The ADF unit root test and KPSS stationarity test results

Variable	Level	First difference
ADF test		
S&P GSCI Energy	–1.71	–12.83***
New COVID-19 cases	–2.46	–3.91**
VIX	–2.22	–6.19***
Global Stringency Index	0.55	–9.79***
KPSS test		
S&P GSCI Energy	0.33***	0.12*
New COVID-19 cases	0.24**	0.09
VIX	0.21***	0.08
Global Stringency Index	0.37***	0.08

ADF test null hypothesis H_0: There is a unit root for the series. KPSS test null hypothesis H_0: The series is stationary. ***H_0 is rejected at the 1%, **5%, and *10% significance level

p-value 0.44. Based on the following results we cannot reject the null hypothesis that there is no serial correlation in the residuals. All of the roots have modulus less than one and lie inside the unit AR roots circle. It implies that the model is stable.

We identify structural shocks in SVAR model by applying zero recursive restrictions in the form of Cholesky decomposition of the error covariance matrix and calculate impulse response functions. The initial order of variables determines the sequence of structural shocks. We assume the following order of variables: new COVID-19 cases, Global Stringency Index, Volatility Index (VIX), S&P GSCI Energy Index. The impulse response functions play the central role in assessing how and to what extent residual shock to one of the innovations linked to the COVID-19 pandemic affects the contemporaneous and future energy commodity prices.

Figure 5 displays the accumulated impulse response of the S&P GSCI Energy Index on the total new COVID-19 cases shock over the 20-days period range. The figures include a black line that reflects the mean reaction function and red lines that depict the confidence interval of two standard deviations around the mean. Figure 5a depicts the shock linked to an epidemic status that reflects an increase in the number of new COVID-19 cases.

Figure 4: The S&P GSCI Energy and the Global Stringency Index over the period from January 2 to September 30, 2020
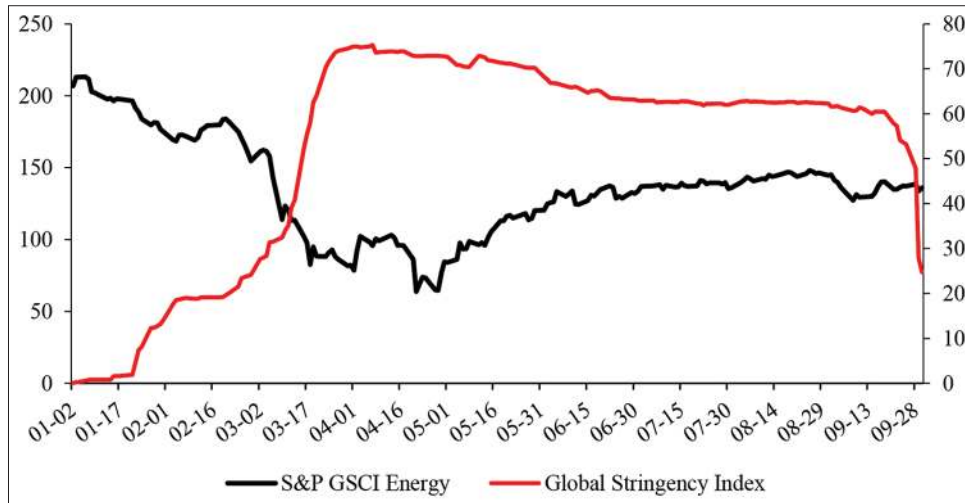

Figure 5: (a and b) Energy commodity price reaction to the increase in the number of total new COVID-19 cases
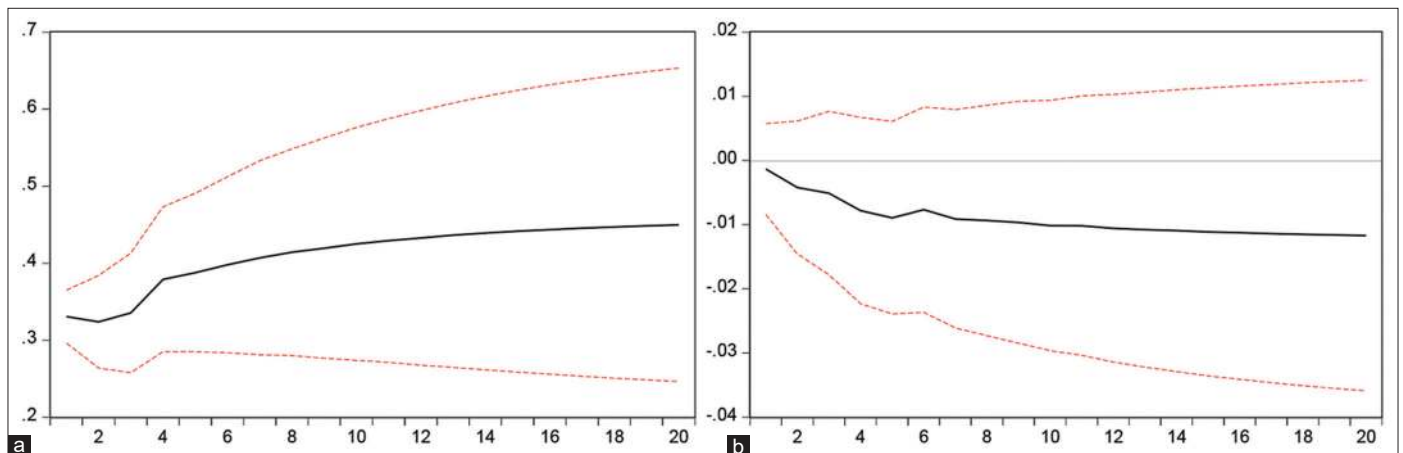
Figure 5b presents the reaction of energy prices on the shock related to the change in epidemic status. The results suggest that the increase in the number of total new COVID-19 cases is associated with a decrease in the S&P GSCI Energy Index. However, the standard error band crosses the zero axis, which implies that the reaction of energy prices to the COVID-19 case shock is not statistically significant. Our results correspond to Sharif et al. (2020) who observe no significant effect of the number of COVID-19 infections on oil prices but are in contrast to those of Narayan (2020).

Figure 6a depicts the shock that reflects an increase in the global stringency of anti-COVID-19 government policy. Figure 6b depicts the response of the S&P GSCI Energy Index to the shock associated with the increase of the Global Stringency Index. It implies that the increase in severity of global anti-COVID-19 government restrictions leads to the decline of energy commodity prices. However, the confidence interval consists of zero on all days apart from the third day after the shock. Thus the reaction of the S&P GSCI Energy Index on the change in the Global Stringency Index is negative as expected and persistent but insignificant for all days after impulse apart from day 3. The results are consistent with research hypothesis 2. To our knowledge, there are no other studies covering the energy commodity market reaction to government anti-COVID-19

responses. However, our results correspond indirectly to Baker et al. (2020), Eleftheriou and Patsoulis (2020), and Ashraf et al. (2020a) who observe the negative impact of government policy on the stock market, and are in line with Baig et al. (2020) and Zaremba et al. (2020) who prove the significant contribution of government restrictions and lockdowns to increased market illiquidity and volatility.

Figure 7a presents the shock that reflects the increase in the stock market volatility measured by the VIX index. The impulse response function presented in Figure 7b indicates the negative reaction of energy prices on the increase of stock market volatility. Moreover, the standard error band does not cross the zero axis, which implies that the reaction is statistically significant. The results of impulse response function analysis suggest that the S&P GSCI Energy Index decline significantly in response to increased stock market volatility. It is in line with hypothesis 3. Our results correspond to Li et al. (2016) who observe an interdependence of energy commodity prices and the stock market uncertainty, and found that exogenous shock can intensify the linkage between them. In our study, the COVID-19 pandemic reflects the exogenous shock. Furthermore, our study results correspond to Ji et al. (2018) who reveal the negative significant oil prices reaction to the stock market uncertainty, particularly in the times of increased uncertainty.

Figure 6: (a and b) Energy commodity price reaction on the increase of severity of anti-COVID-19 government policy
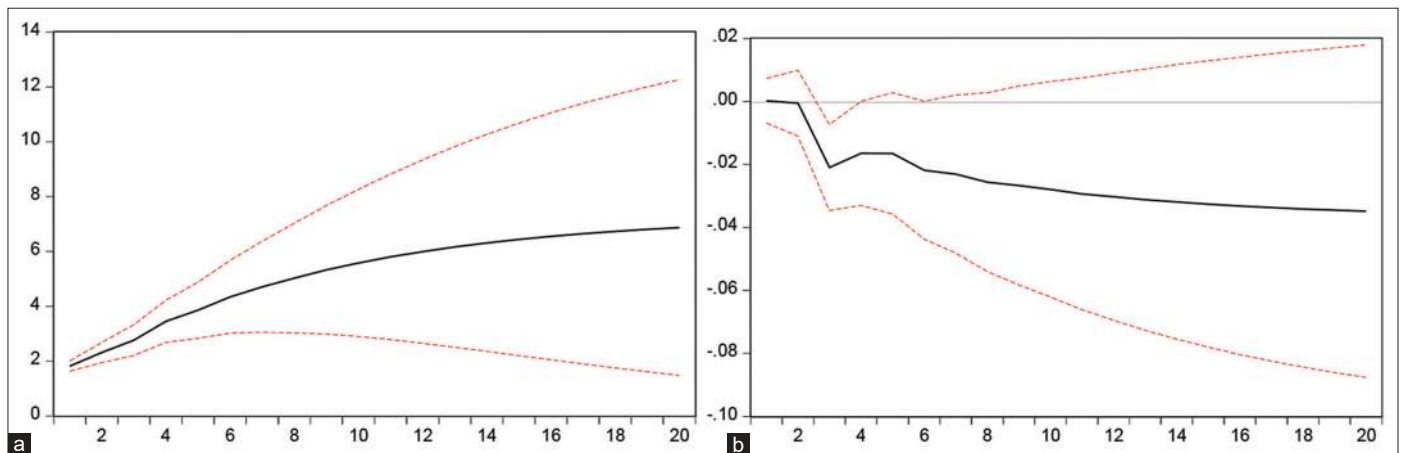

Figure 7: (a and b) Energy commodity price reaction to the increase of stock market volatility
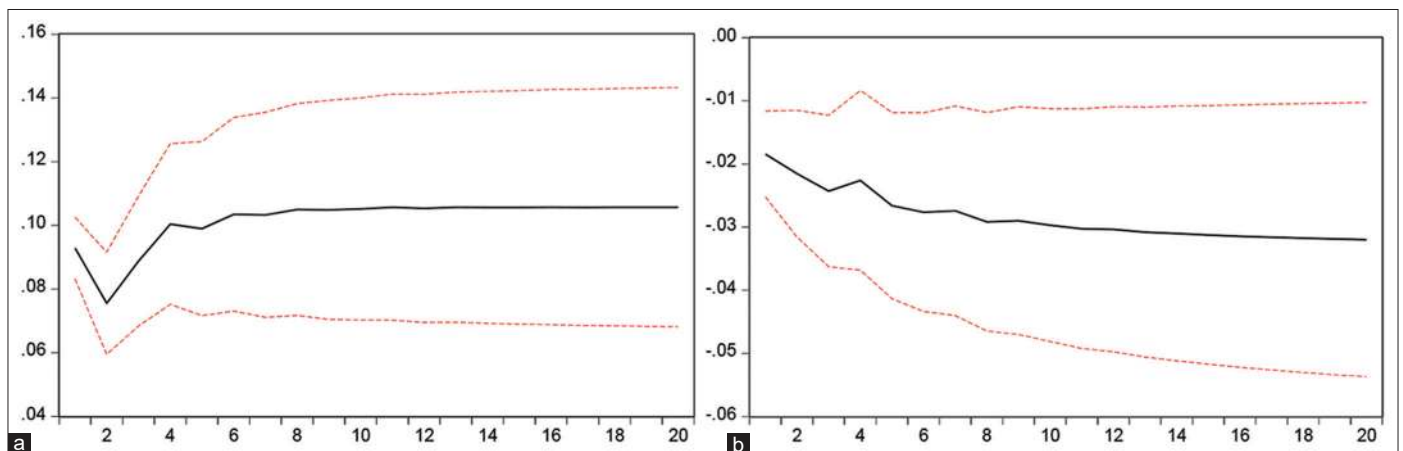
Table 2: Forecast error variance decomposition of the S&P GSCI energy index

Time horizon	standard error	COVID	GSI	VIX	Energies
1	0.331	0.078	0.002	14.751	85.169
2	0.331	0.431	0.026	15.043	84.500
3	0.334	0.385	14.887	12.760	71.968
4	0.342	0.644	15.429	12.719	71.208
5	0.343	0.683	15.325	13.198	70.794
6	0.344	0.727	16.077	13.037	70.159
7	0.346	0.797	16.109	13.022	70.072
8	0.347	0.797	16.278	13.079	69.846
9	0.348	0.799	16.304	13.071	69.826
10	0.349	0.806	16.344	13.078	69.772
11	0.349	0.806	16.400	13.078	69.715
12	0.350	0.812	16.423	13.074	69.691
13	0.350	0.813	16.447	13.076	69.664
14	0.350	0.813	16.461	13.075	69.651
15	0.350	0.815	16.473	13.074	69.638
16	0.350	0.815	16.484	13.074	69.627
17	0.350	0.816	16.490	13.073	69.621
18	0.350	0.816	16.496	13.073	69.615
19	0.350	0.816	16.500	13.073	69.611
20	0.350	0.817	16.503	13.072	69.608
21	0.350	0.817	16.505	13.072	69.606
22	0.350	0.817	16.507	13.072	69.604
23	0.350	0.817	16.508	13.072	69.603
24	0.350	0.817	16.509	13.072	69.602
25	0.350	0.817	16.511	13.072	69.601
26	0.350	0.817	16.511	13.072	69.600
27	0.350	0.817	16.512	13.072	69.599
28	0.350	0.817	16.512	13.072	69.599
29	0.350	0.817	16.512	13.072	69.599
30	0.350	0.817	16.512	13.072	69.599

Table 2 presents the forecast error variance decomposition that exhibits the relative importance of each random shock of one endogenous variable in affecting the other variable. In order to assess the relative importance of linked to the pandemic shocks, we list the forecast error variance decomposition of energy prices on the 30-day horizon.

The results presented in Table 2 suggest that during the first two days the energy prices are driven mainly by its own innovations (approx. 85%) and changes in stock market volatility (approx. 15%). While over the period of more than 3 days the S&P GSCI Energy Index volatility is attributed to energy price shocks (70–72%), stock market volatility (13%), global stringency of anti-COVID-19 government restrictions (15–16%), and only in less than 1% to the change in new COVID-19 cases. When the time horizon increases, the share of each endogenous variable in the volatility of energy commodity prices remains at the same level. It implies that the decomposition forecast error variance converges and proves the model stability.

4. CONCLUSION

Commodity markets, including energies, have been substantially volatile since the global financial crisis, particularly in times of huge uncertainty. The outbreak of the COVID-19 pandemic has hit the global financial markets and has induced a rapid increase in uncertainty. The novel coronavirus substantially affected the supply and demand side of the energy market resulting in changes in oil and natural gas prices.

In this paper, we examine the reaction of the energy commodity market on the COVID-19 pandemic, particularly the epidemic status, the stringency of anti-COVID-19 government policy, and the financial market uncertainty. The empirical analysis is based on the daily data of the S&P GSCI Energy index, the number of global new confirmed COVID-19 global cases, the self-developed Global Stringency Index, and the VIX index over the period from January 2 to September 30, 2020.

By applying a structural vector autoregressive model (SVAR) we observe a significant and negative energy commodity market's reaction to the COVID-19 driven increase in option-implied stock market volatility, measured by the VIX. Moreover, the results indicate the existence of the significant and negative energy commodity prices reaction to the stringency level of the anti-COVID-19 government policy only on the third day after the shock. It should be stressed that we are the first who analyse energy commodity prices' reaction to changes of the Global Stringency Index. Additionally, we reveal no significant impact of global epidemic status, measured by new COVID-19 cases, on energy commodity prices. Our results are consistent with all three research hypotheses.

As the energy belongs to the key markets in the economy, our study has important implications both for financial market participants and entrepreneurs. Investigating the reaction of the energy commodity market to the inevitable, second wave of the COVID-19 pandemic is a challenge for future research.

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