

## Article

# Energy Prices and COVID-Immunity: The Case of Crude Oil and Natural Gas Prices in the US and Japan

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Received: 23 October 2020; Accepted: 26 November 2020; Published: 29 November 2020



**Abstract:** The COVID-19 pandemic storm has struck the world economies and energy markets with extreme strength. The goal of our study is to assess how the pandemic has influenced oil and gas prices, using energy market reactions in the United States and Japan. To investigate the impact of the COVID-19 cases on the crude oil and natural gas markets, we applied the Auto-Regressive Distributive Lag (ARDL) approach to the number of the US and Japanese COVID-19 cases and energy prices. Our study period is from 21 January 2020 to 2 June 2020, and uses the latest data available at the time of model calibration and captures the so-called “first pandemic wave”. In the US, the COVID-19 pandemic had a statistically negative impact on the crude oil price while it positively affected the gas price. In Japan, this negative impact was only apparent in the crude oil market with a two-day lag. Possible explanations of the results may include differences in pandemic development in the US and Japan, and the diverse roles both countries have in energy markets.

**Keywords:** COVID-19; crude oil; natural gas; ARDL; energy shock

## 1. Introduction

Paul Krugman [1] recently stated: “Let’s be clear: we knew or should have known, that something like COVID-19 was going to happen” and it did. The pandemic has changed the world. It slammed into the world economy with extreme strength. The International Monetary Fund [2] forecasts that global economic growth is projected at −4.9% in 2020 with significant differences between developed and developing nations. In the former, economic growth is expected to decrease by −8%, and by −3% in the latter. The deepest anticipated changes in 2020 are observed in the Eurozone (−10.8%), and to be particularly severe in both Italy and Spain (at −12.8%). In the US, which has experienced more daily active cases than Europe since 2 July 2020, economic growth is expected to decrease by −8%. Among developed economies, Japan is forecast to suffer the least decline (−5.8%).

The pandemic has far-reaching consequences for our daily activities. Social distancing, which was introduced to fight viral spread, has profoundly impacted our families, work, and lifestyles. More generally, according to a survey carried out by Statista [3], at the end of May 2020, in the United States, large majorities of respondents decided to stay at home (77%), avoid public places like bars (65%), apply social distancing measures (69%), wear protective face masks outside (65%) or wash their hands more often (73%). During the same period, US citizens were less satisfied with their government’s response to COVID-19 than were Germans or Britons. Only 30% of US respondents of the Statista survey [4] were satisfied or very satisfied with their national government’s response to the pandemic, while in Germany more than 50% of the respondents were satisfied.

In Japan, metropolitan subway use in Tokyo (morning rush) in late May 2020 [5] declined by 60% compared to the average number of users between 20 and 24 January 2020. Social distancing

measures were imposed in a relatively relaxed way, without mandates. A state of emergency was initially introduced in only seven prefectures including Tokyo and then expanded to the entire country in May 2020. On 25 May 2020, the government lifted the state of emergency for all 47 prefectures in Japan.

Although measures undertaken globally were similar, energy markets in different countries have been impacted differently by the COVID-outbreak. For example, energy importing nations fared better than energy exporters for the first time since World War II. Energy exporters experienced a demand drop and a huge price decrease as energy importers reduced import demand through mobility constraints, resulting in improved energy trade balances. Japan relies heavily on imported energy resources, especially oil and gas. Therefore, it is interesting to analyze Japanese energy prices in the context of COVID-19 and compare them to those in the US, which recently became a net oil and gas exporter. To reveal how the pandemic has influenced the prices of energy-exporting and importing nations, our study investigates both.

In doing so, we employ the Auto-Regressive Distributive Lag (ARDL) model to capture the impact of the first COVID-19 pandemic wave on the US and Japanese energy markets. To our knowledge, this is one of the few studies (if not the first) examining the effects of a pandemic on crude oil and natural gas markets for both energy exporting and importing nations with the use of daily data. The study results not only provide valuable information for governments and market participants of the energy markets attempting to mitigate the shocks from the COVID-19 pandemic but also serve as a potential lens for understanding what might occur if a second or third pandemic wave disrupts the world.

The article is organized as follows: after the introduction, how COVID-19 affected the world economy and energy markets is put into context and broadly explained. A literature review on oil price determinants and energy shocks follows. Methods and data are then described, leading to a discussion of results and certain conclusions.

## 2. Study Backgrounds

### 2.1. Coronavirus and the World Economy

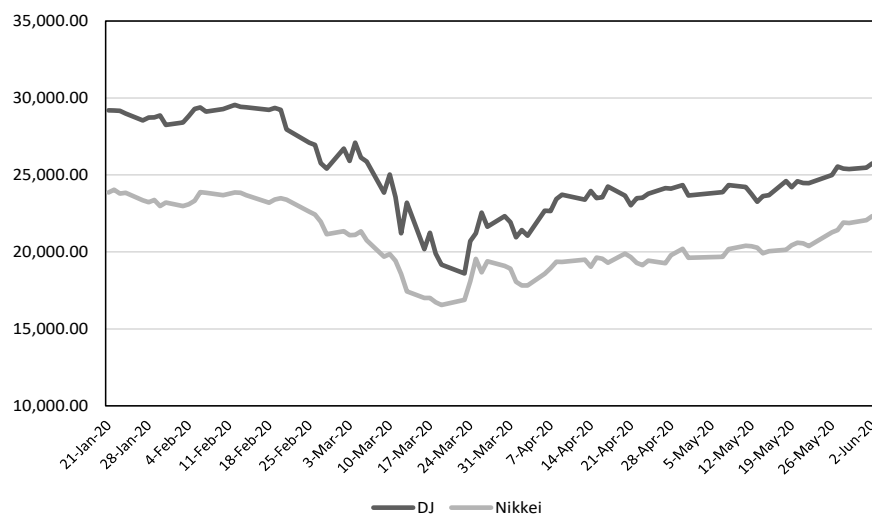
The world economy has been deeply affected by the COVID-19 pandemic. In the international dimension, it is visible in capital and people flows and on a single country's scale, one can observe it in major stock indices changes and unemployment claims.

United Nations Conference on Trade and Development (UNCTAD) [6] forecasts that foreign direct investments (FDI) will experience negative growth of between −30% and −40% during 2020–2021. Worldwide travel restrictions have hit the airline industry particularly hard, with the total number of commercial flights (including passenger, cargo, charter, and some business jet flights) decreasing between January 2020 and early April 2020 from 117,000 to 37,000 [7]. On the other hand, global lockdowns influenced the IT and tech industries as remote work forced people to use internet communication platforms such as Microsoft Teams [8], Cisco Webex [9], or Zoom [10] more widely.

Lockdown also resulted in stock indices changes, which are often treated as leading business cycle indicators. The OECD (Organisation for Economic Cooperation and Development) [11] has observed that the COVID-19 “heightened market risk aversion in ways not seen since the global financial crisis”. Indeed, the Volatility Index (VIX) that is often called the fear index is an indicator of real-time 30-day expected volatility of the US S&P 500 call and put options [12]. VIX skyrocketed between the end of February 2020 and 16 March 2020. This fear index reached similar levels only during the global economic crisis of 2008–2009.

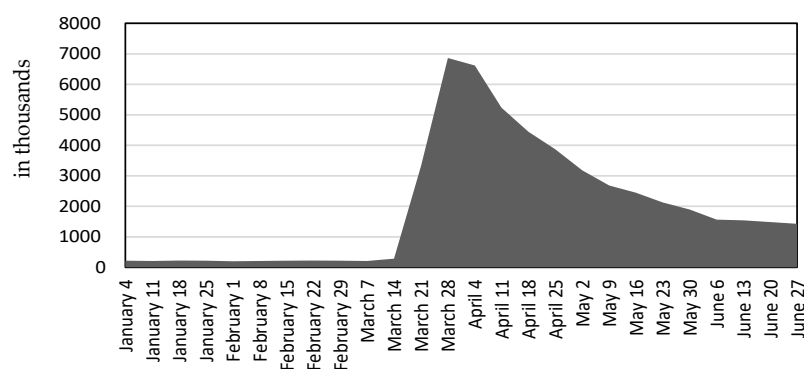
Statista [13] reports that between 6 and 18 March 2020, all major stock indices lost value due to the COVID-19 outbreak, although plummeting indices later experienced record-high one-day gains. The American Dow Jones Industrial Average on 24 March 2020 was a good example of that, and similar

trends were visible in the Nikkei index (the Japanese benchmark), which is also an economic benchmark for the Asia-Pacific region (Figure 1).



**Figure 1.** Dow Jones (DJ), Nikkei 225 (Nikkei) indices between 21 January 2020 and 4 June 2020. The data for the DJ and Nikkei are retrieved from the homepage of ADVFN and Nikkei, Inc., respectively.

At the same time, global lockdown resulted in layoffs in the labor market. In the US, the unemployment rate sky-rocketed after the lockdown restrictions due to the high labor market flexibility. A huge mid-March unemployment increase was reflected in increases in the number of initial unemployment insurance claims per week in the United States (Figure 2).



**Figure 2.** Number of initial unemployment insurance claims made per week in the United States from January to June 2020 (in 1000 s). The source of the figure is based on [14].

Before the effects of the lockdown became apparent, weekly unemployment insurance claims ranged between 212,000 (January 2020) and 282,000 (mid-March 2020). After mid-March, the weekly claims exceeded 7 mln [14]. The Pew Research Center reports that US unemployment was higher after three months of COVID-19 than it had been in the entire 2007–2009 Great Recession. Between February 2020 and May 2020, US unemployment rose from a post-World War II record low of 3.5% to 13% (Table 1) [15], and was the most severely impacted G7 country. By contrast, Japan's performance was among the best of the G7, experiencing job losses of 1.76 mln (in contrast to 30 mln in the US) [16] (Table 1). Japan's unemployment rate in May 2020 was 2.9%, which was still relatively low even compared to 2.4% in January 2020. This relatively moderate COVID-19 impact on unemployment is, however, at least partially explained by Japan's ongoing struggle with deflation, combined with a decreasing population that encourages companies to keep employees rather than laying them off [17].

**Table 1.** Unemployment rate in the US and Japan between January 2020 and June 2020 (in %)

Unemployment Rate	US	Japan
January 2020	3.6	2.4
February 2020	3.5	2.4
March 2020	4.4	2.5
April 2020	14.7	2.6
May 2020	13.3	2.9
June 2020	11.1	no data available

Source: Own elaboration based on [14].

SARS-Cov-2 (COVID-19) pandemic is an extraordinary case for the world economy for many reasons. The most important one is the fact that for many years the global economy has not experienced external supply shocks. Instead, we have rather been used to negative demand shocks that affected business conditions. Yet the COVID-19 pandemic began with a supply shock on global markets as China was forced to reduce its exports by a staggering 17% between January and February 2020 [18]. However, the spread of the virus began to infect other economies as well. With administratively imposed social distancing measures in many countries, demand weakened, and many companies have been temporarily shut down. In this sense, COVID-19 started with a negative supply shock evoking a negative demand response.

## 2.2. Coronavirus and the Energy Sector

A similar shock mix can be also observed in the energy markets. The current situation is different from any shock we have experienced so far. First, because the shale gas fever had transformed the energy markets (both oil and gas), and second because global oil demand in 2020 is forecasted to contract for the first time since the 2009 global recession [19].

With renewable energy use rising, the pandemic undermined the already weakened position of the oil and gas industry. Since the aviation and transport sectors account for 60% of oil demand [19], mobility constraints quickly translated into decreased oil consumption. Daily world oil demand dropped from 100 million bbl in January 2020 to less than 75 million bbl in April 2020 [20]. Behind the COVID-19 influence over oil markets, there is also an unprecedented discussion among the OPEC+ (Organization of the Petroleum Exporting Countries) on stabilizing oil prices. As a result, West Texas Intermediate (WTI) futures (expiring May) in April 2020 turned negative. The natural gas industry long before the coronavirus outbreak was in a difficult situation due to a mild winter that had already reduced demand. The International Energy Agency (IEA) predicts that global natural gas demand in 2020 will fall by 4% with mature European, Asian and North American markets accounting for 75% of this decrease [21].

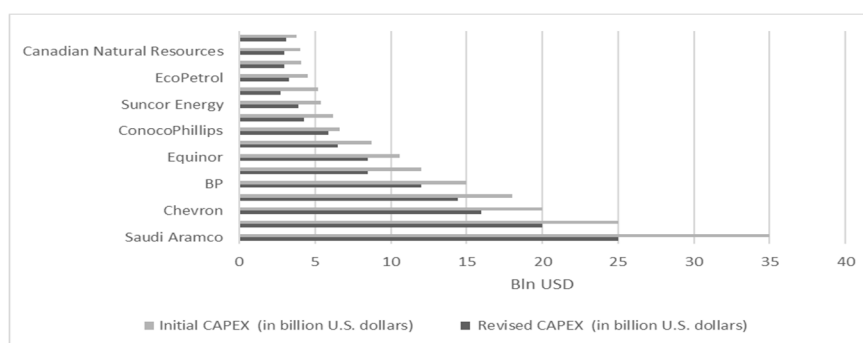
Not only has the COVID-19 pandemic changed the demand for energy resources, but it also impacted their supply, as revealed by (among other things) changes in oil and gas company activity. Between December 2019 and June 2020, the number of oil and gas rigs in the US decreased from 805 to 265 (Table 2). Most of the world's major oil and gas companies have revisited their capital expenditures as a result of coronavirus pandemic in 2020 (Figure 3).

**Table 2.** Number of oil and gas rigs in operation in the US between December 2019 and June 2020.

Period	Number of Oil and Gas Rigs
December 2019	805
January 2020	790
February 2020	790
March 2020	728
April 2020	465
May 2020	301
June 2020	265

Source: own elaboration based on [22].

That includes Saudi Arabian companies, European and North American firms. The biggest revision of CAPEX (Capital Expenditure) is to Saudi Aramco (from 35 bln USD to 25 bln USD) and Chevron (from 25 bln USD to 20 bln USD). BP and Equinor are expected to decrease 2020 investments, respectively, by 3–2 bln USD (from 15 bln USD to 12 bln USD; from 10.6 bln USD to 8.6 bln USD) [23]. In the late-May IEA report [24], the Agency forecasts that global investment in oil and gas is expected to fall by almost one-third in 2020. The IEA also predicts that the shale gas industry will suffer most, with an almost 50% decrease in investments in 2020. Overall, the combined oil and gas industry is expected to reduce investments by 244 bln USD in 2020 (compared to 2019), which constitutes the highest change of any energy sector (including coal, which is forecast to decrease its investments by 74 bln USD [24]). The effects of COVID-19 on oil and gas supply were also visible in supply chain disruptions. Lockdowns affected global supply chains. According to the IEA [24], 22 out of the 28 global floating production, storage, and offloading vessels that were under construction in the first quarter of 2020 were being built at shipyards in China, Korea, and Singapore. Moreover, a major manufacturing center for specialized oil and gas industry engineering equipment is the Lombardy region of Italy, which was among the first locked down areas of Europe.



**Figure 3.** Capital expenditure revision of selected oil and gas producers worldwide in 2020 as a result of coronavirus impact (in bln USD). The source of the figure is based on [23].

A closer look at the oil and gas markets between 23 January 2020 and 30 March 2020 also reveals how hydrocarbon prices were impacted by the COVID-pandemic. During this period, Brent (61.6–19.07 USD/bbl), West Texas Intermediate (WTI, 55.51–14.10 USD/bbl) [25] and the reference OPEC basket (63.26–21.66 USD/bbl) [26] prices were slumping. However, natural gas prices did not drop as much. As the US Energy Information Agency reports, the Henry Hub spot price in the respective period changed from 1.95 USD/million Btu to 1.65 USD/million Btu [27]. Therefore, it is important to check whether oil and gas prices were affected by the COVID-19 outbreak.

The effects of a past disease outbreak on the energy sector are not a common field of research for several reasons. First, such severe pandemics as the Spanish flu (1918) occurred when hydrocarbons were not particularly widespread in use. Second, the reach of more contemporary disease outbreaks such as SARS (Severe Acute Respiratory Syndrome) (2002) and MERS (Middle East Respiratory Syndrome) (2012) was limited to Asian and Persian Gulf countries. The notable difference was A/H1N1, which spread across the globe in 2009. The mortality and contagion rates of the swine flu were lower than SARS and MERS, which renders COVID-19 unique in terms of recent global diseases.

We expect that the US and Japan will experience different degrees of COVID-19 impacts on their oil and gas markets. In particular, since the US is both an energy exporter and importer and has a large number of all COVID-19 cases [28], it is likely to have sustained more severe pandemic effects than Japan. We also anticipate that the SARS-Cov-2 pandemic caused different impacts between crude oil and natural gas markets since crude oil is linked to energy demand in the transport sector, whereas natural gas serves many other uses less impacted by lockdown restrictions.

### 2.3. Theoretical Background

Theoretical underpinnings of our empirical analysis are built upon the literature on hydrocarbons' price determinants and energy shocks because our econometric model looks specifically at oil and gas prices during pandemic-induced energy market shock.

There is a rich body of literature investigating oil price determinants. In those studies, researchers typically check what influenced oil prices or what their effect is on macroeconomic performance. In this way, the literature string focuses on the endo- or exogenous character of oil prices by relating them to economic growth. Our work departs from this perspective as it does not directly refer to the oil price–GDP nexus. However, to design our research in terms of energy price determinants, we have relied on works such as Barsky and Kilian [29,30], Baumeister and Kilian [31,32], Hamilton [33–35], Kilian [36–38], and Kilian and Cheolbeom [39]. In one of the works in this literature string, Hamilton [40] underlines that the real price of oil historically tends to be difficult to predict, and is governed by very different regimes at different points in time. Thus, the COVID-pandemic might be treated as such an external factor unpredictably affecting oil markets. The above mentioned works [33–39] constitute next to Economou [41], who is offering comprehensive shock description, typical literature on oil price shocks.

While the majority of the literature focuses on shocks in the oil markets, some studies focus on the relationship between oil price shocks and natural gas prices, which is relevant to our analysis. One of the works investigating the oil–gas relationship is the paper of Jadidzadeh and Serletis [42], which suggests that real natural gas prices episodically decouple from the real crude oil price. Similar conclusions are reached in the works of Nguyen and Okimoto [43] and Atil et al. [44].

To our knowledge, two of the few studies specifically tackling a pandemic's effects on energy markets were conducted by Kelley and Osterholm [45] and more recently by Aruga et al. [46]. Kelley and Osterholm [45] investigated the impact of the influenza pandemic on the coal market and looked at the US market and the effects of coal supply chains and electricity production. They showed that during a pandemic electricity production plays a vital role in meeting the energy needs of society. In our study, we use the ARDL model, which became popular in studies assessing disease effects. For example, Aruga et al. [46] tested COVID-19's influence on Indian energy consumption, Laguna et al. [47] investigated the influence of climatic variables on malaria outbreaks and Upshur et al. [48] examined the link between pneumonia and influenza cases.

However, our study departs from other literature on energy prices and energy shocks in a few ways. First, our approach focuses not only on the oil market (which is the approach used in most existing literature) but also on the natural gas markets that have been previously assessed only to a limited extent. Second, we investigate the problem of pandemic-induced energy shocks for oil and gas markets, which to our knowledge has not been addressed in the literature. Third, we analyze energy exporting and energy importing nations instead of focusing solely on countries that sell commodities. Fourth, our study uses daily data to achieve a relatively high-frequency analysis. To our knowledge, few studies (with the partial exception of Baumeister et al. [49]) investigate the link between financial and oil markets using daily and weekly data.

### 3. Materials and Methods

To investigate the impact of the COVID-19 cases on crude oil and natural gas markets, we applied the Auto-Regressive Distributive Lag (ARDL) approach proposed by Pesaran et al. [50] on the number of US and Japanese COVID-19 cases and energy prices. The period investigated in this study is from 21 January 2020 to 2 June 2020. The date of 21 January 2020 is used as the initial data period since this is the date when the COVID-19 pandemic became apparent in the US. In this way, we aim to capture the so-called “first pandemic wave”.

The ARDL method is chosen because it can be used to identify both short-run and long-run relationships between time series variables when their order of integration is different. For example, the conventional cointegration methods require all of the variables of interest to be all integrated in



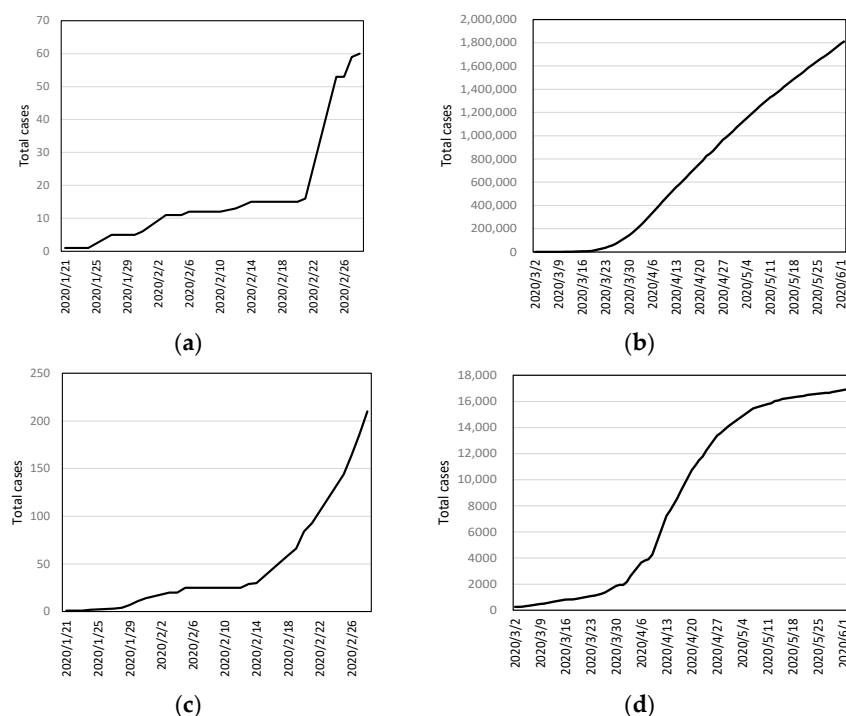
the order of one (I(1)), but in the ARDL method, the variables can be either I(1) or I(0). Furthermore, the ARDL method has its strength in omitted variables and the auto-correlation issue in time series data and can provide valid results even when the sample size is small [51].

To identify the order of integration of all the test variables used in the study, we performed the ADF(Augmented Dickey-Fuller), PP(Phillips–Perron), KPSS(Kwiatkowski–Phillips–Schmidt–Shin), and the Lee–Strazicich [52] stationarity tests with one structural break. To investigate the relationship between the energy prices and COVID-19 cases, we created the following log-linear model for the US and Japanese crude oil and natural gas markets:

$$\begin{aligned} \ln(\text{Energy price}) = & \text{Intercept} + \beta_1 \text{COVID19} + \sum_{i=2}^4 \beta_i \ln(\text{Other energy})_i + \\ & \beta_5 \ln(\text{Economic indicator}) + \beta_6 \ln(\text{Transportation index}) + \\ & \beta_7 \ln(\text{Power and gas index}) + \beta_8 \ln(\text{Unemployment index}) + e_t \end{aligned} \quad (1)$$

Equation (1) is built upon findings presented in the theoretical part with limitation due to lack of daily data, and is a modification of a similar model designed in Aruga and Nyga-Łukaszewska [53]. In Equation (1), Energy price is either the crude oil or natural gas prices for the US and Japan. For US and Japanese crude oil prices, we used the WTI and Platts Dubai crude oil prices (Dubai), which are the primary pricing reference for US and Japanese crude oil markets. Although it is known that the Japan Crude Cocktail (JCC) price is also used to represent the Japanese crude oil price, we used the Dubai price as the Japanese crude oil benchmark price in this study. This is because it is suggested that in addition to this price being the major Japanese import price index, this price reflects the shock to the Japanese economy [54].

Similarly, we used the Henry Hub (HH) and Platts Japan Korea Marker (JKM) prices for US and Japanese natural gas prices since they are the primary natural gas reference prices in these countries. The JKM price is also currently becoming the benchmark price for the Asian LNG spot market. COVID19 is either the US or Japanese cumulative number of COVID-19 cases since 21 January 2020 (Figure 4).



**Figure 4.** Accumulative number of COVID-19 cases in the US and Japan, (a) COVID US before March 2020, (b) COVID US after March 2020, (c) COVID JP before March 2020, (d) COVID JP after March 2020.

*Other energy* includes all other energy prices examined in the study to consider the effects of substitutive effects among the crude oil and natural gas prices. For example, if the model was for the WTI, we included the Dubai, HH, and JKM prices in *Other energy* as presented in Equation (2)

$$\begin{aligned} \ln(\text{WTI}) = & \text{Intercept} + \beta_1 \text{COVID19} + \beta_2 \ln(\text{Dubai}) + \beta_3 \ln(\text{HH}) + \beta_4 \ln(\text{JKM}) + \\ & \beta_5 \ln(\text{Economic indicator}) + \beta_6 \ln(\text{Transportation index}) + \\ & \beta_7 \ln(\text{Power and gas index}) + \beta_8 \ln(\text{Unemployment index}) + e_t \end{aligned} \quad (2)$$

The Economic indicator is an index to capture the effects of the US and Japan's overall economic performance. GDP is the most common index for measuring a country's economic performance but since we used the daily data this index was not available. As an alternative, we used the Dow Jones Industrial Average (DJI) and the Nikkei 225 (NI 225). These two indices are among the premier stock market indices in the US and Japan, respectively. Transportation and power and gas indices denote the indices that capture the performance levels of the transportation and power generation industries. We included these indices in the model because crude oil and gas are highly related to these industries. When the model is for the US crude oil or gas prices, we used the Dow Jones U.S. Automobiles Index (DJUSAU) to capture the performance of the US transportation industry and the Dow Jones U.S. Electricity Total Stock Market Index (DWCELC) to reflect the levels of activity of the US power generation sector. Finally, the Unemployment index represents the cumulative number of search requests for unemployment in the US and Japan, and  $e_t$  is the white noise error term.

Table 3 describes the definition details and sources of the variables used in the study. It is notable from the table that the mean US crude oil and gas prices are lower than corresponding Japanese prices. This is because of what is known as the Asian premium [55]; that is, oil and gas prices of the Asian market have historically been significantly higher than in the US and European markets. It is also apparent from the table that there is a wide gap in the number of people infected by COVID-19 between the US and Japan. The reason for this gap is still unknown but, as shown in the table, the mean number of Japanese COVID-19 cases is less than 1/40th of the US.

Figures 4 and 5 depict the plots of our main time series data: COVID-19 cases and the energy prices. As seen in Figure 5, both US and Japanese crude oil prices exhibited a downward trend until late April and then started to increase after this period. On the other hand, gas prices have distinctive movements between the US and Japan. The US Henry Hub gas price was declining until the end of March and then started to increase after it hit bottom on 2 April 2020, thus containing both downward and upward trends. However, the Japanese JKM gas price has an overall downward trend with a very short upward trend as compared to US gas prices. Similarly, the US and Japanese cumulative COVID-19 cases show that the numbers of cases have a contrastive trend. Although before March 2020, Japan had a higher number of people infected with coronavirus than the US, after mid-March the US cases have skyrocketed, becoming 100 times more numerous than in Japan by end of March. Figure 4 also reveals that while the graph of the US has a linear increasing trend, that of Japan is more like an S-curve in which case numbers are starting to increase at a decreasing rate after May 2020.

**Table 3.** Description of variables.

Variable	Description	Source	Mean	Median	Maximum	Minimum	Std. Dev.
WTI	WTI crude oil price (USD/BBL)	Markets Insider	34.41	32.16	58.34	10.01	13.65
Dubai	Platts Dubai Crude Oil (USD/BBL)	Tokyo Commodity Exchange	39.12	33.59	65.46	18.91	14.58
HH	Henry Hub natural gas price (USD/MMBtu)	Markets Insider	1.79	1.81	1.98	1.55	0.10
JKM	Platts Japan Korea Market LNG price (USD/MMBtu)	TradingView	2.86	2.93	4.08	2.00	0.63



Table 3. Cont.

Variable	Description	Source	Mean	Median	Maximum	Minimum	Std. Dev.
COVID US	The cumulative COVID-19 cases in the US.	Our World in Data	481,276.20	62,212.50	18,11,277.00	1.00	617,308.30
COVID JP	The cumulative COVID-19 cases in Japan.	Our World in Data	5674.97	1230.50	16,930.00	1.00	6750.38
DJI	Dow Jones industrial average index	Markets Insider	25,011.66	24,338.52	29,551.42	18,591.93	2867.26
DJUSAU	Dow Jones U.S. Automobiles Index	ADVFN	229.98	237.12	304.37	134.39	39.73
DWCELC	Electricity Total Stock Market Index	ADVFN	3131.49	3031.10	3659.50	2323.40	329.19
NI225	Tokyo Stock Exchange Nikkei-225 Stock Average	Nikkei Inc.	20,707.52	20,316.77	24,031.35	16,552.83	2074.30
JP transport	Tokyo Stock Exchange Transportation Equipment index	CEIC Data	2375.29	2265.41	2834.12	1994.88	252.20
JP Power	Tokyo Stock Exchange Electric Power & Gas index	CEIC Data	383.49	389.49	409.57	324.37	17.91
UE US	The cumulative US unemployment index	Google Trends	1125.64	500.50	3411.00	6.00	1185.24
UE JP	The cumulative Japanese unemployment index	Google Trends	1237.69	1059.00	2704.00	43.00	809.88

Note: The original Dubai crude oil price data was provided in the Japanese yen (JPY) per kiloliters, so it was converted into USD/BBL. The daily currency rate obtained from Macrotrends LLC was used to convert JPY to USD. WTI, HH, and JKM are the West Texas Intermediate crude oil, Henry Hub natural gas and Platts Japan Korea Marker (JKM) LNG prices. DJI, DJUSAU, DWELC and NI225 are the Dow Jones industrial average index, Dow Jones U.S. Automobiles Index, Dow Jones U.S. Electricity Total Stock Market Index and Tokyo Stock Exchange Nikkei-225 Stock Average.

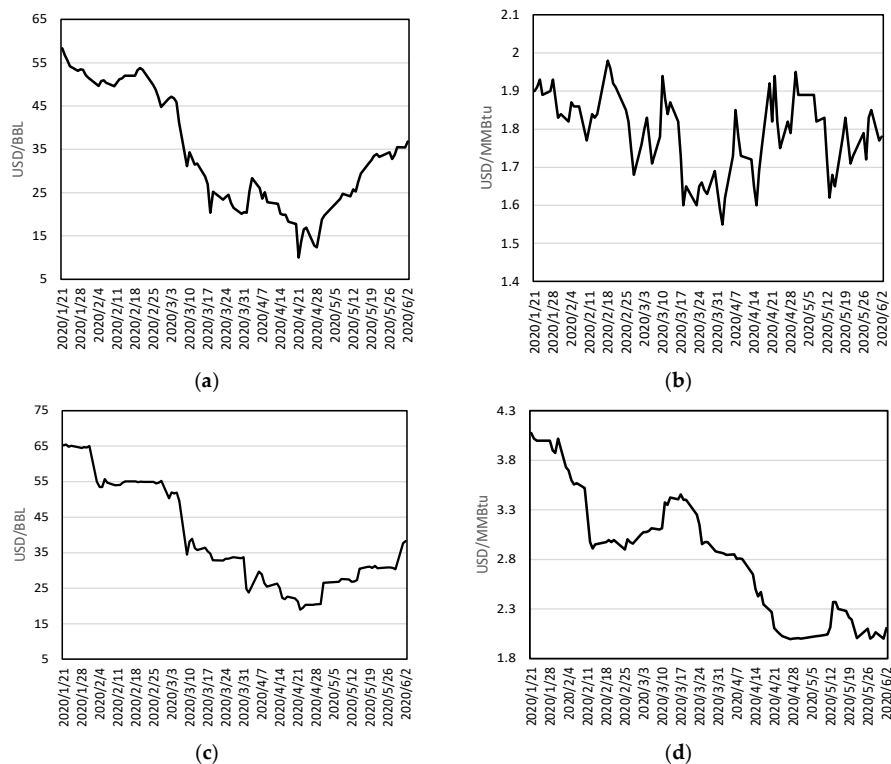


Figure 5. The US and Japanese Oil and natural gas prices, (a) WTI, (b) HH, (c) Dubai, (d) JKM.

Our oil and gas econometric models are estimated with the following ARDL(p,q) model:

$$y_t = a_0 + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \theta_j x_{t-j} + \delta Z_t + \varepsilon_t \quad (3)$$

where  $y_t$  is the oil and gas prices,  $x_t$  is the number of COVID-19 cases,  $Z_t$  is the vector of fixed regressors to consider the exogenous factors affecting the energy prices,  $a_0$  is a constant term,  $\phi_i$  and  $\theta_i$  are the lag polynomial coefficients, and  $\varepsilon_t$  is the white noise error term.

Based on Equation (3) the long-run relationship between the energy prices and the COVID-19 cases are examined using the following conditional error correction model:

$$\Delta y_t = a_0 + \lambda_{yx} EC_{t-1} + \sum_{i=1}^p \phi_i' \Delta y_{t-i} + \sum_{j=1}^q \theta_j' \Delta x_{t-j} + \delta Z_t + \varepsilon_t \quad (4)$$

where  $\Delta$  is the first difference operator,  $EC_{t-1}$  and  $\lambda_{yx}$  are the error correction term and its coefficient, and  $EC_{t-1} = y_{t-1} - \beta_1 x_{t-1} - \beta_0$ . The ARDL bounds F-test for cointegration is performed by testing the null of no cointegration where the null hypothesis is  $H_0 : \beta_i = 0$ . The null hypothesis is accepted if the F-statistic value is below the lower bound (I(0)) and is rejected if the F-statistic exceeds the upper bound (I(1)). If the F-statistic value falls between the lower and upper bound, the cointegration test becomes inconclusive.

To confirm that the residuals of our models are white noise, we performed the serial correlation and heteroskedasticity tests. The former was diagnosed by the Breusch–Godfrey test and the latter was identified by and Breusch–Pagan–Godfrey test. Finally, the stability of the estimated parameters is checked with the cumulative sum (CUSUM) test.

#### 4. Results and Discussions

To confirm the level of integration of the variables of our interest, we performed the ADF, PP, KPSS, and the Lee–Strazicich unit root tests. The results of these tests are presented in Table 4. That table indicates that all our variables are either I(0) or I(1), satisfying the precondition of the ARDL.

Table 5 depicts the results of the ARDL estimation. The optimal number of lag length of the ARDL models is determined with the AIC. The two models at the top of the table illustrate the results of the effects of US COVID-19 cases on US crude oil and natural gas prices. This table shows that a 1% increase in the cumulative number of COVID-19 cases in the US leads to a 0.077% decrease in the WTI crude oil price while a 1% increase in the COVID-19 cases increases the Henry Hub natural gas price by 0.023%.

Table 4. Unit root tests.

	Level				First Differences			
	ADF	PP	KPSS	LS	ADF	PP	KPSS	LS
Ln(WTI)	−2.979	−1.262	0.210 **	−3.622	−0.980 ***	−9.551 ***	0.109	−9.817 ***
Ln(Dubai)	−2.556	−2.529	0.142 *	−3.824	−7.502 ***	−7.771 ***	0.078	−9.195 ***
Ln(HH)	−2.879	−2.879	0.095	−4.559 **	−6.272 ***	−6.299 ***	0.048	−9.124 ***
Ln(	−1.492	−1.482	0.170 **	−1.940	−6.121 ***	−6.174 ***	0.121 *	−9.124 ***
Ln(COVID US)	−0.784	−0.611	0.207 **	−2.834	−6.981 ***	−7.124 ***	0.131 *	−4.866 **
Ln(COVID JP)	−0.916	−1.852	0.179 **	−2.893	−4.208 **	−6.187 ***	0.056	−4.790 ***
Ln(DJI)	−2.319	−2.286	0.159 **	−3.924	−9.652 ***	−9.222 ***	0.114	−13.056 ***
Ln(DJUSAU)	−2.278	−1.850	0.186 **	−3.699	−3.411 *	−6.740 ***	0.082	−8.916 **
Ln(DWCELC)	−2.476	−2.509	0.172 **	−4.062 *	−3.847 ***	−8.562 ***	0.113	−12.114 ***
Ln(NI225)	−2.771	−1.790	0.131 *	−4.656 **	−4.025 **	−5.248 ***	0.111	−8.441 ***
Ln(JP transport)	−3.276 *	−1.584	0.124 *	−3.951	−0.571	−6.166 ***	0.136 *	−8.614 ***
Ln(JP Power)	−0.129	−0.129	0.110	−3.097	−5.450 ***	−5.605 ***	0.200 **	−7.410 **
Ln(UE US)	0.223	−3.679 **	0.121 *	−4.233 *	−7.364 ***	−6.740 ***	0.205 **	−2.130 ***
Ln(UE JP)	−1.756	−12.408 ***	0.207 **	−0.462	−3.912 **	−5.456 ***	0.237 ***	−5.466 ***

Note: All the unit root tests include both constant and a linear trend. \*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10% levels, respectively. ADF, PP, and KPSS are the ADF, PP, and KPSS unit root t-statistics. LS represents the Lee–Strazicich t-statistics with one structural break.

These contrasting results between the crude oil and natural gas markets might reflect differences in their uses. Since crude oil plays a central role in powering automobiles and jets as compared to natural gas, it could be that the decreased number of people using automobiles and airplanes after the increase in the COVID-19 cases reduced crude oil demand, negatively affecting crude oil prices. On the other hand, the IEA [21] suggests that the use of natural gas for power generation has increased in the first quarter of 2020 in the US (due to a switch away from coal for that purpose), and it is suggested that natural gas consumption in North America remained resilient even during the lockdown periods. This could be the reason why COVID-19 cases positively affected US natural gas prices.

Table 5. ARDL estimations.

Variables	WTI and COVID US		Variables	HH and COVID US	
	Coef.	t-Stat		Coef.	t-Stat
Intercept	−1.0032	−0.341	Intercept	−1.2459	−1.366
Ln(WTI)(−1)	0.4670 ***	3.734	LnHH(−1)	0.5916 ***	5.391
Ln(WTI)(−2)	−0.0036	−0.027	LnHH(−2)	−0.0163	−0.128
Ln(WTI)(−3)	−0.0236	−0.182	LnHH(−3)	−0.1721	−1.665
Ln(WTI)(−4)	0.2293 **	2.213	Ln(COVID US)	0.0233 **	2.243
Ln(COVID US)	−0.0769 **	−2.338	Ln(WTI)	0.0454	1.541
Ln(Dubai)	0.3456 **	2.431	Ln(Dubai)	−0.1041 **	−2.460
Ln(HH)	0.4052	1.365	LnJKM	−0.1598 **	−2.128
Ln(JKM)	0.4615 *	1.970	Ln(DJI)	0.2141	1.342
Ln(DJI)	1.1158 *	1.984	Ln(DJUSAU)	0.0583	0.853
Ln(DJUSAU)	−0.0008	−0.004	Ln(DWCELC)	−0.0157	−0.113
Ln(DWCELC)	−1.5038 ***	−3.250	Ln(UE US)	−0.0987 ***	−3.002
Ln(UE US)	0.2803 ***	2.653			
Variables	Dubai and COVID JP		Variables	JKM and COVID JP	
	Coef.	t-Stat		Coef.	t-Stat
Intercept	−1.1475	−0.501	Intercept	3.6891 ***	3.820
Ln(Dubai)(−1)	0.6501 ***	5.987	LnJKM(−1)	0.7716 ***	12.137
Ln(Dubai)(−2)	−0.2200 **	−2.044	Ln(COVID JP)	−0.0003	−0.025
Ln(COVID JP)	0.0297	0.495	Ln(Dubai)	0.0406	0.878
Ln(COVID JP)(−1)	0.0497	0.659	Ln(WTI)	0.0547 *	1.826
Ln(COVID JP)(−2)	−0.1820 **	−2.433	Ln(HH)	0.0133	0.150
Ln(COVID JP)(−3)	0.0926 *	1.695	Ln(NI225)	−0.3430	−1.553
Ln(WTI)	0.2068 ***	3.481	Ln(JP transport)	−0.0692	−0.291
Ln(HH)	−0.1741	−0.876	Ln(JP Power)	0.0722	0.445
Ln(JKM)	0.1480	0.990	Ln(UE JP)	−0.0421	−1.389
Ln(NI225)	−0.3443	−0.759			
Ln(JP transport)	1.2955 ***	2.707			
Ln(JP Power)	−0.7202 *	−1.879			
Ln(UE JP)	0.0200	0.232			

Note: \*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10% levels, respectively. ARDL stands for Auto-Regressive Distributive Lag, coef.—coefficient, t-Stat—t-statistic.

In contrast to the US, only during its second COVID-19 lag did the crude oil model become significant at the 5% level in the Japanese model. The lagged coefficient had the same negative direction as in the case of the US, suggesting that the number of coronavirus cases two days before is negatively affecting Japan's crude oil price. However, coronavirus cases did not have an impact on the Japanese natural gas market.

Table 6 shows our results of the ARDL bounds test for cointegration. The results indicate that in all our models the F-statistics are higher than the upper-bound critical values at the 5% level. This indicates that both the crude oil and natural gas prices are cointegrated with the US and World COVID-19 cases. However, as seen in Table 7, estimations of the long-run coefficients of the cointegrating

equation suggest that it is only the US COVID-19 cases that have long-run impacts on the energy prices. In both crude oil and natural gas models, Ln(COVID JP) was not significant in the Japanese models, implying that Japan's oil and gas markets were not affected by the number of Japan's COVID-19 cases.

**Table 6.** Bounds F-test for cointegration.

Model	F-Stat.	
WTI vs. COVID US	5.7683	***
Dubai vs. COVID JP	10.7793	***
HH vs. COVID US	13.2265	***
JKM vs. COVID JP	5.5742	**

Note: \*\*\* and \*\* denote rejecting the null hypothesis of no cointegration (I(1)) at the 1% and 5% levels, respectively. The 1% and 5% lower bound (I(0)) critical values are 4.94 and 3.62 and those of the upper bound (I(1)) critical values are 5.58 and 4.16, respectively.

**Table 7.** Long-run coefficients estimation.

Models	Variables	Coef.		t-Value
WTI vs. COVID US	Intercept	−3.0324		−0.3399
	Ln(COVID US)	−0.2324	**	−2.0161
Dubai vs. COVID JP	Intercept	−2.0137		−0.5068
	Ln(COVID JP)	−0.0177		−0.3474
HH vs. COVID US	Intercept	−2.0878		−1.3271
	Ln(COVID US)	0.0391	**	2.1462
JKM vs. COVID JP	Intercept	16.1497	***	5.8927
	Ln(COVID JP)	−0.0014		−0.0247

Note: \*\*\* and \*\* denote significance at the 1% and 5% levels, respectively.

Finally, as our cointegration tests revealed that the US crude oil and natural gas prices are cointegrated with the COVID-19 cases, we estimated the conditional error correction ARDL estimations for the US model. Table 8 illustrates the results of these estimations. It is observable from the table that, as seen in Table 5, there was a negative impact from COVID-19 cases on crude oil prices, while the natural gas market had a positive impact from the COVID-19 cases.

**Table 8.** Conditional error correction ARDL estimations.

Variables	WTI and COVID US			Variables	HH and COVID US		
	Coef.		t-Stat		Coef.		t-Stat
Intercept	−1.0032		−0.3408	Intercept	−1.2459		−1.3662
Ln(WTI)(−1)	−0.3308	***	−3.3928	Ln(HH)(−1)	−0.5968	***	−5.9691
Ln(COVID US)	−0.0769	**	−2.3380	Ln(COVID US)	0.0233	**	2.2429
$\Delta(\text{Ln(WTI)})(-1)$	−0.2022	*	−1.7261	$\Delta(\text{Ln(HH)})(-1)$	0.1883	*	1.7894
$\Delta(\text{Ln(WTI)})(-2)$	−0.2058	*	−1.9395	$\Delta(\text{Ln(HH)})(-2)$	0.1721		1.6646
$\Delta(\text{Ln(WTI)})(-3)$	−0.2293	**	−2.2128	Ln(WTI)	0.0454		1.5411
Ln(Dubai)	0.3456	**	2.4310	Ln(Dubai)	−0.1041	**	−2.4602
Ln(HH)	0.4052		1.3648	Ln(JKM)	−0.1598	**	−2.1281
Ln(JKM)	0.4615	*	1.9699	Ln(DJI)	0.2141		1.3419
Ln(DJI)	1.1158	*	1.9844	Ln(DJUSAU)	0.0583		0.8528
Ln(DJUSAU)	−0.0008		−0.0037	Ln(DWCELC)	−0.0157		−0.1134
Ln(DWCELC)	−1.5038	***	−3.2500	Ln(UE US)	−0.0987	***	−3.0015
Ln(UE US)	0.2803	***	2.6532				

Note: \*\*\*, \*\*, and \* denote significance at 1%, 5%, and 10% levels, respectively.

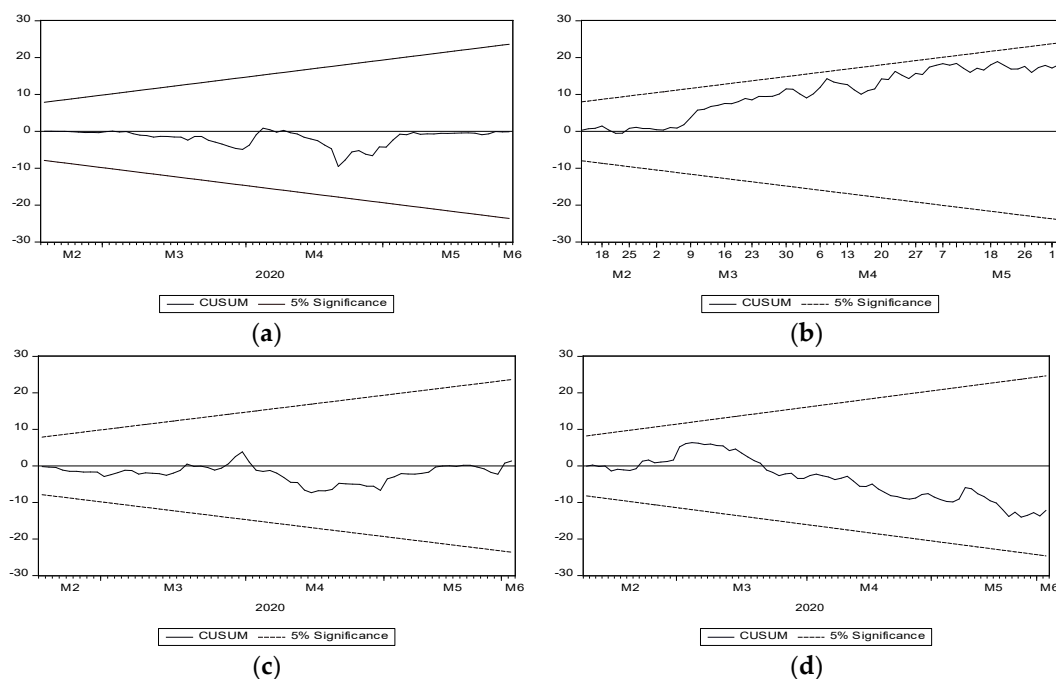
Table 9 and Figure 6 present our diagnostic test results to confirm the validity of the econometric model of the study. The test results in the table indicated that both serial correlation and heteroskedasticity of the residuals were not a problem in our model based on the 5% significance

level. The CUSUM (cumulative sum) diagnostic test for parameter stability also confirmed that all our estimated coefficients satisfy the stability condition at the 5% significance level (see Figure 6).

**Table 9.** Serial Correlation and heteroskedasticity tests.

Model	BG F-stat.	BPG F-Stat.
WTI vs. COVID US	0.5298	0.9844
Dubai vs. COVID JP	1.8686	1.1388
HH vs. COVID US	1.4839	1.6939 *
JKM vs. COVID JP	0.1986	0.8867

Note: \* denotes significance at the 10% level. BG F-stat. and BPG F-stat. denote the Breusch–Godfrey LM and Breusch–Pagan–Godfrey F-test statistics.



**Figure 6.** The CUSUM test, (a) WTI vs. COVID US, (b) HH vs. COVID US, (c) Dubai vs. COVID JP, (d) JKM vs. COVID JP.

## 5. Conclusions

In sum, our results indicate that in the US, both crude oil and natural gas markets were affected by the COVID-19 pandemic, with both short-run and long-run relationships. In the US, the cumulative number of COVID-19 cases had a negative impact on the crude oil price while it positively affected the natural gas price. On the other hand, for Japan, only a short-run shock with a lag was apparent in the crude oil market and no evidence from that shock was visible in the natural gas market. One possible reason for the difference in diverse oil and gas markets reactions to the COVID-pandemic might be greater stability in gas prices being the consequence of preceding warm winters. As a result, market players, especially exporters, have been less optimistic and more cautious about future investments as they had already expected lower gas sales. Another possible explanation for differences in the US and Japanese oil and gas market reactions to the pandemic maybe the severity of the spread of the virus in the US as compared to Japan. The number of US COVID-19 cases is more than a hundredfold greater than in Japan and most states in the US implemented more severe stay-at-home regulations than Japan did. For example, many US states enforced social distancing protocol with fines and penalties for violating lockdown laws. By contrast, in Japan, no such severe lockdown regulations were enforced by the government, and hence, many people continued to commute by public transportation even after a state of emergency was declared [56]. A poll conducted by a private

research company [57] suggests that only 27% of the companies answering the nationwide survey asked workers to work from home and more than half of companies forced their workers to commute to the office even during Japan's state of emergency. Finally, another potential reason is that the US has been both a supplier and consumer of oil and gas while Japan is an importer of both goods. Hence, it could be that the COVID-19 cases caused a dual shock on both the supply and demand sides for the US, while only the demand side of the Japanese oil and gas markets was affected by the pandemic.

The COVID-19 pandemic proved that the oil market is volatile and fragile. Its instability has historically resulted from crude oil economic characteristics connected with the limited price elasticity of supply. This time, in contrast with other energy shocks, the oil market was not determined by the low-price elasticity of demand (see [34]). The fragility of the oil market might derive far-reaching consequences in the future. The pandemic and its continuing threat have changed behavioral patterns in society. Remote work, which was hesitantly introduced initially, is now widely appreciated as an effective way for employees to work without occupying expensive office spaces. Additionally, the COVID-19 threat forced many people to give up on their holiday/free-time activities. If these disruptions also contribute to the wider use of renewable energy sources, the world may emerge from the pandemic better equipped to facilitate a fast-track energy change. In that regard, natural gas, due to "before-lockdown" market conditions, may be relatively more resilient to changes than crude oil, but the COVID-19 pandemic is a challenge for both oil and gas companies. The worst situation is experienced by smaller players unable to withstand lower prices. The biggest national oil companies are either "too big to fail," or are supported by governments. For energy exporters, the pandemic might be a trigger to diversify their economies and decrease reliance on energy exports [28]. For energy importers like Japan, it could be the case that little will change in that respect.

Like any study, our empirical investigation has its research limitations. It is conditioned by an analytical approach informed by a literature review and data availability. Regarding literature, we decided to present only those papers that guided us in our study and positioned our research mainly within the literature strings on energy shocks and the pandemic's effects on energy markets, here limited to hydrocarbons. Since we believe that the COVID-pandemic volatility of daily changes is crucial, we opted for relatively high-frequency data, which became one of the important factors that delimited our empirical investigation. Since our main independent variable, COVID-19 cases, was a daily time series data, we needed to obtain the same frequency data for the other variables as well and this limited the variables used in the study. Extending the period or range of the data sample when it becomes available should be an interesting research step for future research. Furthermore, we also hope to compare the results of this study with other countries in the future.

**Author Contributions:** Conceptualization, H.N.-L., and K.A.; methodology, H.N.-L., and K.A.; software, K.A.; validation, K.A.; formal analysis, H.N.-L., and K.A.; investigation, H.N.-L., and K.A.; resources, H.N.-L., and K.A.; data curation, H.N.-L., and K.A.; writing—original draft preparation, H.N.-L., and K.A.; writing—review and editing, H.N.-L., and K.A.; visualization, H.N.-L., and K.A.; supervision, H.N.-L., and K.A.; project administration, H.N.-L., and K.A.; funding acquisition, K.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This study was funded by the grant for the 2019–2020 academic year from the Faculty of Economics, Saitama University.

**Acknowledgments:** We would like to thank Bożena Leven for proof editing the English of this paper.

**Conflicts of Interest:** The authors declare no conflict of interest.

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