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COVID-19 and the Energy Price Volatility

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Abstract: The challenges of the world economy and their societies, after the outbreak of the COVID-19 pandemic have led policy-makers to seek for effective solutions. This paper examines the oil price volatility response to the COVID-19 pandemic and stock market volatility using daily data. A general econometric panel model is applied to investigate the relationship between COVID-19 infection and death announcements with oil price volatility. The paper uses data from six geographical zones, Europe, Africa, Asia, North America, South America, and Oceania for the period 21 January 2020 until 13 May 2021 and the empirical findings show that COVID-19 deaths affected oil volatility significantly. This conclusion is confirmed by a second stage analysis applied separately for each geographical area. The only geographical area where the existence of correlation is not confirmed between the rate of increase in deaths and the volatility of the price of crude oil is Asia. The conclusions of this study clearly suggest that COVID-19 is a new risk component on top of economic and market uncertainty that affects oil prices and volatility. Overall, our results are useful for policy-makers, especially in the case of a new wave of infection and deaths in the future.

Keywords: COVID-19; pandemic; energy market volatility; announcements; uncertainty; deaths; infections

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1. Introduction

It is expected for someone to think that there is no connection between a pandemic and the energy industry. But when it becomes clear that the pandemic is responsible for uncertainty, the relationship between these two magnitudes acquires a logical basis. Two years after the COVID pandemic appeared in the city of Wuhan in China in 2019 and spread rapidly in Europe and in the USA, it was obvious that consequences were going to be severe for the world economy. The main feature of this pandemic was its rapid and unprecedented negative impact on economic activity and in particular the spread of great uncertainty worldwide. It was then expected for this uncertainty to combine with financial turmoil pushing companies and individuals in taking precautionary measures. Their first measure was to decrease their spending to be able to face impending difficulties if necessary.

The environment created by the financial hardship but mostly by the daily announcements of deaths and infections naturally had a negative effect on the consumers' psychology. In such an insecure environment, it was rather normal to observe a reduction in demand for oil and therefore a reduction in its price. Speaking with numbers, during the first two years of the pandemic, global electricity demand was decreased by an average of 15% [1] resulted in a downward movement of the prices for crude oil and natural gas.

It should be noted that the COVID-19 pandemic period did not have the same characteristics as other periods of uncertainty which were due to a slowing or overheating of the economy, and thus measures to deal with COVID-19 should be different too. In any case, the focus of these measures was on the restriction of free movement and transportation. In fact, travel bans not only applied between different countries but were mainly imposed within countries themselves. So, it was natural for these restrictions on the movement of people and the transport of goods to cause a significant reduction in the demand for fuel, damaging further the energy sector.

At this point it is useful to mention that global organizations and states acted instantly, adopting measures to limit the effects of the pandemic in the global economy. The experience of the past and the tools that technological transformation provides to the policy-makers make decision framework more effective and also more complex. The main objective is to avoid a new universal quarantine of the population in their homes or even partial lockdowns of economic activities.

The main purpose of this paper is to examine the dramatical impact of the COVID-19 on the energy sector during the pandemic period, providing useful results for policy-makers, especially in case of a new wave of infections and deaths in the future.

The rest of this paper is organized as follows. Section 2 discusses the existing literature, emphasizing on the effects of COVID-19 on the energy sector while Section 3 presents the data and hypotheses. Section 4 presents the methodology applied to show the relationship between COVID-19 infections and death announcements with oil price volatility. Section 5 explains the empirical results and Section 6 presents the conclusions and a short discussion for future works.

2. Literature Review

In the recent literature we found studies that investigated the effects of COVID-19 on specific sectors or economic zones or even the global economy. Most of these studies focus on financial markets and the energy sector, while in several cases, macroeconomic factors are also examined. Most of these studies provide useful conclusions, and the effects of the pandemic are expected to remain at the top of academic interest for the next period. The purpose of these studies is to acquire the necessary knowledge to deal with similar cases in the future, in order to limit the negative effects and to reset the real economy and social life on track as soon as possible.

Ref. [2] examines the linkage of the global oil market with the USA energy stock market using their implied volatility indexes. The main conclusion of this study is the existence of a long-run relationship between oil and stock market implied volatility indexes. In a similar way, ref. [3] studied the dynamic correlation between spot oil price fluctuations and the stock uncertainty index for the USA, Japan, China, and Hong Kong in order to find out whether crude oil can be used as a hedging instrument. According to the applied wavelet coherence analysis, crude oil cannot support hedging on a long run period but it can be a hedging instrument in a state of panic, like the pandemic period.

Ref. [4] applied a heterogeneous autoregressive realized volatility model to examine the predictive power for oil-market volatility using an uncertainty index based on the daily newspaper news for the pandemic period. They found that by incorporating such information in their model, forecast accuracy improves significantly.

Ref. [5] applied a nonlinearity autoregressive distribute lag model to examine the crude oil price fluctuation while they also use an event study model to compare how different types of events affect crude oil price fluctuations. In their effort to combine crude oil price fluctuation with what causes it, a state-space model was applied and evidence of strong correlation between event shocks and event types was found.

Ref. [6] attempted to estimate the out-of-sample predictive power of crude oil price volatility in relation to financial ratios and macroeconomic variables which are commonly used in the literature. Her findings suggested that considerable economic profit is possible based on this model while useful implications are also provided for portfolio optimization and asset allocation. On the other hand, ref. [7] examined for the USA the relation between COVID-19 and oil price volatility, the stock market and the geopolitical risk among others.

By applying wavelet approaches they found that COVID-19 effect on geopolitical risk is higher than economic uncertainty in the USA.

Ref. [8] provided a way for increasing energy efficiency and energy saving. They examined the challenges of COVID-19 for the energy sector. In particular, they investigated new practices enforced by the pandemic and the way they affected energy demand and consumption. They found that demand has declined but intensity showed apparent changes as the extra energy used to fight COVID-19 was not negligible for the recovery of the demand for energy, while differences in recovery can also be found between different regions.

Ref. [9] examined the implications of COVID-19 for the sustainable energy transitions. The adopted measures by the states, firms, and individuals have motivated many changes that may influence the sustainable transition of energy. They identified the main impact of lockdown on energy and investigated how economic stimulus packages can shape energy transitions and found that the politics of sustainable energy transitions are at a critical stage.

Ref. [10] examined the risk transmission from the COVID-19 to metals and energy markets and found significant negative volatility transmission from the COVID-19 to gold, palladium, and brent oil markets. According to these results, COVID-19 risk is not transmitted to the industrial metal market but COVID-19 leads to an increase in oil market volatility.

Ref. [11] estimated the price volatility of crude oil and natural gas for the listed firms in the MCX exchange of India. Their results are interesting for policy-makers to assess the appropriate strategy in facing the effects of the pandemic as they find leverage effect of COVID-19 on the price volatility of crude oil but not on the price volatility of natural gas.

Ref. [12] examined the hourly oil price volatility and found a significant increase of volatility in the pandemic period. To achieve that, they built a dataset with hourly oil prices combined with global cases of COVID-19 and deaths and applied an OLS regression model with volatility being one of the proxies of oil price volatility. In addition, ref. [13] attempted to estimate predictors of oil prices and for that he examined the interconnection of oil prices with COVID-19 infections and oil price news. He found that effect on oil prices is more significant when infections exceed the threshold of 84,479, whereas the effect of oil price news conditioned on COVID-19 cases is limited.

Ref. [14] estimated the historical volatility of energy markets during the COVID-19 pandemic period by using infection ratio, economic policy uncertainty index and infectious diseases market volatility. His findings can explain the investors' position in implementing options to protect from risk in the energy market and their willingness to pay excess premium for that.

Ref. [15] investigated the relation between the COVID-19, the crude oil market, and the stock market by observing return and volatility spillover with both a time-domain approach and a frequency dynamics approach. Their analysis showed that spillover return mainly exist in the short term while volatility spillover mainly exists in the long term. They also applied a moving window analysis to conclude that COVID-19 created more risk for investors which resulted in high losses in the short term. It is also interesting that COVID-19 impacts on the volatility of the oil, and stock market was even higher than volatility caused in 2008 by the global financial crisis.

Ref. [16] examined the role of gold as a hedging instrument against crude oil price risks. They applied an asymmetric VARMA-GARCH model to assess the impact of COVID-19 and they found that gold can work as a hedge instrument against oil risks as their results during pandemic show negative coefficient of returns spillovers from gold to oil price returns, meaning that an increase in gold in this period will lead to a less decline in oil price returns. Moreover, volatility spillovers between the gold and oil price returns suggest that significant volatility effects are present.

Ref. [17] examined the predictive power of oil supply, demand, and risk shocks in relation to the realized volatility of the daily oil returns. They applied a heterogeneous autoregressively realized volatility approach and showed that especially financial market-driven risk shocks can improve the forecasting performance for in and out-of-sample. Their conclusions offer to investors a valuable way to use traded assets at high frequency in order to monitor oil market volatility.

Ref. [18] emphasized on vaccines by examining the storage conditions based on their thermal load to cool and found that the cold storage of Oxford–AstraZeneca, Janssen COVID-19, and CoronaVac vaccines in Brazil generates 35-times less environmental impact than Pfizer. They also developed an energy index showing that Oxford–AstraZeneca, Janssen COVID-19, and CoronaVac vaccines have 9.34-times higher energy efficiency than Pfizer.

Ref. [19] considered that COVID-19 led to an economic crisis which has changed the social behavior and reduced the industrial activity and the demand for power worldwide. To examine the impact of COVID-19 on power demand, they quantified the country load reduction of COVID-19, based on the active cases and the lockdown period as proxies. They found that in Germany and Great Britain the power demand was reduced while in France the demand was increased for the period outside the lockdown. During the lockdown, France had a much higher reduction than in Germany and Great Britain. However, the effect of COVID-19 on carbon emissions in the power sector was small.

Other studies focused on the impact of COVID-19 pandemic on stock market returns and stock market volatility.

Ref. [20] examined the response of stock market returns from 64 countries to confirmed deaths from COVID-19. His research covers the period January to April 2020 and shows a negative response of stock markets returns to confirmed deaths. Ashraf's research also suggested that negative response was stronger and faster in the first days of confirmed deaths indicating that market response depends on the period of the outbreak.

Ref. [21] investigated the effect of official pandemic announcements on financial markets volatility as expressed by S&P 500 and found that COVID-19 is a significant source of price volatility in the USA financial markets which thereafter affects the global financial cycle.

The existing literature highlights reasonable questions about the impact of COVID-19 on oil price volatility and in this paper we try providing some answers to this issue.

3. Data and Hypotheses

One question that has caught the interest of the academic community in recent years is the relationship between the pandemic and the oil price volatility. Until 2019 the literature showed that oil prices fluctuate due to the forces of supply and demand. Indeed, several research showed that during normal periods, the demand for oil is shaped by global economic activity, while on the supply side, factors related to technological innovations that improve the oil production process are incorporated.

However, in the last two years, we have observed increasing volatility in the price of oil without any economic event justifying it during the same period. As a result, the academic community has turned its attention to investigating the causes that led to this phenomenon. As it turned out, the intense uncertainty created by the pandemic, first for health reasons and then for the possible effects on the world economy, significantly affected the demand for oil. This demand shock is different from the traditional aggregate demand shock because the decline in consumer confidence is inextricably linked to the fear caused by the virus.

Consequently, one of the main questions raised by the literature is how COVID-19 death announcements and the speed of COVID-19 deaths and infections affect oil price volatility.

In this context, our paper provides answers on three theoretical questions contributing with its findings in the existing literature as follows:

Hypotheses 1. *How the announcements of new cases affect the volatility of the oil price?*

Hypotheses 2. *How the rate of change of cases affect the volatility of the oil price?*

Hypotheses 3. *Do the above influences differ between different geographical areas worldwide?*

The three hypotheses are tested with a general econometric panel model similar to the one proposed by ref. [21] who examined the response of financial market volatility on COVID-19 new cases of infection and the fatality ratio. Yet, this article (ref. [21]) does not examine the volatility of oil prices in relation to the pandemic which is the main scope of our study.

In the empirical analysis we collect daily data for COVID-19 infection announcements and deaths from the World Health Organization. Our daily data also include three crude oil volatility indices, the CBOE 30-day crude oil implied volatility index, the 3-month crude oil implied volatility index, and the Brent 3-month implied volatility index. Further, daily data involve also four market uncertainty indices, namely VIX Volatility Index, VSTOXX Volatility Index, NIKKEI Volatility Index, and CBOE China ETF Volatility Index. Last but not least, daily data concern the Economic Uncertainty index, the Baker, Bloom and Davis index of economic policy uncertainty for Europe which is based on the frequency of newspaper references to policy uncertainty.

In the first stage of analysis, our sample is divided into six main geographical areas, so that the empirical analysis leads to useful conclusions for each area separately and in the second stage of analysis the population of the six geographical areas is an aggregate sample.

4. Methodology

The current study investigates the relationship between COVID-19 infection and death announcements with oil price volatility. Our analysis considers existing economic uncertainty and stock market uncertainty in this relationship to disentangle the effects of these uncertainties from that of COVID-19 deaths and infection announcements.

$$VOL(oil) = \alpha + \beta 1\ COV(f) + \beta 2\ COV(s) + \beta 3\ EU + \beta 4\ MU + \beta 5\ K + \varepsilon \tag{1}$$

where:

VOL(oil) refers to three different measures of oil price volatility,

1. *COV(f)* and *COV(s)* refer to COVID-19-related deaths and COVID-19-related speed of death and infection growth.
2. *EU* stands for economic uncertainty index.
3. *MU* is the market uncertainty index, as reflected by volatility indices in the three largest economic zones, namely in the US (VIX) Europe and Asia (China and Japan) and
4. *K* is a dummy variable representing the day of the week effect, with value one for Monday and zero otherwise.

The reason that our models apply more timeseries regarding the MU variable is due to the fact that the geographical areas are examined individually and each of them is combined with the corresponding stock index.

More details for the variables in our models can be found in the Appendix A.

Our models investigate how COVID-19 death or infection increase (speed) and actual deaths (fatal) affect oil volatility by using the following seven models

$$VOL(oil) = \alpha + \beta 1\ COV(f) + \varepsilon \tag{2}$$

$$VOL(oil) = \alpha + \beta 2\ COV(s) + \varepsilon \tag{3}$$

$$VOL(oil) = \alpha + \beta 1\ COV(f) + \beta 2\ COV(s) + \varepsilon \tag{4}$$

$$VOL(oil) = \alpha + \beta 1\ COV(f) + \beta 2\ COV(s) + \beta 3\ MU + \varepsilon \tag{5}$$

$$VOL(oil) = \alpha + \beta 1\ COV(f) + \beta 2\ COV(s) + \beta 3\ EU + \varepsilon \tag{6}$$

$$VOL(oil) = \alpha + \beta 1\ COV(f) + \beta 2\ COV(s) + \beta 3\ MU + \beta 4\ EU + \varepsilon \tag{7}$$

$$VOL(oil) = \alpha + \beta 1\ COV(f) + \beta 2\ COV(s) + \beta 3\ MU + \beta 4\ EU + \beta 5\ K + \varepsilon \tag{8}$$

In our analysis, we run fixed-effect panel models, and we interpret the fitness of estimated model and significance of coefficients as expressed by adjusted R^2, t-statistics, and significance of t-statistics. Variance inflation factors (VIFs) of our models are between 1.6 and 1.85, significantly lower than 6. Then we investigate whether our models are robust in particular economic zones and under different model assumptions.

5. Empirical Results

In Table 1 we present the descriptive statistics from where we can observe two main results. First, there is an intensive oil price volatility, economic uncertainty, and market uncertainty and second, there is an accelerated growth rate of infections and deaths for the investigated period. The sharp increase in deaths and infection rates as a result of the pandemic COVID-19 and the consequent fear of an escalating crisis raised legitimate questions about the degree of impact of the pandemic in the price of crude oil in international markets as well as the volatility of its price.

Table 1. Descriptive statistics.

	N	Mean	Var	StDev	Min	Max
VOL(oil) [1]	2052	58.86	1627.2	40.33	30.7	325.15
VOL(oil) [2]	2052	45.80	351.9	18.76	26.692	128.891
VOL(oil) [3]	2052	43.06	213.8	14.62	10.5338	103.318
MU [1]	2052	27.68	121.4	11.02	12.91	82.69
MU [2]	2052	27.29	132.0	11.49	12.2389	85.6206
MU [3]	2052	25.75	75.82	8.70	14.26	60.67
MU [4]	2052	28.46	49.27	7.01	19.76	69.28
EU	2052	259.4	20,151	141.9	22.25	807.66
Week	2052	0.1988	0.1593	0.3992	0	1
COV(f)	1912	−3.591	0.2230	0.4722	−5.77	−2.30
COV(s) [1]	1923	−4.306	4.107	2.026	−8.99	3.93
COV(s) [2]	1701	−4.476	2.336	1.528	−7.04	1.60
COV(s) [3]	1678	−4.350	3.166	1.779	−7.03	3.82
COV(s) [4]	1650	−4.262	3.794	1.948	−7.02	5.48

Note: VOL(oil) [1, 2] and [3] are respectively the CBOE 30 day crude oil implied volatility index, Crude oil 3 month implied volatility index, and Brent 3 month implied volatility index. Estimates of 3-month implied volatility. COV(s) [1,2,3] and [4] are respectively the logarithm of (new daily COVID-19 infection case announcements divided by seven days lagged total COVID deaths), the logarithm of (new daily COVID-19-related deaths divided by 7 days lagged total COVID deaths), the logarithm of (new daily COVID-19-related deaths divided by 14 days lagged total COVID deaths), and the logarithm of (new daily COVID-19-related deaths divided by 21 days lagged total COVID deaths). MU[1,2,3] and [4] are respectively the VIX index, VSTOXX Index-EURO STOXX 50 Volatility, the NIKKEI Volatility Index, and the Cboe China ETF Volatility index.

Table 2 shows the results of the individual models presented above for the examined geographical areas of our study.

Our results in Table 2 are based on world panel data, and they indicate that COVID-19 deaths (COV(f)) and speed of death increase (COV(s)) can explain as stand-alone variables 11% and 39% of the oil-volatility (Columns 2 and 3 on Table 1 respectively).

Table 2. COVID-19 death announcements and oil price volatility, panel world data.

Model	1	2	3	4	5	6	7	8
COV(f)	341.2 ***	851.6 ***		943.2 ***	647.4 ***	418.0 ***	145.7 ***	139.8 ***
	(7.52)	(16.14)		(18.84)	(14.81)	(8.20)	(8.21)	(11.63)
COV(s)	4.192 ***		17.58 ***	16.79 ***	6.400 ***	10.72 ***	1.426 ***	1.240 ***
	(7.66)		(33.56)	(35.10)	(11.32)	(20.88)	(6.66)	(8.55)
MU	1.771 ***				2.188 ***		0.954 ***	0.754 ***
	(21.46)				(26.24)		(29.55)	(34.51)
EU	0.0905 ***					0.131 ***	0.0429 ***	0.0324 ***
	(15.57)					(21.15)	(18.86)	(21.03)
C	−6.108	34.33 ***	139.4 ***	106.0 ***	7.200	59.41 ***	9.998 ***	14.89 ***
	(−1.43)	(19.77)	(56.26)	(36.97)	(1.61)	(17.63)	(5.98)	(13.16)
R^2 adj	0.690	0.110	0.397	0.501	0.645	0.605	0.773	0.825
N	1701	2052	1701	1701	1701	1701	1701	1701

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia and Oceania. The number in parentheses represent t-statistics. *** asterisks indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 day lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 day crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 month implied volatility index, and the dependent variable in Model 8 is Brent 3 month implied volatility index.

When market uncertainty (Column 5, Table 2) or economic uncertainty (Column 6, Table 2) is taken into account, the significance of the overall model (adjusted R-square) increases to 64% and 60% respectively. If both Market Uncertainty (MU, expressed by the American VIX index) and Economic Uncertainty (EU) alongside with COV(f) and COV(s) are considered in the model (Column1, Table 2) the adjusted R-square of the model increases to 69% if the dependent variable is the CBOE 30 day crude oil implied volatility index. In the models presented in that Table, COV(f) is the logarithm of total deaths, and COV(s) is the logarithm of new daily COVID-19 deaths divided by seven days lagged total COVID-19 deaths. The model illustrated in Column 7 uses as dependent variable the Crude oil three months implied volatility index, and the model presented in Column 8 uses as the dependent variable in Brent 3 month implied volatility index. The latter models report an even higher (77% and 82%) adjusted R-square. All the dependent variables in all these models are positive and significant at a 1% level, providing robust evidence of significance for world data.

The above observations lead to comparable conclusions with other studies of the same period, which examine the effect of the pandemic on stock values or energy prices or on other products (Refs. [2,7,14]).

From the above we conclude that the pandemic affected the volatility of the price of crude oil globally. This influence is confirmed both by the new cases of infections and by the rate of infections.

Robustness Tests

To test the robustness of our models first we focus on the three major economic areas, Asia, Europe, and North America to find out if our conclusions are in line with global conclusions presented in Table 2. The findings of these analysis are presented in Tables 3–7.

Table 3. COVID-19 death announcements and oil price volatility, European data.

	1	2	3	4	5	6	7	8
COV(f)	349.2 ***	775.4 ***		877.2 ***	458.5 ***	621.2 ***	135.4 ***	130.1 ***
	(4.99)	(11.96)		(16.33)	(6.35)	(10.63)	(4.78)	(6.76)
COV(s)	5.880 ***		12.31 ***	13.18 ***	10.67 ***	6.398 ***	1.610 ***	1.196 ***
	(5.56)		(11.33)	(16.43)	(13.34)	(5.73)	(3.77)	(4.12)
MU	1.249 ***					1.586 ***	0.800 ***	0.664 ***
	(6.45)					(8.04)	(10.22)	(12.48)
EU	0.0887 ***				0.114 ***		0.0427 ***	0.0299 ***
	(6.29)				(7.91)		(7.49)	(7.73)
C	11.87	24.64 ***	118.1 ***	81.05 ***	58.07 ***	15.95 *	13.54 ***	16.28 ***
	(1.37)	(7.25)	(21.65)	(17.56)	(11.33)	(1.75)	(3.88)	(6.86)
R^2 adj	0.713	0.294	0.287	0.613	0.676	0.678	0.780	0.831
N	318	342	318	318	318	318	318	318

Note: The table includes daily aggregated data of European countries. The number in parentheses represent t-statistics. * and *** indicate 10%, and 1% level of significance, respectively. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1-6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Table 3 presents the model's predictive ability in European data, while Table 4 presents the North American data under the specifications of the models presented in Table 2. They illustrate solid predictive power in terms of coefficients and adjusted R-square. In particular adjusted R-square ranges between 70% (Column 1, Tables 3 and 4) and 84% (Column 8, on both Tables 3 and 4).

Table 4. COVID-19 death announcements and oil price volatility, North American data.

	1	2	3	4	5	6	7	8
COV(f)	272.5 **	843.5 ***		553.1 ***	237.5 **	578.0 ***	166.1 ***	181.1 ***
	(2.48)	(7.05)		(5.55)	(2.10)	(5.98)	(3.83)	(6.22)
COV(s)	8.762 ***		20.61 ***	19.57 ***	15.55 ***	12.31 ***	2.520 ***	1.885 ***
	(4.73)		(22.61)	(21.98)	(13.54)	(6.86)	(3.44)	(3.83)
MU	1.148 ***					1.202 ***	0.809 ***	0.685 ***
	(4.59)					(4.61)	(8.18)	(10.31)
EU	0.0772 ***				0.0801 ***		0.0361 ***	0.0250 ***
	(5.21)				(5.24)		(6.17)	(6.36)
C	37.94 **	31.46 ***	156.1 ***	132.0 ***	102.3 ***	63.41 ***	19.96 ***	20.11 ***
	(2.36)	(7.17)	(35.00)	(21.68)	(12.59)	(3.97)	(3.14)	(4.70)
R^2 adj	0.704	0.125	0.624	0.657	0.684	0.678	0.782	0.837
N	309	342	309	309	309	309	309	309

Note: The table includes daily aggregated data of North American countries. The number in parentheses represent t-statistics. ** and *** indicate 5% and 1% level of significance, respectively. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index. The dependent variable in Model 7 is Crude oil 3 months implied volatility index. The dependent variable in Model 8 is Brent 3 months implied volatility index.

On Table 5 we investigate whether by using the VSTOXX Index-EURO STOXX 50 Volatility index as a measure of Market Uncertainty for European data we can have significantly different results. In this case, the results we find are comparable.

Table 5. COVID-19 death announcements, European volatility, and oil price volatility, European data.

	1	2	3	4	5	6	7	8
COV(f)	314.4 ***	775.4 ***		877.2 ***	458.5 ***	603.0 ***	109.4 ***	106.0 ***
	(4.35)	(11.96)		(16.33)	(6.35)	(9.73)	(3.75)	(5.42)
COV(s)	6.155 ***		12.31 ***	13.18 ***	10.67 ***	6.946 ***	1.670 ***	1.165 ***
	(5.81)		(11.33)	(16.43)	(13.34)	(6.18)	(3.91)	(4.07)
MU	1.148 ***					1.444 ***	0.765 ***	0.655 ***
	(6.09)					(7.39)	(10.07)	(12.88)
EU	0.0937 ***				0.114 ***		0.0454 ***	0.0318 ***
	(6.68)				(7.91)		(8.02)	(8.39)
C	16.71 **	24.64 ***	118.1 ***	81.05 ***	58.07 ***	23.92 ***	15.58 ***	17.23 ***
	(2.00)	(7.25)	(21.65)	(17.56)	(11.33)	(2.71)	(4.63)	(7.64)
R^2 adj	0.709	0.294	0.287	0.613	0.676	0.669	0.778	0.835
N	318	342	318	318	318	318	318	318

Note: The table includes daily aggregated data of European countries. The number in parentheses represent t-statistics. ** and *** indicate 5%, and 1% level of significance, respectively. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the VSTOXX Index-EURO STOXX 50 Volatility index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index and the dependent variable in Model 8 is Brent 3 months implied volatility index.

We examine Asian data in Tables 6 and 7, using the Japanese stock market volatility (Table 6) and Chinese stock market volatility (Table 7) index to express market uncertainty.

Table 6. COVID-19 death announcements, Japanese volatility, and oil price volatility, Asian data.

	1	2	3	4	5	6	7	8
COV(f)	1533.7 ***	4018.7 ***		4686.9 ***	3534.3 ***	2359.5 ***	442.6 ***	298.9 ***
	(4.32)	(23.35)		(22.34)	(13.62)	(6.71)	(3.05)	(2.97)
COV(s)	−0.777		13.10 ***	−6.604 ***	−4.588 ***	−2.193	0.232	0.481
	(−0.57)		(7.46)	(−4.65)	(−3.36)	(−1.55)	(0.42)	(1.25)
MU	1.932 ***					2.110 ***	1.076 ***	0.884 ***
	(7.64)					(7.92)	(10.40)	(12.32)
EU	0.0721 ***				0.0812 ***		0.0401 ***	0.0324 ***
	(6.51)				(6.82)		(8.86)	(10.32)
C	−47.27 ***	−30.76 ***	117.9 ***	−74.52 ***	−61.19 ***	−57.67 ***	−1.149	7.374 ***
	(−5.21)	(−7.56)	(14.50)	(−7.42)	(−6.36)	(−6.09)	(−0.31)	(2.87)
R^2 adj	0.740	0.615	0.140	0.654	0.696	0.708	0.798	0.840
N	337	342	337	337	337	337	337	337

Note: The table includes daily aggregated data of Asian countries. The number in parentheses represent t-statistics. *** indicate level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the Nikkei Volatility index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index, and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Tables 6 and 7 show the robustness of the significance data (COV(f)) but they do not confirm consistency for the significance of COVID-19 growth data (COV(s), columns 1, 6–8 of Table 6 and columns 7 and 8 of Table 7). This may be due to the slow growth of these indices in Asian markets, which probably does not reflect the importance of demand for oil consumption worldwide, as the main markets are the European and the North American markets.

Table 7. COVID-19 death announcements, Chinese volatility, and oil price volatility, Asian data.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
COV(f)	2717.6 ***	4018.7 ***		4686.9 ***	3534.3 ***	3720.2 ***	937.1 ***	710.8 ***
	(9.14)	(23.35)		(22.34)	(13.62)	(13.65)	(7.91)	(8.56)
COV(s)	−2.981 **		13.10 ***	−6.604 ***	−4.588 ***	−4.716 ***	−0.671	−0.272
	(-2.20)		(7.46)	(−4.65)	(−3.36)	(-3.34)	(−1.24)	(−0.72)
MU	1.198 ***					1.316 ***	0.909 ***	0.738 ***
	(5.09)					(5.28)	(9.69)	(11.24)
EU	0.0768 ***				0.0812 ***		0.042 ***	0.034 ***
	(6.66)				(6.82)		(9.12)	(10.52)
C	−68.85 ***	−30.76 ***	117.9 ***	-74.52 ***	−61.19 ***	−82.14 ***	-14.71 ***	−3.714
	(−7.33)	(−7.56)	(14.50)	(−7.42)	(−6.36)	(−8.41)	(−3.93)	(−1.42)
R^2 adj	0.717	0.615	0.140	0.654	0.696	0.680	0.791	0.831
N	337	342	337	337	337	337	337	337

Note: The table includes daily aggregated data of Asian countries. The number in parentheses represent t-statistics. ** and *** indicate 5%, and 1% level of significance, respectively. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the Cboe China ETF Volatility index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index, and the dependent variable in Model 8 is Brent 3 months implied volatility index.

A second evidence for robustness is also provided in Table 8 which presents the results of our models using world aggregated data and shows that coefficients are positive and significant irrespectively of which model is applied while adjusted R-square is also sufficient.

Table 8. COVID-19 death announcements and oil price volatility, world aggregated data.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
COV(f)	657.8 ***	1758.7 ***		1391.5 ***	682.3 ***	981.5 ***	277.2 ***	256.2 ***
	(5.93)	(17.26)		(13.96)	(5.33)	(11.20)	(6.25)	(8.64)
COV(s)	5.748 ***		18.15 ***	11.41 ***	10.35 ***	5.497 ***	1.853 ***	1.267 ***
	(5.34)		(12.77)	(9.28)	(9.10)	(4.97)	(4.30)	(4.40)
MU	1.504 ***					1.746 ***	0.831 ***	0.683 ***
	(10.57)					(12.85)	(14.60)	(17.96)
EU	0.0602 ***				0.112 ***		0.032 ***	0.022 ***
	(4.56)				(7.93)		(6.03)	(6.32)
C	4.009	−1.936	139.1 ***	61.20 ***	51.72 ***	0.725	13.07 ***	15.05 ***
	(0.53)	(−0.50)	(21.35)	(8.03)	(7.29)	(0.09)	(4.28)	(7.38)
R^2 adj	0.730	0.466	0.325	0.573	0.640	0.713	0.799	0.852
N	337	342	337	337	337	337	337	337

Note: The table includes world aggregated data. The number in parentheses represent t-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index, and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Third, in Tables 9–11 we test the robustness of our models by replacing one of our variables using world panel data. In Table 9 we investigate the effect of COVID-19 infection speed instead of examining COVID-19 death speed. These models are significant, but they report a slightly lower adjusted R-square, indicating that markets are more worried about death growth rates and actual deaths than COVID-19 infection growth rates. This may be because they regard that economic effect of deaths is more certain and robust than reporting cases that can be manipulated or affected by the number of tests taken.

Table 9. COVID-19 death announcements, infection speed, and oil price volatility, world panel data.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
COV(f)	211.0 ***	851.6 ***		909.5 ***	279.8 ***	548.8 ***	95.00 ***	94.45 ***
	(5.28)	(16.14)		(18.47)	(6.06)	(13.49)	(6.02)	(8.65)
COV(s)	1.890 ***		13.18 ***	13.39 ***	7.789 ***	3.182 ***	0.773 ***	0.760 ***
	(4.41)		(26.97)	(29.69)	(18.53)	(6.75)	(4.56)	(6.48)
MU	1.811 ***					2.397 ***	0.935 ***	0.747 ***
	(25.78)					(33.44)	(33.70)	(38.91)
EU	0.107 ***				0.158 ***		0.0502 ***	0.038 ***
	(21.21)				(29.43)		(25.18)	(27.83)
C	−17.8 ***	34.33 ***	119.0 ***	92.33 ***	43.83 ***	−10.1 ***	7.207 ***	12.79 ***
	(−5.33)	(19.77)	(51.16)	(35.70)	(16.18)	(−2.73)	(5.46)	(14.00)
R^2 adj	0.681	0.110	0.271	0.380	0.571	0.607	0.767	0.815
N	1943	2052	1943	1943	1943	1943	1943	1943

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia, and Oceania. The number in parentheses represent t-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID infection case announcements divided by 7 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index, and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Tables 10 and 11 present the results under different assumptions (2-week and 3-week respectively, instead of 7-day speed) about the COVID-19 death speed. These models are significant and report similar coefficients but convey slightly lower significance than our 7-day basic Model presented in Table 2.

Table 10. COVID-19 death announcements, 2-week speed, and oil price volatility, world panel data.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
COV(f)	342.5 ***	851.6 ***		919.4 ***	448.8 ***	621.7 ***	151.5 ***	145.2 ***
	(7.47)	(16.14)		(18.77)	(8.89)	(14.07)	(8.48)	(12.01)
COV(s)	4.144 ***		15.41 ***	14.45 ***	9.532 ***	6.093 ***	1.313 ***	1.165 ***
	(8.54)		(35.19)	(35.98)	(21.54)	(12.32)	(6.95)	(9.11)
MU	1.751 ***					2.147 ***	0.928 ***	0.727 ***
	(19.56)					(23.72)	(26.58)	(30.80)
EU	0.0861 ***				0.121 ***		0.0418 ***	0.0315***
	(14.54)				(19.40)		(18.12)	(20.19)
C	−5.206	34.33 ***	127.2 ***	93.78 ***	54.03 ***	7.021	10.08 ***	15.16 ***
	(−1.26)	(19.77)	(61.80)	(36.32)	(17.40)	(1.64)	(6.27)	(13.93)
R^2 adj	0.683	0.110	0.424	0.524	0.611	0.644	0.763	0.817
N	1678	2052	1678	1678	1678	1678	1678	1678

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia, and Oceania. The number in parentheses represent t-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s)is the logarithm of (new daily COVID deaths divided by 14 days lagged total COVID deaths), MU is the US vix index, EU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Table 11. COVID-19 death announcements, 3-week speed, and oil price volatility, world panel data.

	1	2	3	4	5	6	7	8
COV(f)	328.2 ***	851.6 ***		850.4 ***	462.8 ***	565.6 ***	154.2 ***	144.5 ***
	(7.09)	(16.14)		(17.81)	(9.31)	(12.66)	(8.60)	(11.94)
COV(s)	4.642 ***		14.20 ***	12.85 ***	8.994 ***	6.405 ***	1.432 ***	1.257 ***
	(10.44)		(37.22)	(35.95)	(22.40)	(14.40)	(8.31)	(10.81)
MU	1.715 ***					2.057 ***	0.890 ***	0.701 ***
	(17.50)					(20.76)	(23.43)	(27.37)
EU	0.0782 ***				0.106 ***		0.0398 ***	0.0301 ***
	(13.02)				(16.88)		(17.10)	(19.15)
C	−0.0438	34.33 ***	119.6 ***	86.73 ***	53.60 ***	11.83 ***	11.87 ***	16.50 ***
	(−0.01)	(19.77)	(66.94)	(35.14)	(17.83)	(2.80)	(7.42)	(15.29)
R^2 adj	0.672	0.110	0.456	0.543	0.611	0.638	0.748	0.808
N	1650	2052	1650	1650	1650	1650	1650	1650

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia, and Oceania. The number in parentheses represent t-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s)is the logarithm of (new daily COVID deaths divided by 21 days lagged total COVID deaths), EU is the US vix index, MU is the economic uncertainty index. R^2 adj is the R-square adjusted. The dependent variable in Model 1–6 is CBOE 30 days crude oil implied volatility index, the dependent variable in Model 7 is Crude oil 3 months implied volatility index and the dependent variable in Model 8 is Brent 3 months implied volatility index.

Table 12 compares the basic Model (Column 1, Table 12) with a model that takes account the weekly effect (Column 2, Table 12). The findings illustrate that there is no significant "day of the week" effect in the data examined, and the robustness of these data remains intact after we account for this factor.

Table 12. COVID-19 death announcement and oil price volatility, world panel data.

	1	2
COV(f)	341.2 ***	338.7 ***
	(7.52)	(7.45)
COV(s)	4.192 ***	4.135 ***
	(7.66)	(7.48)
MU	1.771 ***	1.771 ***
	(21.46)	(21.47)
EU	0.0905 ***	0.0912 ***
	(15.57)	(15.51)
Week		−1.112
		(−0.76)
C	−6.108	−6.260
	(−1.43)	(−1.46)
R^2 adj	0.690	0.690
N	1701	1701

Note: The table includes panel data of six geographical areas, namely North America, South America, Europe, Africa, Asia, and Oceania in columns 1–2. The number in parentheses represent *t*-statistics. *** indicate 1% level of significance. COV(f) is the logarithm of total deaths, COV(s) is the logarithm of (new daily COVID deaths divided by 7 days lagged total COVID deaths), EU is the US vix index, MU is the economic uncertainty index, and week is a dummy variable taking the value one on Mondays, zero otherwise. The dependent variable is CBOE 30 days crude oil implied volatility index. R^2 adj is the R-square adjusted.

Our findings offer a valuable contribution to the existing literature as we provide evidence that COVID-19 death growth rates and deaths affect oil volatility significantly. The pandemic affects the volatility of the price of crude oil worldwide. This result is confirmed both by the new cases of infections and by the rate of infections. These conclusions are verified separately for each geographic area and the world as a whole. The contribution of this study is not limited to the indication that COVID-19 is a new factor of risk that affects oil prices on top of economic and market uncertainty but also provides new measures of risk factor like the speed rate of death.

6. Conclusions

In this study we investigate the relationship between COVID-19 infection and death announcements with oil price volatility. We use the speed rate of deaths as a proposed measure for the COVID-19 risk and we apply panel data from six world geographical areas taking into consideration the existing economic uncertainty and stock market uncertainty in order to separate these effects from the effects resulting from the announcements of COVID-19 deaths and infection. The applied tests show that oil volatility is significantly affected by COVID-19 deaths which indicates that COVID-19 is a new factor of risk which one can argue has intensified the market risk.

The findings of our study underscore the importance of better understanding the effects of a pandemic shock on movements and the volatility of oil prices. In addition, it emphasizes the need for policy-makers and market stakeholders to explicitly consider changes in global health conditions when analyzing the causes and consequences, in order to plan an appropriate response to oil price shocks. In this regard, although lockdown policies of certain economic activities and restrictions in travelling had some positive effects in reducing the transmission of the health crisis, at the same time there were negative effects on the economy. In addition, the policies of governments around the world as well as Central Banks to support economies and individuals by offering them access to affordable financing have sent a clear message of calming the markets and addressing the crisis in many ways.

In particular, the EU has taken bold decisions by setting up a recovery fund for its Member States. Based on the results of our study, such measures are in the right direction and what is proposed at this stage is to create a framework with a permanent form. Such a framework should have two pillars, one institutional and one economic, in order to calm the markets from any concerns about similar cases in the future. The institutional framework will outline possible restrictive measures in countries with high rates of infection, but at the same time, these measures will be supplemented by financial support.

The conclusions of this study can be used as a guide for future decisions of managers, investors, and policy-makers regarding management, asset pricing, and market stability. Risk managers and asset pricing managers have already incorporated the pandemic in their short and medium-term decisions to prepare their business plans. Especially, for the energy companies that affected substantially by the restrictions in travelling and transportation, this study provides interesting considerations. Especially, oil and gas producers, it is crucial to have always a plan B to face similar phenomenon in the future while, individual investors must also take into consideration COVID-19 in their expectations.

In any way, we already know that although vaccines were available in the first semester of 2021 for the public worldwide, the Delta mutation of COVID-19 is spreading rapidly. Nonetheless, for future work, another important factor of this equation is the technological advances and especially the 5G infrastructure which provided significant solutions in business communication and education especially in the more developed countries.

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Appendix A

Table A1. Description of variables used in the study.

(VOL(oil))	CBOE 30 day crude oil implied volatility index.
	Crude oil 3 month implied volatility index. Estimates 3-month implied volatility. IVOLCRUD Index.
	Brent 3 month implied volatility index. Estimates of 3-month implied volatility. IVOLBREN Index.
COVID Deaths (COV(f))	The logarithm of cumulative COVID-19-related deaths
COVID-19 related speed of death and infection growth (COV(s))	The logarithm of (new daily COVID-19 infection case announcements divided by seven days lagged total COVID deaths)
	The logarithm of (new daily COVID-19-related deaths divided by 7 days lagged total COVID deaths)
	The logarithm of (new daily COVID-19-related deaths divided by 14 days lagged total COVID deaths)
	The logarithm of (new daily COVID-19-related deaths divided by 21 days lagged total COVID deaths)
Economic Uncertainty (EU)	The Baker, Bloom and Davis index of economic policy uncertainty for Europe is based on the frequency of newspaper references to policy uncertainty. 10 newspapers from the 5 largest European Union economies (Germany, UK, France, Italy, and Spain) are used: Handelsblatt, FAZ, the Financial Times, The Times of London, Le Monde, Le Figaro, Corriere Della Sera, La Repubblica, El Pais, and El Mundo. The index is constructed based on the number of news articles containing the terms uncertain or uncertainty, economic or economy, as well as policy-relevant terms (scaled by the smoothed number of articles containing "today"). Policy-relevant terms include: "policy", "tax", "spending", "regulation", "central bank", "budget", and "deficit".
Market Uncertainty (MU)	VIX Volatility Index.
	VSTOXX Index-EURO STOXX 50 Volatility.
	NIKKEI Volatility Index.
	Cboe China ETF Volatility index.

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