Crude Oil Price Shocks and Industrial Returns in Pakistan: An Examination through GARCH Based Dynamic Models

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Abstract
This paper attempts to examine the link between crude oil prices and industrial returns in Pakistan using daily data for the period of June-2008 to Jan-2021. Mean and volatility spillover is examined by using ARMA (1,1) GARCH (1,1)-M model. In addition, the time-varying nature of conditional correlation is determined by using DCC-GARCH models. Further, study has also investigated the impact of Covid-19 on the relationship between COP and INDR. Findings of the study provide strong evidence of volatility spillover from crude oil prices to Automobile Assemblers, Oil & Gas, Power Generation & Distribution and Refinery but only scarce evidence is found regarding mean spillover. DCC-GARCH model reveals the time-varying nature of conditional correlation between crude oil prices and all other industries. Moreover, the results also provide some evidence about asymmetric behavior in correlation among crude oil prices to Cement and Refinery.

Keywords: Mean & Volatility Spillover, Crude Oil, Industrial Returns, Time-varying Conditional Correlation & DCC-GARCH models.

Introduction

Crude oil is commonly regarded as the lifeblood of contemporary industry because of its central role as a source of energy in virtually every sector. The global economy's macroeconomic variables are significantly affected as a result. Crude oil prices (COP) have fluctuated dramatically in recent decades, which has affected the operational costs of firms and their revenue streams. The COP has been volatile since 2000. In June 2000 the COP was \$54.5, which reached \$184.94 in June 2008, it is the highest level from 2000 to 2008. Crashing to \$57.06 in the wake of the subprime crisis, COP has been fluctuating between \$21 and \$184 since 2000 at its highest. COP climbed above $100 in 2011 as the global economy recovered from the financial crisis. However, it fell to a record low of $21.25 in 2020, the lowest ever noted. Early April 2020 saw a decline in demand for more than 30 million barrels of oil due in large part to the Covid-19 epidemic (International Energy Agency, 2020). On the other hand, production and commercial activity were restricted by traffic restrictions and quarantine regulations, which have reduced the need for oil. However, the conflict between Russia and Saudi Arabia over oil prices looked to throw fuel on the fire and caused the greatest decline in oil prices in history (Le et al., 2021).

Later on, in May 2022, the price of crude oil has increased far above $116 per barrel as shown in figure 1. Oil price fluctuation affects asset prices and increases economic and stock market volatility, which in turn has an impact on the financial market. This study intends to examine the mean and volatility spillover (MVS) from COP to Pakistan's industrial return. Pakistan's oil consumption is 2.64 billion barrels/day and ranked 170th (Geck, 2017). Pakistan is battling to improve its economic indices and needs more energy to satisfy its industrial needs. The rise in oil prices causes an inflationary tendency that reduces consumer demand, which negatively influences a firm's profitability and may lead to stock market instability (Waheed et al., 2018). However, due to Pakistan’s reliance on oil imports, economic indices and stocks are very susceptible to COP fluctuations (Ali et al., 2013). Consequently, this significant influence or change in price information is reflected in stock prices, which leads to the industry level.

Figure 1: Historical trend of crude oil price 2000-2020

Source: https://www.macrotrends.net/1369/crude-oil-price-history-chart

The notion of "equity valuation" can be used to explain the relationship between COP and the stock market. COP shocks may influence the stock market since the other macroeconomics variables and corporate cash flow are linked to economic conditions. To put it another way, oil prices may have an impact on stock returns (STR) since they raise input costs, which directly affect real output. According to the “equity pricing model,” the price of a stock may be compared to the discounted present value of a company's anticipated future net earnings at any given time. COP is expected to have a detrimental effect on stock value which may diminish expected earnings (Huang et al., 2005). This may also be understood through the "Interest rate channel," which states that if interest rates are high, investors will be more likely to invest in bonds, hence decreasing the value of stocks (Huang et al., 2005).

Numerous research on the influence of rising energy costs on macroeconomic indicators (inflation, unemployment, economic growth) has been conducted (Borzuei et al., 2022; Brown & Yücel, 2002; Kilian, 2008; Labonte & Makinen, 2008; Naryono & Sukabumi, 2020; Ordóñez et al., 2019; Stock & Watson, 2010). Moreover, different econometric methods are used to investigate the relationship depending upon the nature of the analysis i.e., aggregate or disaggregate level (Alamgir & Amin, 2021; Kelikume & Muritala, 2019; Mokni, 2020; Prabheesh et al., 2020; Wei et al., 2019). However, the majority of this research is conducted on developed stock markets. Even though the phenomena of MVS between COP and INDR is not extensively examined especially in developing countries like Pakistan (Malik & Rashid, 2017). Evidence relating COP to the market is plentiful, whereas evidence relating COP to industries is few. Moreover, if Pakistan becomes a member of growing markets in the future and there is a public interest in such events, knowledge of such phenomena would be sought. Using ARMA GARCH models, we investigated the dynamics of the MVS of COP and industrial returns to fill a vacuum in the empirical literature. In addition, all GARCH models seek to explain heteroskedasticity and asymmetry in volatilities but exclude these traits from correlation. The CCC-GARCH models have been criticized for ignoring the impact of time-varying correlation. This work employs the DCC-GARCH model as an extension of the CCC-GARCH model to address these limitations. The DDC-GARCH model modifies the assumption of constant correlation and captures deeper asymmetries than the ADCC-GARCH model. This study, therefore, examines the dynamic nature of conditional correlation. Moreover, the study also captures the impact of the Covid-19 pandemic on this relationship.

The present study uses daily data from June 2008 to January 2021 to analyze the relationship between COP and INDR in Pakistan. The ARMA (1,1) GARCH (1,1)-M model is used to investigate the MVS effects. In addition, DCC-GARCH models are used to examine the time-varying nature of conditional correlation. Moreover, the impact of the Covid-19 pandemic on industrial returns has also been analyzed which adds to the empirical literature. The study observes strong evidence of volatility spillover from COP to Automobile Assemblers, Oil & Gas, Power Generation & Distribution, and Refinery but only scarce evidence is found regarding mean spillover. DCC-GARCH model reveals the time-varying nature of the conditional correlation between COP and INDR. Moreover, the results also provide some evidence about asymmetric behavior in correlation among COP to Cement and Refinery. This study can motivate the policy makers to devise the policies according to the nature of the industries in contract with crude oil prices. Moreover, portfolio investor can use this study to highlight the risky sectors and diversification of portfolio benefits can be taken on that. The study is organized as follows. The second section comprises a review of the relevant literature. The third section discusses methodology and data sources. The fourth section summarizes the results and findings and the last section concludes the study.

Literature Review

An extensive amount of work has already been done to investigate the relationship between COP and stock return (STR). However, the empirical studies mostly focus on the developed stock markets. The issue was first investigated by Jones and Kaul (1996). The authors investigate the impact of COP fluctuations on current and future cash flows in four developed markets (Canada, Japan, the United States, and the United Kingdom) using a conventional present value model and find that differences in stock prices may be partially explained by this effect. The authors discover that the COP has a detrimental effect on STR.

Vector Autoregressive (VAR) models have been widely applied in the literature to examine the relationship between COP and STR. However, the results remain ambiguous. For instance, Huang et al. (2005) observe no association with the US stock market. Kaneko and Lee (1995) note that variations in COP impact stock market behavior in Japan. Huang et al. (1996) establish a significant causal relationship between oil futures prices and individual firm STR, but not with market returns. In addition, they find that returns on oil futures surpass the petroleum sector stock index and three oil firm STR. Sadorsky (1999) explores the relationship between spot oil prices, STR, and economic activity and concludes that both oil price and volatility have significant roles in determining real STR, with evidence of a growing influence since 1986. Faff and Brailsford (1999) examine the sensitivity of Australian industrial STR to a COP component and market returns. Their findings indicate that the oil and gas industries are far more vulnerable than the paper, packaging, and transportation sectors.

Hammoudeh et al. (2004) employed cointegration and ARCH models to investigate the spillover effects and dynamic links between “five daily S&P oil sector stock indices and five daily oil prices for the US oil markets”. The study reveals some volatility spillover between the oil futures market and STR in several oil businesses. Malik and Hammoudeh (2007) employ a tri-variate BEKK-GARCH (1, 1) model to investigate the volatility transmission links between US stocks, COP, and three GCC equity markets. The authors find evidence of bilateral spillover effects between the stock market and COP in Saudi Arabia exclusively. The volatility of oil prices influences the stock markets of other nations. Nandha and Faff (2008) examine 35 worldwide sector indices from Data Stream to see if and how COP shocks affect stock market performance. Using the VAR-GARCH model, Park and Ratti (2008) observed that COP shocks have a significant impact on STR for USA and 13 European countries. On the other hand, Aloui and Jammazi (2009) note that the COP fluctuations have a substantial effect on the volatility of real returns and the probability of regime shift in the UK, France, and Japan.

Arouri and Nguyen (2010) examine the link between COP and twelve European STR. The authors proved that sector returns react differently to changes in COP and that integrating oil assets in a sector stock portfolio improves the risk-return characteristics of the portfolio. Arouri et al. (2011) investigate the volatility spillover effect between the European stock market and COP. Using the VAR-GARCH method, they revealed the presence of a volatility spillover effect between COP and the STR. In addition, the results demonstrate the transmission of volatility between COP and sector STR. Chang et al. (2011) employ multivariate GARCH processes to examine the volatility dependencies between the "West Texas Intermediate" (WTI) oil price and stock indices of several global oil businesses. They uncover unanticipated outcomes, highlighting the lack of volatility links in all return series pairs. Mohanty et al. (2011) investigated the relationship between COP shocks and STR at the industry level and found substantial positive exposure in twelve of the twenty GCC sectors evaluated. Awartani and Maghyereh (2013) use indices proposed by Diebold and Yilmaz (2009) and observe bidirectional relations between COP and GCC stock markets. They identified a substantial informational flow from oil returns and volatility to GCC stock exchanges, but little movement in the opposite direction. In terms of returns and volatility, it appears that the oil market offers other markets more than it receives. The empirical findings from the sample are consistent with an information transmission mechanism between oil and equities in GCC nations in which oil plays a key role. Using multivariate GARCH models, Sadorsky (2012) studies the volatility spillovers between COP and the stock prices of renewable energy and technology businesses. The author illustrates that COP volatility negatively affects output and job growth.

Most of the prior studies focus on the developed stock markets. Some researchers also analyzed emerging and developing economies using different econometric methodologies but their results are inconclusive. For instance, Maghyereh (2006) applies an unconstrained VAR approach and finds that COP shocks have no significant influence on the 22 emerging stock markets returns. Basher and Sadorsky (2006) analyze the influence of COP fluctuations on a large number of emerging STR using a multi-factor international model that allows for unconditional and conditional components. They find convincing evidence that COP risk influences STR in developing economies. Cong et al. (2008) claim that COP shocks have no statistically significant influence on the actual STR of the majority of Chinese stock market indexes, except for the manufacturing index and a few oil enterprises. A rise in the volatility of oil has little influence on the majority of STR, but it may promote speculation in the mining and petrochemical indices, hence increasing STR (Chong et al., 2016).

Using Diebold and Yilmaz's (2010) return and volatility spillover index, Wang and Zhang (2014) analyze the impact of China on the global oil market in terms of MVS. The authors show that there is asymmetry and bi-directionality in the return and volatility spillovers from China to global oil markets. Intending to investigate the dynamic impact of COP volatility on stock prices over time, Caporale et al. (2015) built a bivariate VAR-GARCH model using weekly data from 10 Chinese industrial indexes. Aggregate demand-side shocks were demonstrated to have a negative effect in all cases except for the consumer services, banking, and oil and gas sectors. Furthermore, the banking sector and the oil and gas sector both responded negatively to supply-side shocks, suggesting that industry stocks fluctuate with COP. Similarly, COP volatility between 2009 and 2012 was analyzed by Chiwanza et al. (2015) using an econometric GARCH model and its effect on stock indexes in Zimbabwe. Researchers found evidence that COP shocks were included in Zimbabwean stock indices.

Teixeira et al. (2017) examine the influence of COP on STR and the considerable asymmetric impact of COP on individual business stocks by analyzing data from 54 Portuguese enterprises from 1993 to 2013. COP shocks and economic policy uncertainty have a disproportionate impact on stock market conditions, as shown by You et al. (2017). Another component of the historical literature examines the dynamic relationship between COP and STR (For instance, see Aloui & Jammazi, 2009; Broadstock & Filis, 2014; Choi & Hammoudeh, 2010; Filis et al., 2011; Prabheesh et al., 2020). The time-varying correlations research by Choi and Hammoudeh (2010) was expanded to include the S&P 500 index and the prices of Brent oil, WTI oil, copper, gold, and silver. They showed that since 2003, commodity correlations have grown, making it harder to hedge a portfolio with other instruments. Using a BEKK model, Broadstock et al. (2012) investigate the dynamic link between COP swings and Chinese energy stocks across time. They discovered that the connection has strengthened considerably since the height of the global financial crisis in 2007-2009. Further, Broadstock and Filis (2014) analyze the dynamic relationship between COP shocks and the returns on the US and Chinese stock markets. Using a Scalar-BEKK model, they find that STR in the United States is more sensitive to COP change than those in China. Nadal et al. (2017) work with the DCC-GARCH model and Joo and Park (2017) work with the GARCH in the mean model show, however, that COP uncertainty has time-varying repercussions on STR.

Ahmad (2017) studies the dynamic dependence between COP and clean energy stocks using time-varying conditional correlations and reveals time- and event-dependent volatility spillovers. Recently COP and STR relationships in key oil-exporting and oil-importing nations are studied by Mokni (2020) using a time-varying asymmetric quantile regression model. The results show that the distribution of conditional STR is quite diverse and changes over time in response to changes in the COP. Moreover, the stock markets react more strongly to declines in COP than to increases. Alamgir and Amin (2021) observe that in south Asian countries high global COP positively affects STR. Moreover, China Wei et al. (2019) conclude that COP significantly impacts STR either directly or indirectly. Moreover, this relationship still exists in the long run irrespective of structural breaks. This implies that STR and COP are linked in the long run. Khan et al. (2021) note that oil price fluctuations have a positive impact on stock market development in Pakistan. Similarly, for the Chinese stock market, Ahmed and Huo (2021) observes bidirectional spillovers between STR and COP. In a similar line, Ji et al. (2020)

explore the dynamic dependency between BRICS STR and different types of oil shocks. The study has used the Structural VAR and CoVaR approach. The study observes that the BRICS stock markets are exposed to a considerable risk spillover from the oil-specific demand shock.

Despite this, several studies examine the oil market's impact on the stock market and the dynamic link between the two. Extensive earlier research examines the link between oil market volatility and stock performance (Chang et al., 2013; Choi & Hammoudeh, 2010; Hammoudeh & Aleisa, 2004; Hammoudeh et al., 2004; Jones & Kaul, 1996 ; Kling, 1985; Nandha & Brooks, 2009; Wang & Zhang, 2014). While there is a plethora of research on the dynamic relationship between COP and STR, information on the dynamic relationship between COP and INDR is far more limited. Thus, the current research addresses this knowledge vacuum by exploring the effects of oil market volatility on other sectors.

Methodology

The methodology is divided into two parts. First of all the GARCH-in-mean model is implied to check the return and volatility spillover and then dynamic correlation is captured by using DCC-ADCC GARCH models. The study analyses the daily closing prices of Crude Oil WTI Futures and seven industrial indices to examine the mean and volatility spillover (MVS) from the crude oil market to other industries (Automobiles Assemblers, Cement, Chemicals, Fertilizers, Oil & Gas, Power Generation & Distribution and Refineries). The period of the sample is thirteen years, commencing in June 2008 and concluding in January 2021. The data comes from the Pakistan Stock Exchange and the State Bank of Pakistan. The rationale for selecting these industries is the contribution of these sectors towards country's GDP and economic growth. Returns on crude oil WTI futures are computed with the following formula:

$$r_t = \ln\left(\frac{COP_t}{COP_{t-1}}\right) \tag{1}$$

Where COP_t is crude oil price of day "t" in terms of rupees/barrel and COP_{t-1} is crude oil price of day "t-1" in terms of rupees/litter.

Econometric Models

The study has employed GARCH-in-mean (GARCH-M) two-step process developed by Liu and Pan (1997) to explore the mean and volatility transmission from crude oil to other sectors. In the first step, the relevant exchange rate return series are modeled using an ARMA(1,1)-GARCH(1,1)-M econometric model.

$$r_{p,t} = \iota_o + \iota_1 . r_{p,t-1} + \iota_2 . v_{p,t} + \iota_3 . \varepsilon_{p,t-1} + \varepsilon_{p,t}, \varepsilon_{p,t} \sim (0, v_{p,t}) \tag{2}$$

$$v_{p,t} = \kappa_o + \kappa_1 . \mu_{p,t-1}^2 + \kappa_2 . v_{p,t-1} \tag{3}$$

Where, $r_{p,t}$ is the daily return of currency markets at time t and, $\varepsilon_{p,t}$is the residual return. The purpose of introducing the ARMA (p, q)-GARCH structure into the model is to modify the data's serial correlation.

In the second step, the effect of return and volatility transmission across markets is studied by getting the standardized error term and its square in the first stage and putting them into the return and volatility equations of various industries along with the Covid-19 dummy

$$r_{q,t} = \iota_{q,o} + \iota_{q,1}.r_{q,t-1} + \iota_{q,2}.v_{q,t} + \iota_{q,3}.\varepsilon_{q,t-1} + \pi_q.\varepsilon_{p,t} + \pi_q.COVI\_19 + \varepsilon_{q,t}, \varepsilon_{q,t} \sim (0, v_{p,t}) \quad (4)$$

$$v_{p,t} = \kappa_o + \kappa_1.\mu^2_{p,t-1} + \kappa_2.v_{p,t-1} + \zeta_q.e^2_{p,t} + \zeta_q.COVID\_19 \quad (5)$$

Where, $\varepsilon_{p,t}$ is the standardized error term and captures the mean returns and spillover effects. For volatility spillover, the exogenous variable $\varepsilon^2_{p,t}$ “the square of the standardized error term” is included in the conditional volatility equation and is defined as $e^2_{p,t} = \frac{\varepsilon^2_{p,t}}{\upsilon_{p,t}}$. COVID-19 is a dummy variable that is capturing the effect of the COVID pandemic outbreak from the period Dec-19 to the Present.

The previous model suggests that the correlation is constant over time, even though the correlation may change over time. Moreover, the insutries behaviour is not constant in nature and exhibiting the dyanamic nature. In this instance, the dynamic conditional correlation GARCH (DCC-GARCH) model is utilized, while Cappiello, Engle, and Sheppard's ADCC-GARCH model addresses the possibility of asymmetric information (2006). DCC handles correlations and volatility in two processes. The correlation grows somewhat when two equities move together. The correlation between two equities decreases as they move in different directions. The effect of stock movement may be increased during downturn markets. Correlations are often thought to depart from the long run meaning only briefly. Asymmetric DCC or ADCC models have a stronger tail dependency in the lower tail than symmetric DCC models do in both the upper and lower tails of the multi-period joint density.

DCC is defined as …

$$Q_t = \bar{R} + \sum_{i=1}^{m} \gamma_i \left(\varepsilon_{t-i}\acute{\varepsilon}_{t-i} - \bar{R}\right) + \sum_{i=1}^{n} \psi_i \left(Q_{t-1} - \bar{R}\right) \quad (6)$$

ADCC is defined as …

$$\sigma_t = \min(\varepsilon_t, 0)\,, \bar{N} = \frac{1}{T}\sum_{t=1}^{T} \sigma_t \acute{\sigma}_t \quad (7)$$

Results & Discussion

Table 1 displays the descriptive data for this study. Mean, Variance, Skewness, and Kurtosis are the first four pivotal moments in descriptive statistics.

Table 1: Descriptive Statistics

	COP	AA	CEM	CHE	FERT	OG	PGD	REF
Mean	-0.000269	0.000695	0.000475	0.000522	0.000762	0.000166	0.000407	0.000173
Median	0.000188	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.722541	0.080383	0.089224	0.343604	0.871251	0.093488	0.094346	0.099388
Minimum	-1.324217	-0.121152	-0.106047	-0.541320	-0.092929	-0.244497	-0.097715	-0.098539
Std. Dev.	0.038256	0.013855	0.017581	0.019499	0.020526	0.015013	0.015160	0.021683
Skewness	-10.33819	-0.338969	-0.005058	-6.101094	22.87269	-1.426797	0.120699	0.064164
Kurtosis	477.2375	8.648055	5.758146	257.5484	975.3853	27.11010	8.276101	4.945828
Jarq. Bera	31198638	4480.529	1053.318	8992007.	1.31E+08	81612.87	3862.367	526.5178
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Obs.	3323	3323	3323	3323	3323	3323	3323	3323

All observed industries had positive mean returns, with Fertilizer-FERT having the highest mean return (0.07 percent) and Oil & Gas-OG having the lowest (0.01 percent). Compared to Automobile Assemblers-AA, the Refinery-REF industry is more volatile, having the largest standard deviation (2.16 percent), while the Automobile Assemblers-AA business is less unpredictable. The maximum daily earnings and losses for each industry are shown by the maximum and minimum values. For all industries except Power Generation and Distribution-PGD and Refinery-REF, the return distribution is negatively skewed, as measured by negative skewness statistics. In addition, all Kurtosis statistics are positive and larger than 3, suggesting that the series is leptokurtic, i.e., its distributions have broader tails than normal distributions with the same mean. In addition, the Crude Oil Prices (COP) exhibit a mean return of 0.026 percent and a standard deviation of 3.82 percent. Negative values of Skewness and positive values of Kurtosis imply that data are negatively skewed and leptokurtic, respectively.

Table 2: Mean and Volatility Spillover from COP-to-Other Industries – ARMA GARCH Model

COP=Crude Oil Prices, AA=Automobile Assesmblers, CEM=Cemenet, CHEM=Chemicals, OG=Oil & Gas, PGD= Power Generation & Distribution, REF= Refinaries. Values in parenthesis are p-values or significance level.

The findings from the ARMA GARCH (p, q) model are displayed in above Table 2. The absence of substantial variations in the mean spillover results across all businesses indicates that fluctuations in oil prices have little effect on the returns of all these industries. When the

	COP	AA	CEM	OG	PGD	REF
ι_o	**8.04E-05 (0.8208)**	0.000423 (0.2799)	0.000512 (0.3298)	0.000776 (0.0234)	0.000548 (0.2574)	-0.000272 (0.6467)
ι_1	**0.098271 (0.8194)**	0.359615 (0.0003)	0.196049 (0.1967)	-0.035530 (0.8312)	-0.814094 (0.1992)	0.075798 (0.6254
ι_2	**0.644625 (0.1136)**	1.995458 (0.3905)	0.982367 (0.6019)	0.131858 (0.9435)	2.596183 (0.1683)	2.362082 (0.1040)
ι_3	**-0.143412 (0.7390)**	-0.182513 (0.0731)	-0.078362 (0.6108)	0.151066 (0.3659)	0.841697 (0.1842)	0.040901 (0.7955)
π	-	1.67E-05 (0.4812)	-9.56E-05 (0.7232)	-0.000193 (0.2914)	-0.000301 (0.1524)	-0.000199 (0.5372)
π*COVID_19	-	0.003513 (0.0000)	0.000405 (0.5860)	0.000315 (0.5442)	0.002148 (0.0001)	0.001691 (0.0520)
κ_o	**8.71E-06 (0.0000)**	7.55E-06 (0.0000)	9.60E-06 (0.0000)	7.04E-06 (0.0000)	6.79E-06 (0.0000)	0.000434 (0.0011)
κ_1	**0.866560 (0.0000)**	0.842530 (0.0000)	0.871592 (0.0000)	0.775463 (0.0000)	0.800541 (0.0000)	0.600000 (0.0000)
κ_2	**0.128513 (0.0000)**	0.119147 (0.0000)	0.092974 (0.0000)	0.173973 (0.0000)	0.158951 (0.0000)	0.150000 (0.0122)
ζ	-	-1.45E-10 (0.0144)	2.98E-10 (0.1343)	1.25E-09 (0.0000)	1.36E-09 (0.0000)	-6.38E-09 (0.0000)
ζ*COVID_19	-	4.05E-05 (0.0468)	1.66E-09 (0.1656)	4.09E-09 (0.0000)	7.57E-09 (0.0000)	-3.93E-09 (0.6547)

influence of the COVID-19 outbreak (dummy variable) is captured using an interaction dummy (i.e., *COVID-19), the findings become significantly positive for all industries except for Cement-CEM and Oil & Gas-OG, suggesting the impact of the pandemic on the financial markets. In short, the presence of the COVID-19 epidemic has repercussions for businesses. Similarly, volatility spillover is found to be significant for all industries except for the Cement (CEM) industry, which demonstrates substantial evidence of volatility spillover from COP to INDR. In addition, the negative volatility spillover indicator for Automobile Assemblers (AA) and Refinery (REF) suggests that volatility in COP is lowering volatility in these two industries. Most of these enterprises rely on oil and oil inputs, while several key industries, such as Oil & Gas and Refineries, rely totally on imported oil. Therefore, any change in the volatility of global COP would have a significant impact on these companies. Using the same COVID-19 outbreak (dummy variable) with volatility spillover (i.e., *COVID-19), all findings become considerably positive for all industries except Refinery-REF and Cement-CEM, confirming the pandemic's influence on financial markets. It is asserted that an unfavorable shock in one market has variable consequences on the return and volatility of other markets. Shocks induced by one market may only affect the other markets in one way, such as mean or volatility. Volatility spillover is widely used as a proxy for risky assets, making volatility analysis more pertinent than mean or return spillover analysis (Joshi, 2011).

Table 3: Mean Spillovers from Crude Oil Prices-to-Other Industries – ARMA Model

	COP	CHE	FERT
ι_o	**8.04E-05** **(0.8208)**	0.002123 (0.0000)	0.000761 (0.0903)
ι_1	**0.098271** **(0.8194)**	3.099221 (0.0000)	-0.050517 (0.8890
ι_2	-	-	-
ι_3	**-0.143412** **(0.7390)**	3.099221 (0.0000)	0.097704 (0.7874)
π	-	0.000268 (0.4571)	-0.000842 (0.0000)
π*COVID_19	-	0.001332 (0.1948)	0.002578 (0.0173)

CHE=Chemical, FERT=Fertilizers. Values in parenthesis are p-values or significance level.

Table 3 shows the estimates of mean spillovers from crude oil prices to industries using an ARMA (p, q) Model for two industries: chemicals (CHE) and fertilizers (FERT). The use of an ARMA model reveals that the return data for these two businesses are homoscedastic, which causes the variance to be constant, resulting in no GARCH series in the provided table. The results of mean spillover are only significant against Fertilizer-FERT, implying that any change in crude oil prices affects the returns of this industry. Furthermore, the negative sign indicates that the mean returns on crude oil prices are reducing the returns on the Fertilizer-FERT industry. Meanwhile, when the COVID-19 outbreak (dummy variable) is used, the findings become substantially more favorable, indicating the impact of the pandemic on financial markets.

First, the appropriate univariate GARCH model is identified and the DCC GARCH model findings are given in Table 4. The lower Akaike information criteria are used to examine the appropriateness of the acceptable univariate GARCH model after using the GARCH, GJR/TARCH, and EGARCH models. This table shows the impact of historical residual shocks (θ_1) and lagged dynamic conditional correlation (θ_2) along with associated p-values. All industries effectively meet the required level of stability. As a result, the DCC model can be used to measure time-varying conditional correlation. The parameters of (θ_1) are significant for all industries, implying that past residual shocks have an impact on conditional correlation. On the other hand, the parameter (θ_2) is significant for cement, chemicals, fertilizer, oil and gas and refinery, indicating that these industries have lagged dynamic conditional correlation.

Table 4: DCC GARCH Models & Estimates Between Crude Oil & Industries

Industries	**Selected Models**	**Crude Oil**	
		$\boldsymbol{\theta_1}$	$\boldsymbol{\theta_2}$
Automobile Assemblers	EGARCH	-0.00458 (0.0405)	0.090489 (0.9487)
Cement	GJR/TARCH	-0.007800 (0.0141)	-0.666710 (0.0170)
Chemicals	GJR/TARCH	-0.0009 (0.0000)	-0.98452 (0.0000)
Fertilizers	EGARCH	-0.00055 (0.0000)	0.400824 (0.0000)
Oil & Gas	GJR/TARCH	-0.00276 (0.0505)	0.318385 (0.0078)
Power Generation & Distribution	GARCH	-0.006413 (0.0426)	-0.461398 (0.5464)
Refinery	GJR/TARCH	0.008897 (0.0226)	0.870905 (0.0000)

p-values or significance value are in parentheses.

Table 5: ADCC GARCH Models & Estimates B/W Crude Oil & Industries

Industries	Selected Models	Crude Oil		
		θ_1	θ_2	θ_3
Automobile Assemblers	GJR/TARCH	-0.005714	0.665263	0.020722
		(0.0437)	(0.2305)	(0.4368)
Cement	EGARCH	-0.006842	0.450552	0.047612
		(0.0010)	(0.1482)	(0.0007)
Chemicals	GJR/TARCH	0.000473	0.687991	0.005614
		(0.9228)	(0.2139)	(0.7511)
Fertilizers	GARCH	-0.000893	0.794431	-0.012506
		(0.0000)	(0.0000)	(0.6090)
Oil & Gas	GJR/TARCH	-0.004810	0.397287	0.005535
		(0.0450)	(0.0392)	(0.0562)
Power Generation & Distribution	GJR/TARCH	-0.004935	0.808252	0.013392
		(0.0251)	(0.0073)	(0.0130)
Refinery	GJR/TARCH	-0.000435	0.276085	0.063160
		(0.9374)	(0.3539)	(0.0017)

p-values or significance level are reported in parenthesis.

Table 5 exhibits the findings of the univariate ADCC model and estimates between exchange rates and industries. Again, the appropriateness of the suitable univariate GARCH model is assessed by the lower Akaike information criteria by employing GARCH, GJR GARCH, and E-GARCH models. The first two parameters of this table are the same as that of DCC GARCH models i.e., the impact of the past residual shocks (θ_1) and lagged dynamic conditional correlation (θ_2). In this model, the primary interest is to discuss the results of asymmetric effects i.e. (θ_3). The parameter (θ_3) is only significant and positive for Cement, Power Generation and Distribution, Oil and Gas and Refinery which indicates the correlation increase with the negative news in these industries. In short, the asymmetric effect is present in only these industries.

Implications

These insights may be utilized by investors to invest in the energy industry by concentrating on less risky sectors. In addition, diverse energy policymakers may utilize these findings to design policies for a variety of industries. Due to the unanswered empirical and conceptual problems, this study can be explored in several ways. A comparison study, for instance, may be done in the future to analyse the phenomena of spillover in more depth by including other emerging markets in the sample. In addition, all GARCH models used in this study (GARCH, GJR GARCH/TARCH, and EGARCH) were applied to the whole distribution. Consequently, an investigation into extreme movement utilizing tailed distribution may be conducted soon.

Conclusion

In this article, we examined two significant concerns in the empirical financial markets' literature: the mean and volatility spillover from crude oil price to industrial returns, as well as the time-varying conditional relationship between these markets. First, the average spillover findings demonstrate that an increase in oil prices has a substantial negative influence on the Chemicals sector's industrial returns. It indicates that the outputs of the industry are highly dependent on oil and oil inputs. Consequently, a significant increase in oil prices tends to increase expenditures while lowering earnings. Even though the technology and telecommunications industries also exhibit a drop in returns during the market freeze, this demonstrates that during a crisis, this industry is similarly impacted by rising oil and oil input costs. Due to its modest size or market capitalization, this sector's industrial returns may vary. Similarly, the results of volatility spillover are shown to be highly negative for virtually all industries except for refineries, which have a moderating effect on volatility. During the time of the market freeze, a similar trend is observed. Second, there is a conditional relationship between crude oil and different industrial returns that varies with time. The results indicate that the vast majority of these industries exhibit dynamic conditional correlation, with some indications of asymmetric conditional correlation as well. Further, the study note that covid-19 pandemic has a significant impact on the financial market.

Future Directions

The current study has not incorporated the other commodities markets effects and macroeconomics variables such as discount rate, inflation, money supply etc that could have effect the overall perfomcen of industries in depth. Future researchers can cover this limitation of the current study by examining the effects of other commodities markets across industries by using different other techniques like, panel data analysis, co-integration and dynamic panel analysis across different industries of different countries and regions as well. Due to the unanswered empirical and conceptual problems, this study can be explored in several ways. A comparison study, for instance, may be done in the future to analyse the phenomena of spillover in more depth by including other emerging markets in the sample. In addition, all GARCH models used in this study (GARCH, GJR GARCH/TARCH, and EGARCH) were applied to the whole distribution. Consequently, an investigation into extreme movement utilizing tailed distribution may be conducted soon.

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