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Oil prices and sectorial stock indices of Pakistan: Empirical evidence using bootstrap ARDL model

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Abstract

Purpose: Oil prices play an important role in the Pakistani stock market. In this regard, we examine the relationship between oil prices and sectorial stock prices in the context of Pakistan.

Design/methodology/approach: To fulfill the objectives of this study, we use a newly developed methodology called the bootstrap ARDL model. Moreover, we compare the results of the Bootstrap ARDL model with the standard ARDL model. In addition, this study uses Granger Causality in Quantile test to examine the causal relationship among the underlying variables.

Findings: Results indicate that the co-integration exists between oil prices and sectoral stock prices for the Automobile, Cement, and Power Generation and Distribution sectors. However, no co-integration is found for the other sectors. On the contrary, other sectors represent degenerate cases. Moreover, Granger causality is employed to show short-run causality among the given variables. The estimates based on the granger causality test indicate that short-run causality exists between oil prices and most of the sectors.

Originality/Value: Rising oil prices and their effect on stock prices are important concerns in the context of Pakistan. This study extends the literature by examining the effect of oil prices on the sectorial stock prices of Pakistan. Moreover, it also examines the effect by using a new and robust technique called the bootstrap ARDL model.

Practical implications: Overall, the findings based on the new and robust technique can be useful for making investment or policy decisions. Policymakers are advised to follow the guidelines to make relevant decisions.

Keywords: Bootstrap ARDL, Oil prices, sectorial stock indices, Pakistan

JEL Classification: F31, G15

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1. Introduction

Several investigations have been conducted to investigate the nexus between stock prices and oil prices (Joo and Park 2017; Bouri 2015; Sukcharoen et al. 2014; Creti et al. 2014; Driesprong et al. 2008; Maghyereh and Abdoh, 2022). These studies state that due to the influence of oil prices on corporate cash flows and earnings, oil prices influence stock prices (Arouri et al., 2012). Furthermore, it is also enlightened by the theory of equity valuation, which describes the nexus between stock prices and oil prices. This theory states that discounted future cash flows regulate the stock prices and macroeconomic variables affect these future cash flows. Moreover, oil prices are also one of the macroeconomic factors. Therefore, it also affects future cash flows (Jouini 2013).

The prior studies support a positive connection between oil prices and stock or future prices in the oil-exporting countries (Ali et al., 2022; Uche et al., 2022a; Chang et al., 2019a; 2019b; Kilian and Park 2009; Lean, et al., 2010, 2015), while they provide negative findings in the oil-importing countries (Badeeb and Lean 2016).

However, various studies have been conducted to study the connection between stock prices and oil prices using different techniques (see, for example, Hashmi and Chang, 2021; and Uche et al.,2022b; Syed et al., 2019; Park and Ratti, 2008; Killian and Park, 2009; Shafi et al., 2015; Badeeb and Lean, 2018; Archer, et al., 2022). Park and Ratti (2008) studied the influence of oil prices on stock market prices in the US and 13 European countries using Multivariate VAR (Vector Autoregressive). They concluded that variations in oil prices do not affect the US stock market. In contrast, oil prices negatively affect stock prices in all European countries except Norway since Norway is an oil-exporting country. Hashmi et al. (2021a, 2021b, 2022) & Arouri and Nguyen (2010) mentioned that stock return has a different reaction to changes in oil prices. This reaction is due to different industries where the stock is related. They studied the nexus between stock prices and European oil prices by employing data from Dow Jones Stoxx 600 and twelve European industrial sector indices. They concluded that the oil prices of the oil-related industries negatively affect stock returns.

In contrast, those industries that use oil as output material positively correlate with stock returns. Elyasiani et al. (2011) examined the effect of industry stock returns of thirteen United States industries on oil prices by using the univariate GARCH model and dividing those industries into four categories named as oil-related, oil substitute, oil user and financial industries. They concluded that oil prices have a direct impact on oil substitutes and oil-related industries; however, it has an indirect effect on financial industries and oil user industries. It means that oil-related and the Oil substitute industries have a positive link with variations in oil prices. In contrast, oil users and the financial industries are hurt by changes in oil prices. Using the predictive regression model, Narayan and Gupta (2015) tested whether equity returns of the US stock market can be predicted from the oil prices. They concluded that favorable oil price variations are not suitable for forecasting equity returns but negative changes help forecast the equity returns of the stock markets.

Irshad et al. (2014) found no long-run connection between gold, stock, and oil price by applying the Johansen Cointegration test. Using the ARDL bounds test, Tursoy and Faisal (2018) concluded the existence of long-run cointegration between stock, gold and oil prices. Benkraiem

(2018) mentioned that in the long term, stock market prices are significantly associated with energy prices. Raza et al. (2016) explored the asymmetric nexus between oil prices, gold and stock market return by applying NARDL (Nonlinear Autoregressive Distributive Lag) model in Malaysia and a few emerging markets. They concluded that stock prices in emerging markets are negatively affected by the oil price. These same consequences were found by Basher et al. (2012).

Furthermore, Hu et al. (2017) investigated the nonlinear connection between oil prices and the stock market in China using the SVAR and NARDL models. They concluded that oil price shocks due to demand significantly influence stock market returns. Kisswani et al. (2017) investigated the asymmetric relationship between oil prices and stock market return by using NARDL (Nonlinear ARDL) model in ten sectors of Kuwait. They concluded that oil price has an asymmetric long-run impact on stock market return for a few sectors, including consumer services, consumer goods, industry and real estate, and banks.

However, previous studies show mixed results and provide unsatisfactory conclusions using traditional methodologies such as the ARDL model (Pesaran et al., 2001). Consequently, such inferences can misguide business executives and policymakers. In addition, few other studies used the nonlinear ARDL model, which divides exogenous variables into two series. One comprises partial sum of negative variations, and the other comprises a partial sum of positive variations. Keeping in mind the limitations of ARDL and NARDL, McNown et al. (2018) introduced the bootstrap ARDL model. The novel bootstrap ARDL model is based on the ARDL bounds test proposed by Pesaran et al. (2001) and provides more benefits than traditional cointegration approaches.

In contrast, Pesaran et al. (2001) made some assumptions while developing a bound testing approach, including assumptions about the independent variable's homogeneity. Therefore, ensuring that the dependent variable is integrated at the first difference I(1) and degenerate cases are absent is essential. Therefore, our study extends the existing literature using a novel approach called the bootstrap ARDL model.

Some recent research used the Bootstrap ARDL test in different frameworks. For example, Goh Soo Khoon et al. (2017) used Bootstrap Autoregressive Distributive Lag (BARDL) model to study the relationship between Exports, Foreign Direct Investment (FDI) and Gross Domestic Product in specific Asian countries and compared BARDL results with other cointegration tests. They concluded that other cointegration techniques show that the FDI affects the growth in the long run in only one of the seven Asian countries. In contrast, BARDL results show that the FDI affects the growth in all countries in both the long and short run. Tong Teng et al. (2020) conducted the research using BARDL (Bootstrap ARDL) technique to study the nexus between energy consumption, economic growth and carbon emission in emerging seven (E7) countries. They concluded that the leading cause of carbon dioxide emission is energy consumption, leading to difficulties in global warming. Chang, 2020, Chang and Rajput, 2018, Chang et al., 2018, and Cheng-Feng Wu et al. (2020) studied the relationship between Economic growth (EC) and financial development (FD) by using Bootstrap Autoregressive Distributive Model (BARDL) across Asia's major economies such as China, India and Japan. They concluded that the government of Japan and India should keep their steps for financial development as an apparatus to nurture economic growth because the economy works as an engine to endorse financial development for endurance.

In China, some principles should be made by the government. Caglar (2020) used the BARDL test model to examine the importance of foreign direct investment inflows and renewable energy consumption in reducing environmental degradation. He mentioned that results show few cointegration relationships among variables. He has recognized significant long-run relationships in a few countries between FDI (Foreign Direct Investment), REC (Renewable Energy Consumption) and Economic growth. For instance, Chang et al. (2020c); Derindag et al. (2022); Nawaz Kishwar et al. (2019) investigated the connection between natural resources and financial growth. They concluded that capital, natural resources, financial development, economic growth and labor are cointegrated in the long run.

Furthermore, economic growth and domestic production are boosted by financial development. The hypothesis that natural resources are a blessing is valid, whereas value is added to economic growth by labor and capital. Moreover, the result shows the two-way causal connection between financial development and economic growth.

Nevertheless, none of the above studies used BARDL (Bootstrap Autoregressive Distributive Lag) model on oil prices and the sectoral stock price of Pakistan. We use the BARDL model in the context of our study because it provides more reliable results than previous cointegration techniques. McNown et al. (2018) introduced the bootstrap autoregressive distributive lag (BARDL) model. Bootstrap ARDL model offers a supplementary test on the significance of coefficients on the regressor's lagged level that will provide a better understanding of the status of the model's cointegration. This model helps address the fundamental weaknesses of Pesaran et al. (2001) ARDL bounds test model, such as the power and size properties of the ARDL bounds testing approach. Moreover, the bootstrap ARDL model helps eradicate the possibility of indecisive inferences. Readers may refer to Arfaoui and Yousaf (2022), Esmaeil, et al. (2020), Gupta, et al. (2021), Hesami, et al. (2020), Plakandaras, et al. (2019), and Yıldız, et al. (2021) for other issues related to oil prices and read Darsono, et al. (2022), Kim (2021), Ravinagarajan and Sophia (2022), TajMazinani, et al, (2022), and Yadav (2022) for other issues related to stock prices.

The motivation behind conducting this research is that this study uses a new cointegration technique: Bootstrap ARDL. The BARDL model will study the nexus between Pakistan's oil prices and sectoral stock prices. The findings from this investigation will help policymakers and investors to know about the impact of fluctuations in oil prices on the sectoral stock prices of Pakistan. Through this research, we are making two contributions. First, this research uses the bootstrap ARDL model to study the association between Pakistan's sectoral stock prices and oil prices. This research differs from the previous one, which was conducted to study the relationship using different cointegration techniques. Second, this research contributes to the current literature by paying devotion to Pakistan while examining the relationship between sectoral stock prices and oil prices.

2. Literature Review

The central part of empirical and theoretical research has been to study the association between oil price fluctuations and stock price movements. Huang et al. (1996) examined the relationship by employing the Unrestricted Vector Autoregressive Model (UVAR), concluding that no association exists between oil prices and the S&P500 market index. On the contrary, Sadorsky (1999) also employed a vector autoregressive model with the GARCH effect to examine the relationship and the concluded significant link between aggregate stock price and oil prices. Papapetrou (2001) showed that fluctuations in oil prices negatively impact stock prices because they negatively affect a company's output, such as production.

Chang et al. (2020a, 2020b); El-Sharif et al. (2005) examined the extent and nature of the nexus between equity prices and crude oil prices in the Oil & Gas sector of the United Kingdom. They collected the daily data for 13 years. They concluded a significant positive impact of oil prices on stock prices of Oil & Gas sectors, where they found weak nexus between oil price volatility and equity values in different sectors such as banking industries, mining, technology and transport. Maghyereh and Al-Kandari (2007) studied the relationship between GCC countries' stock markets and oil prices and applied asymmetric cointegration tests by Breitung Gourieroux (1997) & Breitung (2001) and employed monthly data for eight years. They concluded that in GCC countries, oil prices have an asymmetric impact on stock prices in the long run. They also claimed that in GCC countries, stock markets might be affected by oil prices due to inflation which in turn has an impact on the GCC economy's discount rate and internal interest rate through their impact on the availability of liquidity.

Gohar et al. (2022); Chang et al., (2022); Nandha and Faff (2008) further examined the association among the given variables and concluded a significant favorable influence of oil prices on the stock prices in oil-exporting countries. Ramos and Veiga (2011) studied the relationship and concluded that the influence of oil prices on a specific nation's stock depends on the oil need level of that specific country. Filis et al. (2011) inspected the time-varying nexus between the stock price and oil price of oil-exporting (Brazil, Canada, and Mexico) countries and oil-importing (Germany, the Netherlands, and the United States of America) countries. They employed the data from January 1987 to December 2009 and applied the DCC-GARCH-GJR model. They concluded that oil prices had a negative influence on stock prices except in the year 2008. They concluded that during the economic crisis, there was a positive and significant association between oil prices and stock prices. Aloui et al. (2012) mentioned in their study that in the 25 emerging markets of oil-importing countries, there is no relationship or insignificant impact of oil prices on stock prices. Wang et al. (2013) examined the effect of shocks in oil prices on the stock markets in oil-importing and oil-exporting nations. They used the Vector Autoregressive Analysis technique using the data from January 1999 to December 2011. They mentioned that the reaction of stock markets to oil price shocks depends on whether a country is a net exporter or net importer of oil, and fluctuations in oil prices arise from total demand or total oil supply. The net position & importance of oil price shocks in the oil market defines the relative contribution to a country's economy. Canada and de Gracia (2014) researched the European market to examine the association between oil prices and stock prices. They concluded that oil prices significantly negatively affect the stock prices in 12 oil-importing markets.

Reboredo & Rivera-Castro (2014) studied the connection between oil prices and stock markets in the USA and Europe for 11 years. They used Multiscale Analysis of Correlation and Wavelet Decomposition. They concluded that before the crisis period, there was an insignificant influence of oil prices on stock prices. In contrast, there was a significant influence on oil prices and stock prices after the crisis. using the data from 1998 to 2013, Ftiti et al. (2016) examined the nexus between the stock market volatility of G7 countries (USA, UK, Japan, Italy, Germany, France and Canada) and oil prices. They concluded that in the medium and short run, the nexus between oil prices and the stock market is more noticeable, whereas, in the long run, the link between these two variables is feeble.

Shaeri & Katircioglu (2018) studied the association between oil prices and transportation and technology stock prices (US stock exchange-listed firms) using data for 25 years. Using the cointegration and unit root tests, they determined the cointegration and stationarity properties of the data. They mentioned that as the firms are highly dependent on oil because they use oil as an input, fluctuation in oil prices has a positive and significant effect on the stock prices of transportation and technology firms.

Marashdeh and Afandi (2018) examined the influence of oil prices on the stock market return in major oil-producing countries (Russia, Saudi Arabia, and the USA). They used the VER (Vector Error Correction) model on the data from January 2000 to May 2015. They looked at the exchange rate, interest rate, inflation, industrial production, oil production, oil prices, and stock market prices. They concluded that if the oil supply shocks create oil shocks in Russia, then stock market returns are positively influenced by shocks in oil prices. In contrast, the USA stock market return is negatively affected by shocks in oil supply. Results for Saudi Arabia show that the impact of oil supply shock was not clear on stock market return. In the meantime, these countries (Russia, Saudi Arabia, and the USA) stock market returns positively influence oil price shocks created by demand.

Additionally, Davoudi et al. (2018) used the GARCH model to study the impact of oil price shock on stock market prices by employing the data from 1993 to 2014 in Iran. They used distinct pointers like consumer price index, exchange rate, and oil price. They concluded that exchange rate and oil price have a positive influence on Tehran's stock market, whereas the stock market is not affected by the consumer price index.

Youssef and Mokni (2019) examined the nexus between oil prices and stock prices in the oil-exporting and oil-importing countries and found a different result. For example, they concluded that the nexus is positive between oil prices and stock prices in oil-importing countries because variations in oil prices can change the profit of oil-importing companies. In contrast, they concluded that net oil-exporter countries have a weaker impact. Chang et al. (2020b) studied the impact of oil prices on stock prices by applying the Quantile ARDL model. The results suggested a negative impact of oil prices on stock prices.

Additionally, by applying the Structural Vector Autoregressive model, Köse and Ünal (2020) mentioned a negative association between stock price and oil price. Mensi et al. (2020) applied the dependence-switching copula technique to observe the relationship between oil price fluctuations and Islamic stock markets. They concluded that Islamic stock markets provide safe shelter from fluctuations in oil prices.

Enwereuzoh et al. (2021) studied the effect of oil price shocks on the stock prices of oil-exporting and importing nations. They collected the monthly data from January 2000 to July 2018 and used a regression framework. They concluded that stock prices in oil-importing and oil-exporting nations responded differently to oil price shocks. Agarwalla et al. (2021) researched short-run and long-run links between these oil price shocks and stock price movements using Vector Error Correction (VEC) model and Johansen's cointegration test. They concluded that there is long-run cointegration between oil price shocks and stock price movements. They also mentioned that the international price of crude oil significantly influences Indian stock prices.

3. Data & Methodology

3.1. *Data*

This study investigates the effect of oil prices on the sectoral stock prices of Pakistan. The monthly data for crude oil is collected from Energy Information Administration, and data for sectoral stock prices of Pakistan is collected from Business Recorder. The data is collected from the period of November 2008 to December 2019 (Which means that this study has 134 observations). The independent variable in this study is oil prices. The dependent variables are the ten sectors of Pakistan: Automobile, Cement, Commercial Banks, Insurance Companies, Investment Banks & Companies, Power generation and distribution, Chemical, Refinery, Oil & Gas, and Technology & Communication. Ultimately, we use an interest rate as a control variable. The data for interest rates is collected from International Financial Statistics. In their study, Chin et al. (1986) and Sadorsky (2001) mentioned that interest rate is significant while explaining stock prices. Table 1 shows the descriptive statistics in which Jarque-Bera demonstrate that all the null hypothesis are rejected significantly at a 1% significance level except for the Oil and Gas sector. However, Figure 1 shows time series plots of the variables.

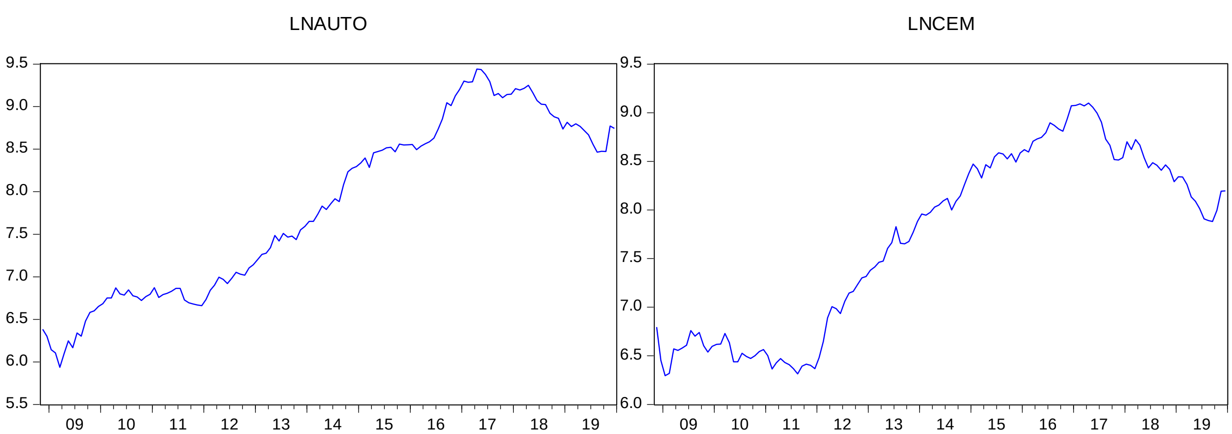
Table 1: Results of the descriptive test statistics

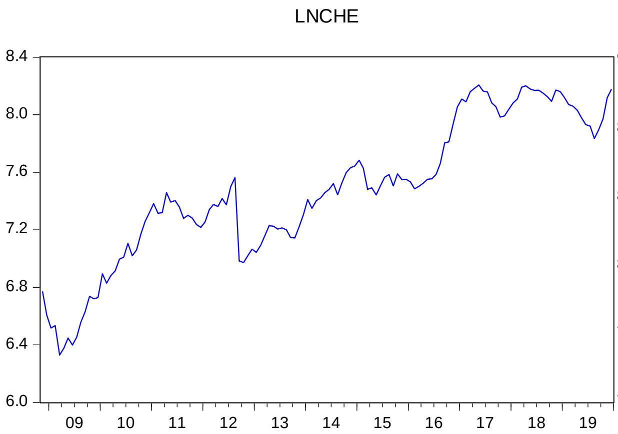
Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
AUTOMOBILE	3988.337	3448.454	0.769	2.372	15.428***
CEMENT	3210.996	2416.329	0.610	2.343	10.717***
CHEMICAL	1966.538	907.866	0.501	2.035	10.807***
COMMERCIAL BANKS	5597.496	2646.911	-0.065	1.406	14.287***
INSURANCE	94.611	55.295	3.209	20.744	1988.027***
INSURANCE BANK AND COMPANIES	592.592	348.966	0.295	1.619	12.584***
OIL & GAS	3413.780	1114.831	0.168	2.197	4.236
POWER GENERATION & DISTRIBUTION	4284.385	2303.766	0.059	1.614	10.807***
REFINERY	954.819	459.972	1.092	3.244	26.976***
TECHNOLOGY AND COMMUNICATION	839.108	350.942	0.271	2.103	6.133**
INTEREST RATE	8.177	0.656	-0.467	1.804	12.862***
OIL PRICES	71.170	21.475	0.113	1.674	10.101***

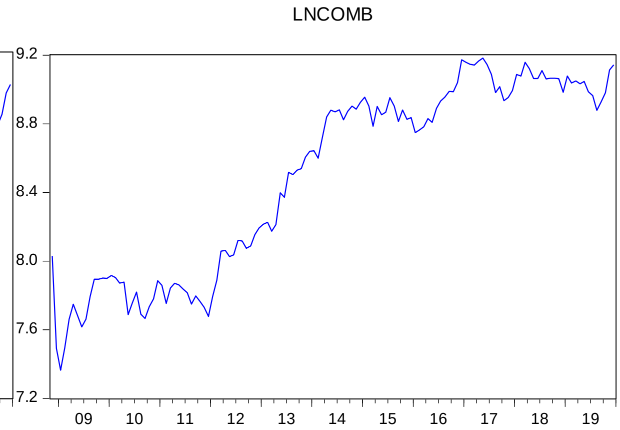
Note: ***, **, and * denote significance at a 1%, 5%, and 10% significance level, respectively.

3.2. Methodology

This research aims to discover the influence of oil prices on the sectoral stock prices of Pakistan. This research is engaged in using Bootstrap test statistics from a single dynamic error correction requirement of ARDL. In the cointegration techniques, the independent variable impacts the dependent variable. Therefore, an increase in the independent variable will cause an increase in the dependent variable and vice versa.




LNCHE
8.4
8.0
7.6
7.2
6.8
6.4
6.0
09 10 11 12 13 14 15 16 17 18 19


LNCOMB
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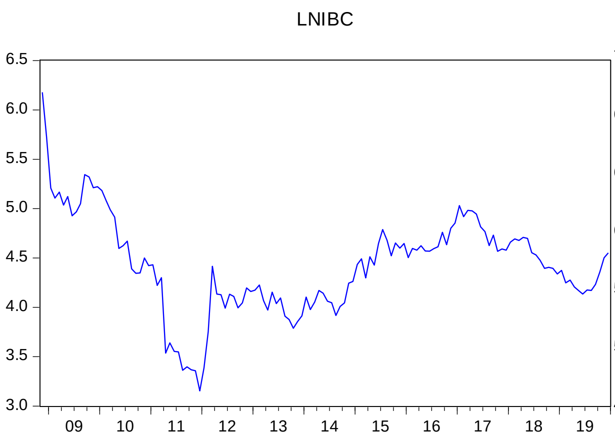
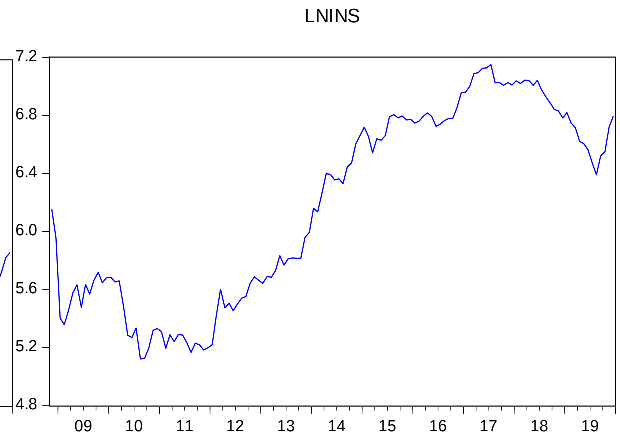
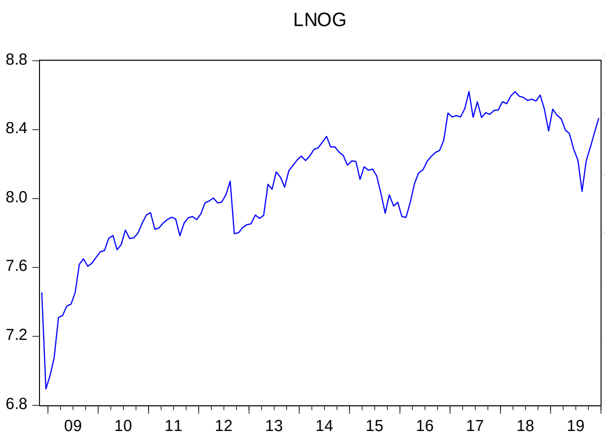
8.8
8.4
8.0
7.6
7.2
09 10 11 12 13 14 15 16 17 18 19


LNIBC
6.5
6.0
5.5
5.0
4.5
4.0
3.5
3.0
09 10 11 12 13 14 15 16 17 18 19


LNINS
7.2
6.8
6.4
6.0
5.6
5.2
4.8
09 10 11 12 13 14 15 16 17 18 19


LNOG
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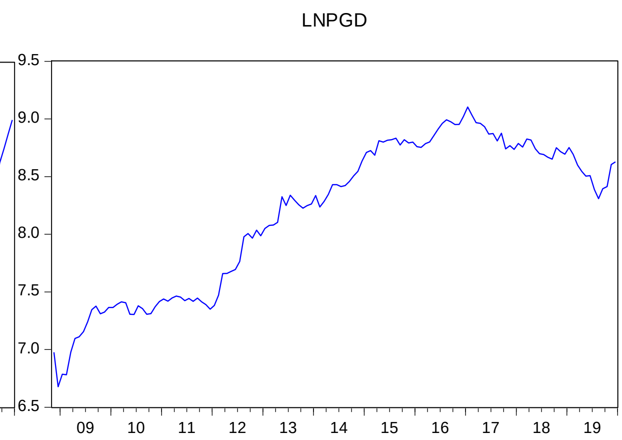
8.4
8.0
7.6
7.2
6.8
09 10 11 12 13 14 15 16 17 18 19


LNPGD
9.5
9.0
8.5
8.0
7.5
7.0
6.5
09 10 11 12 13 14 15 16 17 18 19

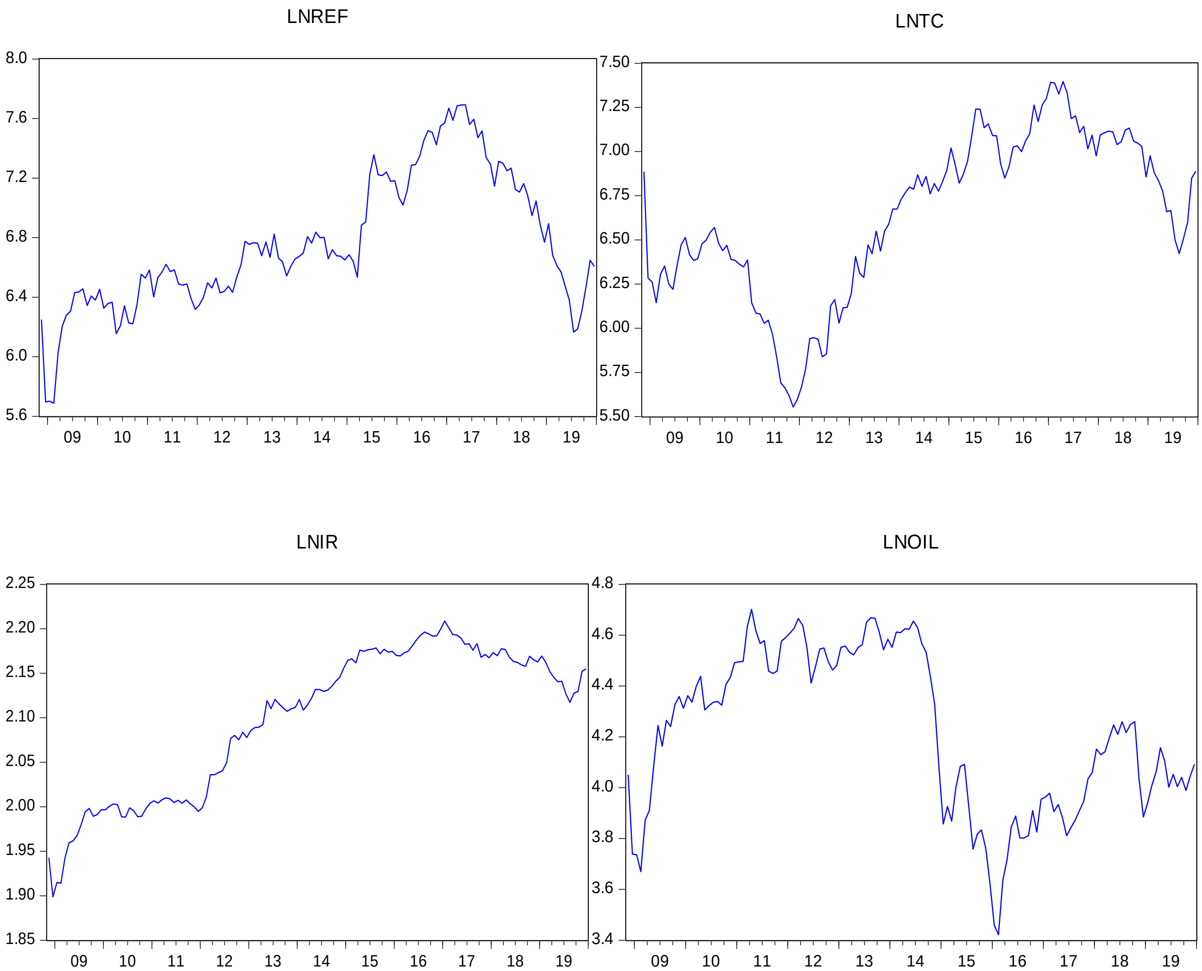


Figure 1: Time series plots of all the variables used in our paper

The bootstrap is used in estimating the ARDL model (Pesaran et al. 2001); consequently, the ARDL model can be explained by the following equation in our study:

$$\Delta LnSP_t = a_0 + \sum_{k=1}^{n1} \alpha_1 \Delta LnSP_{\mathrm{t}} + \sum_{k=0}^{n2} \alpha_2 \Delta LnOIL_{\mathrm{t}} + \sum_{k=0}^{n3} \alpha_3 \Delta LnIR_{\mathrm{t}} + \mu_1 LnSP_{\mathrm{t-1}} + \mu_2 LnOIL_{\mathrm{t-1}} + \mu_3 LnIR_{\mathrm{t-1}} + \vartheta, \quad (1)$$

where α_1 to $\alpha 3$ denote short-run coefficients, μ_1 to μ_3 denote the long-run coefficients, SP_{t} denotes the sectoral stock prices, IR_{t} denotes the interest rate, OIL_{t} denotes the oil prices at time t, and Ln with each variable also denotes that a natural logarithm characterizes all variables. For investigating cointegration among all variables, a bound test is used where the null hypothesis is $\mu_0 = \mu_1 = \mu_2 = 0$.

We employ the bootstrap ARDL cointegration model developed by McNown et al. (2018). It is used to study the cointegration between oil prices and sectoral stock prices. The advantage of the bootstrap ARDL model is pact with the size and properties generated while using the traditional ARDL model developed by Pesaran et al. (2001). Furthermore, this model can integrate a new cointegration test to increase the F-test's and T-test's power. Pesaran et al. (2001) have mentioned two situations for the identification of cointegration. First, the coefficient of lagged dependent variable must be statistically significant, and the second one is that the coefficients of error correction must be statistically significant. Pesaran et al. (2001) also mentioned that you should use critical values (lower and upper bounds) for the first case, and there are no critical values for the second condition.

Additionally, this model helps address the inconclusive issue that may arrive using the traditional ARDL cointegration model (McNown et al., 2018). The advantage of applying the bootstrap ARDL model is that it generates critical values by extracting the indecisive areas which occur in the conventional ARDL model. So, the benefit of using the bootstrap ARDL test is that it offers an additional test on the importance of the lagged level of regressors that delivers a better understanding of the cointegration status of the model. So, the bootstrap ARDL model can be explained by the following equation:

$$\Delta LnSP_t = a_0 + \sum_{k=1}^{n1} \alpha_1 \Delta LnSP_{\mathrm{t}} + \sum_{k=0}^{n2} \alpha_2 \Delta LnOIL_{\mathrm{t}} + \sum_{k=0}^{n3} \alpha_3 \Delta LnIR_{\mathrm{t}} + \mu_1 LnSP_{\mathrm{t-1}} + \mu_2 LnOIL_{\mathrm{t-1}} + \mu_3 LnIR_{\mathrm{t-1}} + \mu_4 \text{ɖ}D1_{\mathrm{t}} + \vartheta, \tag{2}$$

where a_0 is the constant term, Δ is the first difference, ϑ indicates the error term, α_1, α_2 and α_3 indicate short-run coefficients for variables, $\mu_{1,}$ $\mu_{2,}$ $\mu_{3,}$ and μ_4 demonstrate long-run coefficients for variables, SP_t is the stock price. IR_{t} denotes the interest rate, OIL_{t} denotes oil prices at time t, and Ln with each variable denotes that a natural logarithm characterizes all variables, and $D1_{\mathrm{t}}$ denotes a dummy variable that shows and deals with the structural changes in the equation.

Table 01: The correlation between oil prices and sectorial stock prices.

Correlation (t-Statistic)	LNAUTO	LNCEM	LNCHE	LNCOMB	LNIBC	LNINS	LNIR	LNOG	LNOIL	LNPGD	LNREF	LNTC
LNAUTO	1											

LNCEM	0.953	1.000										
	(36.240) ***	-----										
LNCHE	0.909	0.777	1.000									
	(25.032) ***	(14.178) ***	-----									
LNCOMB	0.963	0.962	0.856	1.000								
	(41.087) ***	(40.488) ***	(19.014) ***	-----								
LNIBC	0.094	0.152	-0.130	0.055	1.000							
	(1.079)	(1.767) ***	(-1.506)	(0.638)	-----							
LNINS	0.949	0.956	0.784	0.946	0.302	1.000						
	(34.562) ***	(37.606) ***	(14.506) ***	(33.470) ***	(3.641) ***	-----						
LNIR	0.948	0.972	0.818	0.962	-0.030	0.898	1.000					
	(34.354) ***	(47.392) ***	(16.338) ***	(40.496) ***	(-0.340)	(23.437) ***	-----					
LNOG	0.875	0.795	0.923	0.881	-0.201	0.756	0.856	1.000				
	(20.752) ***	(15.075) ***	(27.562) ***	(21.362) ***	(-2.352) **	(13.265) ***	(19.032) ***	-----				
LNOIL	-0.527	-0.548	-0.307	-0.436	-0.581	-0.638	-0.421	-0.099	1.000			
	(-7.117) ***	(-7.533) ***	(-3.703) ***	(-5.566) ***	(-8.206) ***	(-9.508) ***	(-5.338) ***	(-1.145)	-----			
LNPGD	0.953	0.977	0.818	0.963	-0.008	0.907	0.999	0.850	-0.444	1.000		
	(36.248) ***	(53.026) ***	(16.331) ***	(41.171) ***	(-0.092)	(24.780) ***	(359.409) ***	(18.526) ***	(-5.694) ***	-----		
LNREF	0.819	0.843	0.690	0.754	0.134	0.772	0.833	0.721	-0.399	0.839	1.000	
	(16.379) ***	(17.976) ***	(10.943) ***	(13.172) ***	(1.552)	(13.967) ***	(17.275) ***	(11.938) ***	(-5.005) ***	(17.698) ***	-----	
LNTC	0.842	0.885	0.617	0.841	0.476	0.908	0.804	0.638	-0.614	0.816	0.760	1.000
	(17.909 ***	(21.893) ***	(9.016) ***	(17.866) ***	(6.210) ***	(24.974) ***	(15.527) ***	(9.522) ***	(-8.929) ***	(16.208) ***	(13.433) ***	-----

The negative values in the table show a negative correlation between the variables, and the positive value shows a positive correlation among variables. The bracket value shows the t- statistics in the table. *** show significance at a 1%, 5%, and 10% significance level, respectively.

3.3. Granger Causality Test

We use the Granger causality test based on the Bootstrap autoregressive distributed lag (BARDL) model to find the short-run association between sectoral stock prices and oil prices. Suppose there is no cointegration between dependent and independent variables after estimating long-run association. In that case, we apply the Granger causality test for dependent and independent variables, which includes lagged differences on independent only. This study will check whether $\eta^2 = 0$ in equation no. 02. However, they create a stationary and linear combination if there is cointegration between dependent and independent variables. In such a case, the Granger causality test should include the independent variable has lagged level and lagged differences on the independent variable, in other words, to check whether η^2 or $\mu^1 = 0$ and η^3 or $\mu^2 = 0$.

4. Empirical Analysis

Table 2 shows the correlation among the variables where a negative sign shows a negative link, whereas a positive sign shows a positive link. Findings indicate that all variables have a positive link except oil prices. Oil prices show a negative correlation with all the variables. Insurance banks and companies show a positive and negative correlation with variables.

Table 3 UNIT ROOT TEST AT LEVEL AND FIRST DIFFERENCE

Variables	**ADF at Level**	**ADF at First Difference**	**KPSS at Level**	**KPSS at First Difference**
AUTOMOBILE	-1.186	-5.612***	13.388***	1.170
CEMENT	-1.270	-9.056***	15.383***	0.739
CHEMICAL	-0.463	-9.449***	25.075***	1.618*
COMMERCIAL BANKS	-0.483	-11.996***	24.480***	1.439
INSURANCE	-0.488	-6.742***	19.657***	0.850
INSURANCE BANK AND COMPANIES	-10.211***	-14.044***	19.806***	-1.517*
OIL & GAS	-1.454	-13.164***	35.447***	1.056
POWER GENERATION & DISTRIBUTION	-1.288	-11.559***	21.528***	1.371
REFINERY	-1.468	-6.917***	24.029***	0.181
TECHNOLOGY AND COMMU	-1.421	-13.093***	27.678***	0.003
INTEREST RATE	-1.815*	-12.242***	144.209***	2.080**
OIL PRICES	-2.059**	-9.535***	38.364***	0.039

Note: In this table, the unit root test result has been written, which shows that the whole data is stationary at the first difference in the ADF test, and all the data is stationary at a level in the KPSS test. ***, ******, and ***** denote significance at a 1%, 5%, and 10% significance level, respectively.

As autoregressive distributed lag (ARDL) and nonlinear ARDL models require checking the stationary of the data, a bootstrap ARDL model also requires checking the stationary of data. So, to check the stationarity of data, we use two types of tests to know whether the data have unit roots. We employ ADF (Augmented Dickey-Fuller) and KPSS (Kwiatkowski-Phillips-Schmidt-Shin) to examine whether a variable is integrated at zero I(0) or at one I(1). Under the ADF test, we have a null hypothesis that data has a unit root; under the KPSS test, we have a null hypothesis that data is stationary. Table 3 shows the unit root tests (ADF. and KPSS test statistics) conducted at the level and first difference. In the ADF test, the null hypothesis is accepted for all variables at level, meaning the variable has a unit root except for insurance banks and companies and oil prices. These two variables reject the null hypothesis of ADF test statistics with a 1% significance level and a 5% significance level. However, the null hypothesis of ADF test statistics is rejected by all variables at a 1% significance level at the first difference, which means the data is stationary at the first difference under ADF test statistics. So, we can say that the data is I(1) under ADF test statistics.

KPSS test statistics also inform that all variables reject the null hypothesis with a 1% significance level and accept the null hypothesis except for two variables: chemical and insurance banks and companies. Both variables reject the null hypothesis with a 10% significance level. So, we can say that all the variables are I(0) under KPSS test statistics.

Moreover, this study uses the ARDL and Bootstrap ARDL tests to study the connection between oil prices and sectoral stock prices. This model uses a bound test to know the long-run and short-run nexus between variables. Thus, Table 4 shows the results of the bound test of variables.

Table 4 BOUND TEST FOR ARDL MODEL

Variables	**F-Statistics**	**Conclusion**
AUTOMOBILE	1.838	No Long-run cointegration
CEMENT	1.951	No Long-run cointegration
CHEMICAL	1.157	No Long-run cointegration
COMMERCIAL BANKS	2.868	No Long-run cointegration
INSURANCE BANK AND COMPANIES	32.720***	Long-run cointegration
INSURANCE	1.994	No Long-run cointegration
OIL & GAS	1.384	No Long-run cointegration
POWER GENERATION & DISTRIBUTION	2.567	No Long-run cointegration
REFINERY	2.527	No Long-run cointegration
TECHNOLOGY AND COMMUNICATION	4.729**	Long-run cointegration
Significance Level	Lower Bound	Upper Bound
10%	2.63	3.35
5%	3.1	3.87
1%	4.13	5

Note: ***, **, and * denote significance at a 1%, 5%, and 10% significance level, respectively.

Table 4 presents the results of all variables for the bounds test. Whereas there are the critical values that inform that variable is significant at what significance level. It informs that either variable is significant with a 1%, 5% or 10% significance level. In the bound test, F-statistics values inform that if the value of the F-statistic is more significant than the upper bound, then there is a long-run relationship. If the value is lower than the lower boundary, then there is no long-run relationship. The relationship is inconclusive if the value lies between the upper and lower boundary. Hence, the bound test informs that all the variable has no long-run relationship except two variables, which are Insurance Bank and Companies and Technology and Communication. Whereas the F-statistic of Commercial Banks lies between the upper and lower boundary, it is inconclusive. However, the bound test notifies that no cointegration means that oil prices do not influence sectoral stock prices in the long run. The reason behind this insignificant result can be that the sectoral stock prices behave contrarily to negative and positive variations in oil prices. Basher et al. (2018) also mentioned in their study that stock price responds differently to the changes in oil prices according to their states, which are bearish, bullish, and normal.

Table 5 Long-run & Short-run estimates of the ARDL Model

	PANEL A	
Variables	**Interest Rate**	**Oil Prices**
Automobile	12.976(10.645) ***	-0.208(-0.719)
Cement	11.894(13.995) ***	-0.050(-0.236)
Chemical	5.212(2.307) **	-0.009(-0.0159)
Commercial Banks	8.680(5.7456) ***	0.415(1.219)
Insurance	9.142(7.836) ***	-0.068(-0.255)
Insurance Banks & Companies	1.799(0.801)	-1.050(-2.396) **
Oil & Gas	3.381(3.713) ***	0.145(0.635)
Power Generation & Distribution	8.118(121.342) ***	-0.022(-1.689)
Refinery	3.278(2.308) **	-0.693(-1.705) *
Technology & Communication	11.579(2.023) **	0.518(0.591)

The bracket value shows the t- statistics in the table, which informs us about the significance level. ***, ****, *** shows that data is significant at a 1%, a 5%, a 10% significance level.

Table 6 RESULTS OF DIAGNOSTIC

Note: ***, ******, and ***** denote significance at a 1%, 5%, and 10% significance level, respectively. While **S** for

			PANEL B			
	Δ IBC (-1)	**Δ IBC (-2)**	**ΔPGD (-1)**	**ΔPGD (-2)**	**ΔREF (-1)**	**ΔREF (-2)**
Automobile						
Cement						
Chemical						
C. Banks						
Insurance						
I B & C	-0.085 (-1.170)	0.148 (2.076) **				
Oil & Gas						
Power G & D			0.192 (2.401) **	0.032 (0.41940)		
Refinery					-0.030 (-0.347)	0.143 (2.262) **
Tech & Com:						
Variables	**ΔOIL**	**ΔOIL (-1)**	**ΔOIL (-2)**	**ΔIR**	**Δ IR (-1)**	**Δ IR (-2)**
Automobile	0.036 (0.448)	0.044 (0.382)	-0.107 (-0.946)	4.378 (5.567) ***		
Cement	-0.006 (-0.227)			7.663 (10.511) ***	-0.543 (-0.537)	2.519 (2.688) ***
Chemical	0.006 (0.062)	-0.037 (-0.272)	-0.277 (-2.126) **	1.990 (2.199) **	-1.364 (-1.514)	
C. Banks	0.147 (2.648) ***	-0.148 (-1.798) *	0.005 (0.062)	5.768 (10.702) ***	0.114 (0.144)	-0.900 (-1.647)
Insurance	-0.008 (-0.244)			3.994 (5.224) ***		
I B & C	-0.098 (-1.858) *			9.465 (6.682) ***		
Oil & Gas	0.270 (4.345) ***			4.320 (6.841) ***	0.388 (0.477)	-1.590 (-2.855) ***
Power G & D	-0.003 (-1.360)			8.116 (157.037) ***	-1.438 (-1.501)	-1.520(- 2.084) **
Refinery	0.135(1.409)	0.208 (2.178)		7.399 (7.614) ***	-1.839 (-1.625)	
Tech & Com:	0.033 (0.412)	0.157 (2.192) **		7.934 (10.011) ***		

Variables	**Adj. R^2**	**ECM**	**LM**	**RESET**	**CUS(CUS^2)**
Automobile	0.995627	-0.083106***	0.865027	2.356205	S (S)
Cement	0.995578	-0.113455***	0.511209	0.244690	S(S)
Chemical	0.973908	-0.048399*	0.419885	0.086294	S(U)
Commercial Banks	0.992748	-0.059770**	0.682785	0.001169	S(S)
Insurance	0.986986	-0.111718***	0.361338	1.524306	U(U)
Insurance Banks & Companies	0.927178	-0.093395***	0.807794	1.888036	S(U)

Oil & Gas	0.973561	-0.083845***	0.868580	3.673937*	U(S)
Power Generation & Distribution	0.999952	-0.138162***	10.78617***	5485.443***	S(U)
Refinery	0.964623	-0.079547**	0.029481	4.709118**	S(U)
Technology & Communication	0.978847	-0.039210	0.444448	0.895284	S(S)

CUSUM and $CUSUM^2$ tells that this model is stable, **U** for CUSUM and $CUSUM^2$ tells that this model is unstable. $CUSUM^2$ results are in brackets.

Additionally, this study uses the ARDL test to examine the linkage between oil prices and sectoral stock prices. So, Table 5 shows estimations of the ARDL model. Panel A in Table 5 shows the results of long-run estimation in which all the variable has a positive and significant long-run association with interest rate except Insurance Bank and Companies, which shows a positive relationship but an insignificant impact. On the contrary, all the variables show a negative relationship except commercial banks, oil and gas, and technology and communication because they have a positive relationship with oil prices. All the variables have an insignificant impact except insurance banks, companies, and Refineries because they are significant at 5% and 10% significance levels.

Panel B in Table 5 shows short-run estimations of the ARDL test. In the table, positive coefficients show a positive relationship, whereas negative coefficient shows a negative relationship. In the estimation, all the dependent variables have an insignificant impact except commercial banks, insurance banks, and companies because they are significant at 1% and 10% significance levels at lag (0) of oil. At lag (1) of oil, only commercial banks and technology and communication have a significant impact, whereas, at lag (3), only chemicals have a significant impact. At lag (0) of interest rate, all variables are significant at a 1% significance level except Chemical, which is significant at a 5% significance level. At lag (1), all the variables are insignificant, whereas, at lag (2) of interest rate, the variables are insignificant except Cement, Oil and gas (these are significant at 1% significance) and power generation and distribution, which is significant at 5% significance level. The Refinery, Insurance bank and companies show a significant impact at a 5% significance level at lag (2). In contrast, power generation and distribution significantly impact at a 5% significance level at lag (2). While looking at the result of the diagnostic test in table 5 shows that the ARDL technique is stable for most variables (Table 6), where adj R^2 shows the gosh fit of the model because its value is more significant than 0.30 for all the sectoral stock prices.

Table 7 demonstrates the results of the Bootstrap ARDL model. As mentioned in the unit root test, that data is stationary at the level or the first difference, which means we can use the bootstrap ARDL approach to examine the long-run cointegration between the oil price and sectoral stock prices of Pakistan. The BARDL approach examines the critical values containing F*, t*-dependent, and t*-independent. This approach also calculates the statistic values that contain F, t-dependent, and t-independent. If the estimated statistics values exceed the critical values, there is no long-run association between variables. Table 6 presents the long-run linkage between sectoral stock prices and oil prices. The results show a long-run cointegration between oil prices and sectoral stock prices of Automobile, Cement, and Power Generation and Distribution.

In contrast, the oil prices do not have long-run cointegration with the sectoral stock price of Chemical, Commercial Banks, Oil and Gas, and Refinery. The estimates show a degenerate case# 02 for the sectoral stock prices of Chemical, Commercial Banks, Insurance, Companies and Companies, Oil and Gas, Refinery, and Technology & Communication, because of these t-dependent values sectoral stock prices are not significant. Table 8 shows the Granger Causality between the variables. There is short-run causality from Cement and Insurance to the interest rate is significant at a 1% significance level and 5 % significance level, respectively. In contrast, other variables do not show the short-run causality from variables to the interest rate. The interest rate has short-run causality with the Automobile and Insurance sector that is significant at a 1% significance level.

In contrast, interest rate does not show the short-run causality with other variables. Commercial Banks, Insurance, Power Generation and Distribution, and Technology and Communication show that the short-run causality from these variables to oil is significant at a 1% significance level. Automobile and Cement show the short-run causality to the oil that is significant at a 5% significance level. Chemical, Oil and Gas, and Refinery indicate short-run causality to oil that is significant at 10% significance level. In contrast, other variables do not show causality to the oil. Oil shows short-run causality to Refinery and Insurance Bank and Companies that are significant at 5% and 10% significance levels.

Table 7: Results Bootstrap ARDL model

VARIABLES	F	F^a	T-Dep	$T\text{-}Dep^a$	T-OIL	T^{-oil}	T-IR	$T\text{-}IR^a$	Cointegration Status
AUTOMOBILE	5.718	4.367	-4.058	-2.885	0.463	5.876	3.959	8.68	Cointegration
CEMENT	3.366	3.152	-3.099	-3.03	0.051	3.768	11.315	7.209	Cointegration
CHEMICAL	1.593	4.531	-1.975	-3.039	0	3.759	2.441	7.154	Degenerate Case #2
COMMERCIAL BANKS	2.463	3.393	-2.06	-2.978	2.395	5.305	6.684	8.231	Degenerate Case #2
INSURANCE	7.539	3.592	-3.679	-3.276	0.06	4.001	24.836	10.126	Degenerate Case #2
INSURANCE BANK AND COMPANIES	4.751	4.115	-3.076	-2.718	3.451	3.361	0.833	6.239	Degenerate Case #2
OIL & GAS	2.48	3.71	-2.642	-3.033	0.325	4.182	3.48	6.914	Degenerate Case #2
POWER GENERATION & DISTRIBUTION	9.1	6.433	-4.324	-4.171	1.851	9.414	19.625	17.369	Cointegration
REFINERY	2.543	3.549	-2.582	-3.146	4.153	4.999	2.345	7.934	Degenerate Case #2
TECHNOLOGY AND COMMUNICATION	4.511	4.415	-1.491	-2.648	0.647	4.701	12.366	8.01	Degenerate Case #2

Note: This table shows the results of the Bootstrap ARDL approach. F shows the F-statistic values. T-Dep, T-Oil, and T-IR indicate the T-statistics of the dependent variables, Oil and Interest rate, respectively. $T\text{-}Dep^a$, T-Oil, and $T\text{-}IR^a$ show critical values at a significance level of 10%.

Table 8: Results of Granger Causality

VARIABLES	INTEREST RATE		OIL	
AUTOMOBILE	**AUTO-IR**	**IR-AUTO**	**AUTO-OIL**	**OIL-AUTO**
	0.889(0.4136)	*10.133***(0.00008)*	*4.701**(0.0107)*	1.205(0.303)
CEMENT	**CEM-IR**	**IR-CEM**	**CEM-OIL**	**OIL-CEM**
	*9.885***(0.0001)*	0.441(0.6442)	*4.737**(0.0104)*	0.359(0.6993)
CHEMICAL	**CHE-IR**	**IR-CHE**	**CHE-OIL**	**OIL-CHE**
	1.615(0.2029)	1.769(0.1746)	*2.661*(0.0738)*	0.012(0.9877)
COMMERCIAL BANKS	**COMB-IR**	**IR-COMB**	**COMB-OIL**	**OIL-COMB**
	1.039(0.357)	1.217(0.2996)	*4.793***(0.0099)*	0.060(0.9415)
INSURANCE	**INS-IR**	**IR-INS**	**INS-OIL**	**OIL-INS**
	2.746(0.068)*	*10.306***(0.00007)*	*8.048***(0.0005)*	1.237(0.2936)
INSURANCE BANK AND COMPANIES	**IBC-IR**	**IR-IBC**	**IBC-OIL**	**OIL_IBC**
	0.288(0.7501)	2.084(0.1287)	0.036(0.9649)	*2.764*(0.0668)*
OIL & GAS	**OG-IR**	**IR-OG**	**OG-OIL**	**OIL-OG**
	2.125(0.1236)	2.032(0.1352)	*2.393*(0.0955)*	1.457(0.2369)
POWER GENERATION & DISTRIBUTION	**PGD-IR**	**IR-PGD**	**PGD-OIL**	**OIL-PGD**
	0.162(0.8508)	0.028(0.9727)	*4.899***(0.009)*	0.798(0.452)
REFINERY	**REF-IR**	**IR-REF**	**REF-OIL**	**OIL-REF**
	1.501(0.227)	0.958(0.387)	*3.040*(0.051)*	*3.941**(0.022)*
TECHNOLOGY AND COMMUNICATION	**TC-IR**	**IR-TC**	**TC-OIL**	**OIL-TC**
	0.744(0.477)	1.865(0.159)	*5.461***(0.005)*	0.624(0.538)

Note: IR represents the Interest Rate (Independent Variable), and OIL indicate the oil prices (Independent Variable). The values that are in the brackets show the p-value of the coefficient. ***, ******, and ***** denote significance at a 1%, 5%, and 10% significance level, respectively. The italic values show the significant Granger causality.

5. Conclusion

We explored the short-run and long-run association between oil prices and stock prices of ten sectors of Pakistan by employing the newly developed technique known as the Bootstrap Autoregressive Distributive Lag model introduced by McNown et al. (2018). This cointegration-checking process applies a bootstrap methodology for resampling test statistics of the traditional ARDL model proposed by Pesaran et al. (2001). It creates the perfect critical values that support removing the inconclusive decisions that the traditional ARDL model failed to remove. Furthermore, this model provides additional test statistics on the independent variable's legs, allowing us to check for degenerate cases in the ARDL approach to avoid the study's unauthentic inferences. We indicated the degenerate cases in our study for the Chemical, Insurance, Insurance Bank and Companies, Oil and Gas, Refinery, and Technology & Communication, using sectoral stock prices as the dependent variables. We explored that lagged dependent variable’s t-statistic is insignificant. Based on our result, we found that there is a long-run association between the Automobile, Cement, and Power Generation and Distribution sectors. However, for the other sectors, there are degenerate cases.

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