UNIVERSITY OF VAASA

SCHOOL OF ACCOUNTING AND FINANCE

Risto Soininen

IMPACTS OF OIL PRICES ON STOCK MARKET INDEXES: NORDIC EVIDENCE

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UNIVERSITY OF VAASA
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Author: Risto Soininen
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ABSTRACT

The current study was designed to investigate the impact of oil prices on the stock index in the Nordic markets. To complete the study, Brent crude oil price and OMX Nordic 40 Index were used as variables representing the global oil price and Nordic stock market index respectively. The OMX Nordic 40 Index was used as a variable representing the entire Nordic stock markets. The main method of analyzing the data was the Vector Autoregressive (VAR) Model. However, before modeling the data using vector autoregressive, a preliminary analysis was conducted to determine the correlation of the variation as well as seasonality (presence of unit roots) and cointegration. The Spearman rank correlation indicated that variables Brent crude and OMX Nordic 40 Index are weakly correlated. Even there is the presence of negative correlation; it is not significant. Also, the ADF test indicated that the variables have seasonal factors and are cointegrated. To complete the VAR modeling, the dataset was first differenced to remove seasonal factors. The VAR Model provided evidence of the positive influence of oil prices on the Nordic stock market index. The nature of influence is positive but less significant. The analysis further indicated that the positive effects on the Nordic stock market subsequently turns negative before gradually leveling off at zero. That is, the stock market index increases and then decrease due to shocks in the oil prices. However, in the long term, the impact of shocks of the oil prices do not last more than four months.

KEYWORDS: Oil prices, VAR Model, Nordic stock markets, OMXN 40 Index

1. INTRODUCTION

The last decade has seen difficulties in oil prices. However, the market participants have not enjoyed the period as much. The decade has seen volatility and crashes. The 2008 crash is associated with the period's financial crisis and Great Recession. The second crisis in the oil market may be on-going. Oil prices have fallen from 100 dollars a barrel in 2014 to almost 30 dollars recently. Incidentally, stock prices have also been falling, and these moves in the stock market coincide with oil prices. The usual assumption is that a decline in the price of a barrel is good for the economy but the tendency for stocks to fall with a fall in oil prices is baffling.

In 1987 October 19, there was a market crash dubbed the Black Monday market crash. The crash baffled many researchers because it had little economic explanations and various theorists tried to come up with reasonable explanations. The introduction of automated trading was one of the theories that were advanced by these theorists but in the real sense, the crash seemed to come from nowhere. This 1987 stock market follows a broader pattern that nearly all stock market crashes and recessions have been following in the past 50 years. The 1987 October stock market crash coincided with an abrupt change in oil prices. The 1987 Dow Crash preceded a fall in oil prices in the wake of disputes with OPEC. Stocks and oil prices are somewhat entangled. The S&P 500 is mostly correlated with oil prices, but this is a peculiar phenomenon given that the relationship between oil and stock is virtually non-existent. This is despite the fact that energy forms only 3% of the US economy (Routledge, Seppi, & Spatt, 2000). The stock market is composed of hundreds of individual stocks from a range of industries, and so it baffles many that stock prices coincide with prices of oil. Over almost 50 years, oil prices and stock market prices have been moving in almost an entirely lock step (Marketwatch 2015). Correlation can be either perfect positive correlation or perfect negative correlation. A zero correlation means that there are entirely random price relations between securities and oil prices.

Kilian and Park (2009) came up with a model of examining the relationship between these two. Basing their research on data obtained from the stock market and the crude oil market, they found out that demand and supply in the oil world had different impacts on the US economy, especially the sectors that influenced the stock exchange prices. They found out that the combined and oil-specific shocks caused by demand were more important in understanding the United States Stock Market behaviour. This observation was reached by observing that some sectors of the US economy coincided with side shocks in the oil market.

At the industrial level, equity returns respond uniquely to U.S oil production as compared to non-US oil production. Equity returns for the United States are negatively affected by a negative United States oil supply shock. These stocks are seen to be unresponsive to the non-US supply shocks. It has been observed that the price of crude oil since 1970 has responded to some of the economic forces that drive the stock market. (Hamilton 2003).

One of the biggest limitations in the existing works on the relationship between oil prices and the stock market indexes is that crude oil is treated as exogenous to the US economy. This is widely because the energy sector contributes only 3% to the US economy (Routledge et al. 2000). The generally accepted fact is that crude oil prices respond to some of the forces that determine stock prices. This, therefore, means that the existing literature does not have a well-defined regression model of stock returns and the crude oil prices. The second limitation in the current literature on the topic is that the researchers assume that they can determine the impact of crude oil prices on the stock market without first analyzing the causes of these oil price increases. The existing literature considers the extent to which supply and demand shocks in the oil market affect the United States Economy (Kilian & Park, 2009) and the degree to which the importance of these supply and demand shocks evolve over a given period (Sadorsky, 1999). Using the criterion that has been employed by the previous research may lead to biased results and may find no statistical relationship or statistical relationships that get unstable over time.

1.1. Research questions

Guided by the research background provided in the above section, three questions were developed to be answered by the current study namely:

1. Is there any significant correlation between oil price and stock index in the Nordic market?

2. Do shocks in the oil prices have a significant impact on the Nordic stock market in the long term?

3. Does oil price volatility have a significant positive impact on the stock returns in Nordic Markets?

1.2. Research hypotheses

The formulated hypothesis to be tested by the current study concerns the influence that shocks in the global oil prices may have on the stock market index but with a focus on the Nordic market. In essence, the hypotheses will be tested using data from the Nordic stock markets. The researcher used the traditional global oil price index to determine whether oil prices directly and significantly affect the selected Nordic stock market indices and it also compares the stock returns to the shocks in the global oil market but with a focus on the Nordic countries. With the main purpose of determining the pack of oil prices, the current study extends literature on the understanding of the impact and the correlation that may be existing between the oil price and the stock indices in the Nordic markets. Therefore, the main hypotheses to be tested are as follows:

- **H1**: There is significant correlation between oil price movements and the stock index in Nordic markets

- **H2:** Oil prices has significant positive influence on stock index in Nordic markets

- **H3:** Shock in the oil prices have significant long term impact in the Nordic stock market index

1.3. Purpose of the study

Changes in oil prices have been long considered an important factor in understanding fluctuations in the stock exchange. Economists have not reached a consensus on the exact relationship between the two.

This thesis looks at the impact that oil prices has on the stock market. It compares the stock returns to the shocks in the global oil market. The main research focus is on Nordic counties and is done by using data from OMXN40 index which consists the 40 most-traded stock classes of shares from the four stock markets operated by the OMX Group in the Nordic countries namely Copenhagen, Helsinki, Reykjavik and Stockholm.

1.4. Structure of the study

The research paper is divided into eight main sections covering different topics. The first section provided a comprehensive introduction to the study by describing the study, the research problem, purpose as well as hypotheses to be tested. The second section contains comprehensive discussion on the theoretical background of the current study by essentially describing the (1) crude oil markets, (2) OMXH40 index, and (3) oil price fluctuation. In the third section, the researcher discussed various currently available literature related to the problem being investigated. The discussion considered three main areas namely (1) industry portfolios and oil shocks, (2) predicting future stock market returns with oil prices, and (3) existing gaps in the current literature. The fourth section, entitled data, presented a discussion on the data collection, data description, and descriptive statistics while the fifth section described the main methodology to be employed in the study. The results of the empirical data analysis are presented in section six while discussion of the results and conclusion of the study are presented in sections seven and eight respectively. The last section also contains a discussion on the recommendations for future research direction.

2. THEORETICAL BACKGROUND

This section deals with the definition of the terms that are most relevant to this thesis. The chapter will try to explain the meanings of these terms in a deeper context as defined by scholars and economists. The section is vital as it will help in understanding the stock market and the terms that are related to the stock exchange, as it is important in this thesis. The section will also define the terms that are relevant to the oil industry in a deeper context.

2.1. Crude oil markets

Crude oil is considered one of the economically mature market in the world (Kristoufek, 2018). Relatively small companies often undertake production of crude oil but the product is robustly traded globally. Mainly the global supply and demand forces determine the price (Liu, Schultz, & Swieringa, 2015); the demand is rapidly growing in developing countries. OPEC also has some ability to not only influence but also control and regulate crude oil market, especially the prices and production (Charles & Darné, 2014). However, their influence has been shrinking due to the emergence of new non-OPEC country supplies. Crude oil has been used traditionally as a benchmark for global oil prices. As explained by Kristoufek (2018), there are some global benchmarks for crude oil such as the Brent ICE, Western Canadian Select (WCS), Dubai Crude, and West Texas Intermediate (WTI) crude oil.

Since the early 1990s, prices in the global oil market have been increasing steadily, which, as explained by Conrad, Loch, and Rittler (2014), reflects the rising demand for crude oil. As explained by Charles and Darné (2014), the demand for crude oil has significantly increased within the last two decades, mainly rising from developing nations. According to Ortiz-Cruz et al. (2012), crude oil prices have increased by more than 700% within the last decade mainly due to rising demands. Apart from rising demand, other factors are attributed to the rising crude oil prices globally. For instance, Kristoufek (2018) showed that crude oil prices have been rising steadily due to low spare capacity. Other researchers such as Liu, Schultz, and Swieringa (2015), Lahmiri (2017), and Liao et al. (2016) have also identified additional factors causing a steady rise in crude oil prices to include geopolitical concerns and a weak dollar. As explained by Lahmiri (2017), geopolitical concerns related to wars, revolutions, and political instability in OPEC member countries especially Turkey, Nigeria, and Iran are a great driver to fluctuations of crude oil prices.

According to Conrad, Loch, and Rittler (2014), the global crude oil market is characterized by a high level of volatility whereby prices are constantly changing their trajectories and behaviors at different economic situations. Furthermore, it has been discovered that the large upward or downward swings exhibited by the crude oil market is caused by fluctuations in extraction costs, demand, as well as reserves (Lahmiri, 2017). According to An et al. (2014), supply and demand have been and will remain a significant factor in determining global crude oil prices. In addition, several researchers have shown that oil supply depends on geopolitical events while demand depends on oil consumption (Conrad, Loch, & Rittler, 2014). Other factors affecting the supply include and oil tank levels and the decision by OPEC to adjust production levels (Charles & Darné, 2014). An et al. (2014) asserted that the behavior of oil investors also significantly affects the oil supply. For instance, recently, there have increased speculative behaviors with a diverse set of investments such as pension funds, hedge funds, and investment banks thereby affecting crude oil market globally.

2.2. OMX Nordic 40 index

The OMX Nordic 40 Index, also abbreviated as OMXN40, is a special capitalization-weighted index that provides a measure of performance of the Nordic stock markets, basically, the Nordic Stock Exchange (Henriksson et al., 2016; Xu, 2014). As explained by Hummel (2015), the index was established on October 2, 2006, and is composed of 40 most traded stocks in the Nordic Stock Exchange, which essentially represent four stock markets in the region namely the Stockholm, Helsinki, Copenhagen, and Reykjavík (Hummel, 2015; Henriksson et al., 2016). The base date the OMX Nordic 40 Index is December 28, 2001, with a value of 1000 units (Hummel, 2015). In addition, the 40 listings are from different sectors such as apparel retail, automotive systems, brewers, building products, construction, diversified banks, diversified commercial services, electric utilities, health care, industrial machinery, and pharmaceuticals among others (Hummel, 2015).

The OMX Nordic 40 Index represents the performance of the stock exchanges in the Nordic region. In essence, each country's stock exchange is represented in the OMX Nordic 40 Index. Therefore, the performance of the OMX Nordic 40 Index is directly determined by the collective performance of stock exchanges in the region (Henriksson et al., 2016). As explained by Xu (2014), OMX Nordic 40 Index has been experiencing steady performance over the past but characterized by some fluctuations as well as difficulties.

The currently available literature has not provided empirical evidence of the link between OMX Nordic 40 Index and crude oil prices. However, in general, some past empirical studies have shown that shock in the oil prices negatively affects the stock market (An et al., 2014; Liao et al., 2016; Chen et al., 2016). In such a case, the stock market index such as OMX Nordic 40 Index is assumed to be negatively impacted.

2.3. Oil price fluctuation

Since the oil crisis in 1973/4, oil prices have regularly been fluctuating due to forces of demand and supply which makes it a global phenomenon (Conrad, Loch, & Rittler, 2014). As explained by Gao et al. (2017), fluctuations in oil prices usually come at unexpected times. Despite the recent great strides in understanding oil price fluctuations and forecasting capability, still, variations, especially within the last 40 years, have caught economists and analysists unexpectedly (Chen et al., 2016). Central banks, economists as well as household have implemented various measure to counter oil price fluctuations in vain, that is, such measures have not effectively controlled or predicted oil price fluctuations (Ding et al., 2017). The figure below shows the Inflation-Adjusted weekly Brent and WTI crude oil price fluctuation between 2011 and 2018 in dollars per barrel.

Figure 1. Brent and WTI oil price fluctuations (US Energy Information Administration 2018)

Several authors have investigated causes of oil price fluctuations, and the literature has evolved substantially since the first oil crisis in 1973. During the early 1980s, it was perceived that fluctuations in oil prices are caused mainly by a disruption in the flow of production level due to political events such as evaluations and war in oil-rich countries (Lahmiri, 2017; Gao et al., 2017). Subsequent researchers showed that there are other important factors except wars and revolutions in such countries. Furthermore, researcher Wang and Wang (2016) indicated that revolutions and wars in OPEC countries are not a significant driver to oil price fluctuations. In addition, authors Conrad, Loch, and Rittler (2014), Charles and Darné (2014), and Zhu et al. (2016) established that fluctuations in global oil prices are attributed to shifts in demand.

Lately, researchers Zhuang, Wei, and Zhang (2014), and Chen et al. (2016) established that the most significant determinant of oil price fluctuation includes shifts in consumption (demand) and business cycles. As explained by Ding et al. (2017) and Gao et al. (2017), the demand for crude oil expands alongside the expansion of global economy thereby putting upward pressure (demand) on oil prices. According to Liao et al. (2016), shifts in the stock demands is also linked to substantial fluctuations in oil prices. As explained by An et al. (2014) and Zhu et al. (2016), shifts in stock demand lead to fluctuations in oil price expectations.

Oil price fluctuations drastically affect the entire economy, and because of that some governments, especially in industrialized nations, have responded by imposing pricing ceilings on their domestic crude oil (Zhuang, Wei, & Zhang, 2014; Ding et al., 2017). However, as explained by Ding et al. (2017), such reactions have resulted in the worsening of the situation; the price ceiling has caused a shortage and a long line at gas and oil stations. According to Chen et al. (2016) and Zhuang, Wei, and Zhang (2014), some governments have also reacted by limiting retail purchases, introducing speed limits, as well as banning automobile traffic on certain days such as Sundays.

Over the past, economists have introduced some mechanisms of measuring oil price fluctuations. As explained by Liao et al. (2016), one common approach of measuring the fluctuation is by relating oil prices to past value of key determinants and itself; this is the central idea employed in the *Vector Autoregression* (VAR) modeling of future oil prices. A second approach is to use the views or expectations of the policymakers (Wang & Wang, 2016); they may have more information that is not captured by the econometric models. A third approach is to use financial market futures as measures of oil price fluctuations (Conrad, Loch, & Rittler, 2014). However, as explained by Ding et al. (2017), this method is only valid when risk premium is clearly defined. Another method that has been used to measure oil price is the consumer expectations (Zhuang, Wei, & Zhang, 2014).

3. LITERATURE REVIEW

In 2006, the Financial Times attributed the decrease in the United States stock market to the increase in oil prices, which was a result of the political instability in the Middle East. The same newspaper argued that sharp rallies in equity markets on October 2006 were in a wake of a slide in crude oil prices on that day. Chen, Roll and Ross (1986) on the contrary held that changes in oil prices had no effect on the stock prices. Other researchers like Huang, Masulis and Stoll (1996) found no negative correlation between stock market changes and the price of oil. The above discussions show that there had been no empirical conclusions that have been statistically determined by researchers to relate the oil prices to the stock market indexes.

As a result of the critical role played by oil in the stability of the global economy, the fluctuations observed in oil prices are bound to have a significant effect on the stock returns. The global dependency on oil as the major source of fuel makes the effects of oil price destabilization a global phenomenon. The nature of the stock market shocks, their magnitude, and direction are all dependent on the context of the countries as it differs from one to another. Additionally, these stock market shocks are also dependent of the presence or absence of oil exports from the nations. Most of the recent studies in the domain of global oil prices have demonstrated that the oil prices have eminent effects on the stock market especially in the developed countries. Contrary to assumed expectations, developed nations without oil drills and reserves are most significantly affected by the variations in global oil prices that destabilizes the stocks markets. This way, the relationship between the stock markets and the global oil prices is negative as higher oil prices culminate in deeper drops in stock markets (Driesprong et al., 2008; Miller & Ratti, 2009; Basher et al., 2012). For all the dimensions of the relationship between oil prices and stock market fluctuations, it is critical to addresses the issue from its root. This understanding could only be retrieved through the assessment of the causes in oil price changes. One of the most predominant causes of the changes in global oil prices are the unprecedented supply shocks. The supply shocks emanating from various sources such as political instability have been seen to have negative correlation with the stock market (Cunado & Gracia, 2014). Similarly, the United States (U.S.) is also affected by the variations in oil prices. However, in the U.S. stock market, the relationship between oil price change and stock market conditions takes the positive form. This is because stock market returns are positively affected by an increase in oil price due to the growth in the global economy. Papapetrou (2001) shows that oil prices affect the emerging markets in both the short term and the long-term timelines. Similarly, Faff and Brailsford (2000) also realized that the significance of the destabilization of oil prices revolves around the fact that it has an eminent relationship with the stock markets. This way, oil price variations are also perceived to be as critical as stock market prices especially in Australia where both variables dictate the health of the economy. The importance assigned to oil prices and stock market prices in the Australian stock market is attributed to the fact that most results of the reviewed studies indicate that there was a significant positive correlation between oil prices and the stock exchange.

One of the most confirmatory is that by Williams (1938) who points out that the any asset price changes in accordance to the prediction of its discounted cash flows. Since discounted cash flow in not constant in any case, then there is no argument against the fact that there is the possibility of a disturbing variable that culminates in the altering of the discounted cash flow, which in turn affects the prices of the asset. In this case, the asset is oil. Using this relationship, the most logical argument would be that increases in oil prices are bound to result in the cost of the commodity to the end users. The increase of the prices, which trickles down as a higher price to the end users then diminishes the shareholder value, which is a limitation to the generation of profits. Therefore, the relationship between oil prices and shareholder value is such that the increase in the former causes the decrease in the latter. This way, increases in the oil prices create a series of effects that end up decreasing stock market prices. However, this theory by Williams (1938) does not specify whether o not the oil-producing capacity of the country under analysis plays any role in the relationship. This way, the theory has a limitation as it does not expound on the variations in oil-producing nations and those without the reserves. Even so, this limitation was addressed by Bjornland (2009) who demonstrates that the fluctuation in global oil prices has a significant effect on both oil-producing and non-oil-producing countries with the only difference being the directions of the effects. For instance, the increases in oil prices in the producing countries is bound to culminate in positive effects through the stabilization of the stock market prices through internal market forces. To illustrate the arguments he presents, Bjornland (2009) points out that the national revenue of the nation could increase with the escalation of global oil prices in such as way that it would translate to an increase in expenditure and investments. The increase in expenditure and investment is bound to result in the realization of more employment opportunities, which in turn promotes national productivity. With the improved national productivity, the stock markets are likely to stabilize or improve both of which as positive responses in terms of stock market prices. Therefore, the increase in oil prices trickles down to the other aspects of the economy in such as way that they improve stock market conditions, which denotes a positive market response.

Conversely, the trends demonstrated by oil-importing nations are different from those in the oil-producing ones. One of the studies that has effectively tackled the relationship between oil prices and the stock market prices in the oil-importing countries is that by Hooker (2002). In this study, Hooker (2002) points out that the relationship between oil prices and stock market prices in the oil-importing nations is negative. He proceeds to explain that when the oil prices increase, the production process of the industries also escalates since they are eminently dependent on oil as the major source of fuel for the production processes. The increase in the costs of operation realized by the escalating oil prices culminates in the increase in the prices of the products to compensate of the operational deficits realized by the increased costs of production. The increase in the product prices then affects the demand curves for the products as less customers will be able to afford the commodities at a higher price for the same quality. Similarly, the increasing product prices also reduce customer spending in such a country. The overall effect is that the nation undergoes a series of market changes that compel firms to lay off their employees as a strategic adaptation to the increasing costs of operation. By laying people off, the firms are bound to reduce on the operational costs. Consequently, the increase in oil prices results in the growing rampancy of unemployment. The unemployment then affects national productivity in a manner that triggers the onset of negative impacts on the nation's stock market prices. This way, Hooker (2002) demonstrates that the increasing oil prices result in the destabilization of stock market prices.

Even though the changes in the global oil prices have significant direct effects on the stock market prices, the most dominant reason for the observed fluctuations is usually the destabilization effect of the phenomenon in terms of creating market uncertainties. The oil prices have been observed to change drastically. While most market changes take time to create permanent effects, the global dependence on oil renders all the changes in the commodity's price highly destructive as the volatility of the prices creates an array of financial uncertainties especially in the stock market. Consequently, these escalation in prices is referred to as oil price shocks as it is not only prompt but also unavoidable. This gives oil the ability to destabilize the global economy at an instant. Using the Autoregressive Conditional Jump Intensity, Chiou and Lee (2009) found out that oil price volatility negatively influenced the S&P 500 index. From this study, the practitioners came to the conclusion that increased oil volatility caused unexpected negative asymmetric effects on the S&P 500 index. From their study, Chiou and Lee (2009) also made the observation that the major events that lead to changes in oil prices at the global scale occur in the GCC stock markets which demonstrate trends of high volatility. This notion has been observed and tested using several methods including the GARCH model by Arouri and Nguyen (2010) that was deployed to study the effects of oil prices on the stock returns of European Countries as an alternative to the conventional aggregate stock market returns index. Using this GARCH model, Arouri and Nguyen (2010) realized that oil prices influenced a significant part of European sectors such as financials, and oil and gas among others. As observed in the previous sections, the effects of the oil prices on the oil-producing nations and the oil-importing countries differs. Consequently, Arouri and Nguyen (2010) opted to use the seemingly unrelated regression (SUR) for the analysis of the trends observed in oil-exporting countries to study the impact of oil price changes. Using this model, they discovered that positive oil price shocks had a positive impact on stock market returns.

The ability of oil prices to destabilize the global market and create a series of unprecedented uncertainties in the financial sector has drawn the attention of most researchers in the field. From these efforts, there are several papers that have recently called to attention the changes in future oil market behaviours. Most of these study were focused on the periods between 2003 and 2008 when the great depression in the global market was observed and most industries and markets in the world crumbled. One of these studies include the ones by Ready (2013), and Baker and Routledge (2011). In most cases, the financial studies of this magnitude take more than a decade as longitudinal studies as the matter calls for the intricate assessment of the observed trends and patterns in the market. Therefore, some of the practitioners in the field could render the information from a short period as less credible based on the set standards in the field. Even so, no such studies existed at the time of the development of this report. Therefore, even though the period of data being used here is short, monthly frequency gives the allowance for enough data to examine the relations between stock prices and the two shocks in the oil world, over smaller sub samples. For the samples involved in the study to be assessed with a higher level of accuracy, Ready (2003) and Baker and Routledge (2011) resorted to the categorization of the samples into four sub-periods between the observed time frame between 1987 and 2012. The four sub categories were distributed as follows:

- 1986 to 1991: Accounting for oil glut of the mid 1980s and the first Gulf war
- 1992 to 2003: A time of low stable prices in oil which also saw the ".com boom" and bust in United States markets
- 2003 to mid-2008: This period saw big rises in oil prices as well as worries about "financialization" of goods
- 2009 to 2011: This was the period referred to as the post-crisis period

As one might expect, the first (1986 to 1991) and the third (2003 to mid-2008) periods were when oil received the highest media coverage. These periods were also characterized by their potential in affecting the supply to create impacts that were more prominent that in the other periods.

Aggregate analysis determines that on average, 20% of the variations in the total stock returns in the period 1975-2006 can be directly linked to the shocks in the crude oil market (Malik & Ewing, 2009). Thus, oil price is an important determinant of the United States overall stock returns. A significant part of the contribution can be directly attributed to shocks in demand of oil. Despite this, the response of stock returns seems to be affected or driven by changes in dividend growth and variations in the expected returns. Only shocks that affect the precautionary demand for oil provide a plausible explanation for a negative correlation between stock market indexes and the inflation that was seen in the post-war period. This was determined through a series of research by Kaul and Seyhun (1990). The response of industry-specific stock market returns to the shocks in demand and supply is more significant at the industry level, but the degree of the replies differs significantly among various sectors.

Kling (1985) noted that an increase in oil prices is associated with a decline in the stock market. Jones and Kaul (1996) determined that there is a stable negative correlation between stock returns and the changes in prices of oil. Wei (2003) concluded that there is zero correlation between the two and that the decline in the stock prices in the US in 1974 cannot be explained by the increase in oil prices in 1973-1974.

Kilian and Park (2009) looked at the effects of world crude oil shocks about the stock market. In their study, they found out that oil prices had a positive correlation to stock market indexes. However, they did not look at the effects of a non-US oil price shock on the US economy, but rather they looked at the oil market as a whole when coming up with their model.

Ott (2015) examine different sub periods. He found out that from the first sub period, there was a strong correlation between supply shocks and stock market returns. These supply shocks and market returns are presumably driven by huge movements in prices as an adjustment to the large price movements around the Gulf war. Other events that might have triggered the observed trends include the subsequent oil glut of the 1980s. He also found out that there was a contrary pattern in the 2003 to 2008 period as the strong relation during the oil prices in the period appear to be driven by a consistent correlation among smaller movements in the monthly price. The 2009-2012 post-crises period also offers some interesting insight as it indicates that even though this period was followed by a precipitous drop in the prices of oil, they have since risen up to near pre-crisis levels.

The 2009-2012 period also attracted significant press coverage as a result of the stage's characterization by an unexpected diversion in global oil markets. European Brent index (EBCI), which was nearly perfectly correlated with the U.S. WTI since its inception, has since the Gulf crisis been trading at premiums of between 5 percent to 10 percent or higher. Even so, the two indices are no longer correlated on a monthly basis. Moreover, there was an observation that the previously recorded correlation of 0.9 in the pre-crisis period then dropped to below 0.6 after the crisis. Interestingly, the supply shocks identified by the WTI are damaging but not important during this period, but when the same is done with Brent index, the significance returns. This coincides with anecdotal prove that the WTI is more impacted by a nation's transport conditions since 2009, and is gradually being replaced by Brent index as the true measure of world oil markets. (Ready 2013.)

3.1. Industry Portfolios and Oil Shocks

This section combines the knowledge discussed in the previous section in the illustration of the relationship between oil prices and stock returns. This will be done with the intention of getting a better understanding of the mechanisms by which the prices of oil shocks impact any economy. For this relationship to be understood, it is critical to investigate the relationship between oil shocks and industry shock returns. Elyasiani, Mansur and Odusami (2011) conducted a study which indicated that the industries related to consumer expenditure contain the strongest harmful loadings on the oil supply impacts. On the other hand, the industries which use high amounts of oil have the strongest positive effect on demand shocks. From this argument, it is evident that the hypothesis of the paper has been proved to the factual as oil price shocks act primarily on the consumer expenditure rather than a direct effect from increased input costs. Even so, the identification strategy can be further supported by the fact that the findings indicate that the increases in oil prices due to high oil demand seem to be affected by an addition of activities in high oil-use industries.

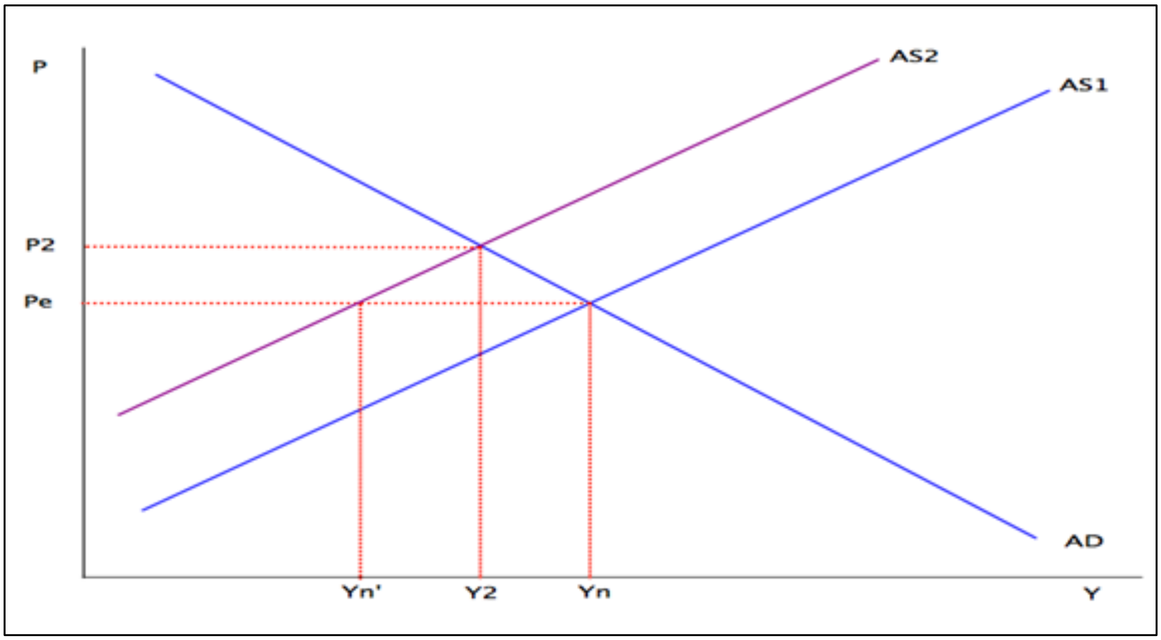

Figure 2. Supply shocks (IEA 2016)

Figure 3 gives an additional demonstration of the arguments presented in the previous section. From the figure, it is evident that by loading on the supply shock, which can be computed as a function of the relative importance of crude oil as the most basic input for the 48 selected industries, the importance of oil is calculated using the input-output tables obtained from the BEA. The x-axis encompasses the chart represents the dollars of oil needed to produce a dollar of output for each of the industry. As discussed in the previous sections, there is a shortage of systematic patterns that take into account the oil use and oil supply impacts on beta as indicated in the figure. Instead, the most common practice is the use of industries with an eminent reliance on customer spending such as the clothing industry and restaurants that are mostly affected by the impacts of the fluctuation in oil prices especially during instances of an increase in the global rates. Therefore, this avail sufficient evidence that oil shocks usually trigger consumer spending shocks as opposed to significantly impacting the oil-thirsty industries.

3.2. Predicting future Stock Market Returns with Oil Prices

Driesprong, Jacobsen and Maat (2008) point out one of the most baffling points about the correlation between oil prices and the share market by deploying the predictive correlation. In their study, they indicate that prior to the 2000 global economic crisis, increases in oil prices majorly predicted low stock returns in the coming months. When the same correlation was used to examine the demand and supply shocks, it is evident that all types of shock contribute to the onset of such trends in the global market.

Leite, Antonio and Marcelo (2016) find that results of the regression of aggregate United States market returns indicate a relationship with the changes in oil prices. From this relationship, they find that past oil prices classified into demand and supply shocks. However, when the pre-crisis results are put into consideration, the result seemed to be equally prevalent in both demand and supply to extent that this alteration in future returns represents changes to the present discount rate (Casassus & Higuera, 2012). From this relationship, it is evident that the results point out that the level of oil prices is vital than the source of the shock. For instance, when using the example of a passenger vehicle ownership, it is likely that there is a near imperfect measure of user oil demand. In fact, Millard and Schipper (2011) show that Japan drivers drive only half as many miles as United States drivers. This could be used to explain the variation in the beta readings of the two nations.

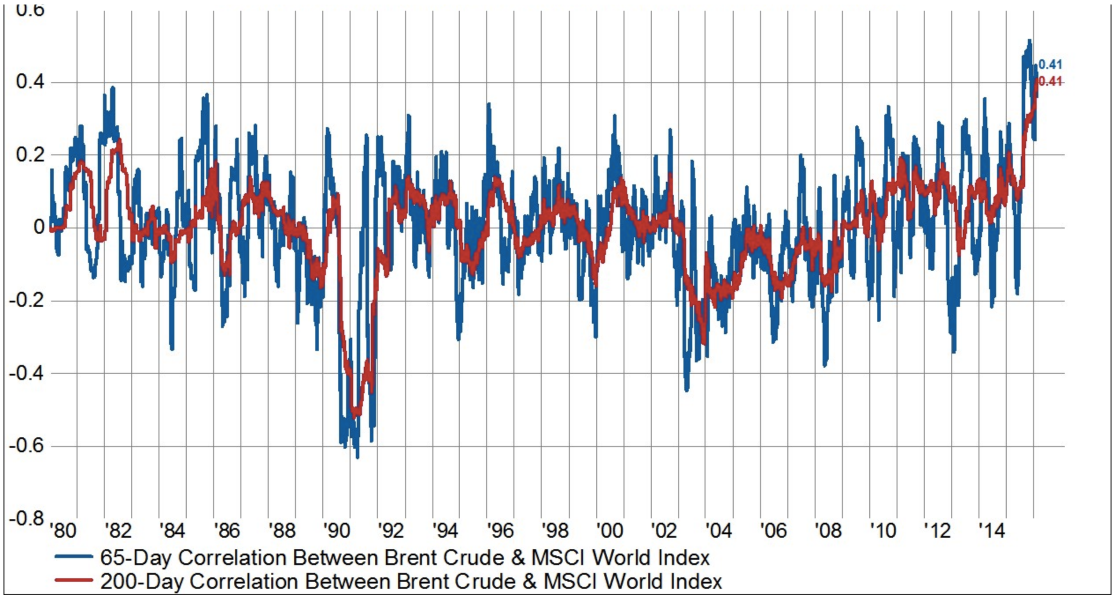

Figure 3. Correlation between oil and MSCI World Index (Bush 2016)

Figure 4 shows correlation between Oil ans MSCI World Index over period of 1980 to 2016. Stock prices and oil prices have been moving in more positive correlated fashion recently than any point since 1980.

4. DATA

In this section, the researcher describes the data that were used in the analysis to complete the dissertation by testing the hypothesis in order to answer the questions about the research phenomenon being investigated. The section includes a discussion on the data source, data collection, the variables, as well as data descriptions as presented below.

4.1. Variables and Data Collection

The results of the review of the empirical literature, as presented in the previous section, indicates a broad range of data series and time periods used by several past researchers. The current thesis examines how global oil prices affects the Nordic stock markets and guided by the results of the literature review on what other previous researchers have used as well as the main objectives and hypotheses to be tested, for the current thesis the main variables to be considered consists of Global Oil Price and OMX Nordic 40 Index.

The data collected consisted of monthly close prices for the period between January 2009 and October 2018. The starting point for the sample is January 2009 which is justified by the need to eliminate the impact of global financial crisis which might have dire consequences on their relationship. The 2007/8 financial crisis had a dire effects on the market returns globally and including such periods might hinder the ability to obtain the correct impact of global oil prices. The period included provided enough observation for determining the strength as well as the nature of any existing relationship between the variables under consideration.

OMX Nordic 40 Index was used as the dependent variable of the study measuring the impact of oil prices on the Nordic stock markets. The index was created on October 2, 2006, and is composed of 40 most-traded stock classes operated in four major stock markets in the Nordic countries. The variable provides a measure of the changes in the entire Nordic stock markets. The data on *OMX Nordic 40 Index* were downloaded from nasdaq.com, which is one of the leading providers of historical data for stock market and indices. The data downloaded consisted of monthly close price for the chosen research period.

Brent Crude Futures was used as the independent variable measuring changes in the global oil prices. It was used as a direct measure of changes in global oil prices. Data for *Brent Crude Futures* was downloaded from Bloomberg.com, which is another leading provider of stock market and indices historical data. Similarly, the data downloaded consisted of monthly close price for the chosen research period.

4.2. Data Description

For both the variables, that is, OMX Nordic 40 Index and Brent Crude Futures, the data collected refers to the quoted prices excluding dividend payouts. The monthly units essentially refer to the average values computed using daily close prices for each month. In essence, for OMX Nordic 40 Index, it was computed as the average of daily close index values for each month while Brent Crude Futures it was computed as the average daily close price for each month. For each variable, 2009 was used as the base year. In addition, prices were expressed in nominal terms.

As explained by Reboredo (2012), Sadorsky (2012), and Inkpen and Moffett (2011), there are three different measures of global oil prices namely Dubai, Brent, and *West Texas Intermediate* (WTI), which are considered the benchmarks in the industry. Due to the availability of data and wide usage by previous researchers, we chose to use the Brent as the preferred measure of global oil prices as expressed in dollars per barrel. As explained by Inkpen and Moffett (2011) and Sadorsky (2012), Brent Crude is considered to be a good indicator or measure of global oil prices, which informed its choice in the current study. Also, since the study is based on Nordic countries, which is part of Europe, Brent is the best benchmark for oil prices to be used because it is commonly sold in the region. As explained by Ajmi et al. (2014) and Reboredo (2012), Brent is extracted from the North Sea and is lightweight and low in sulfur. It comprises of Ekofisk crude, Oseberg crude, Forties Blend, and Brent Blend (Reboredo 2012; Sadorsky 2012; Ajmi et al. 2014).

Conversely, the OMX Nordic 40 Index is an index of stock market prices but for the Nordic markets only. It was created on October 2, 2006, as a capitalization-weighted stock market index consisting of 40 most-traded stock classes in the Nordic markets. The 40 stocks are picked from four markets in the Nordic market operated by the OMX namely the Helsinki, Stockholm, Reykjavík, and Copenhagen. The base year for the index is 2001 with a value of 1000. Being an index, OMX Nordic 40 basically provides a measure of stock price movements and is computed using market prices of selected stocks on weighted average. The index beset describes the market and compare the returns on specific stock market investments.

Data for all the variables considered, namely the Brent Crude Futures and OMX Nordic 40 Index, were transformed into their natural logarithms before carrying out the statistical analyses. As explained by Feng et al. (2013), the logarithmic transformation does not affect the existing relationship between variables but rather help achieve normality before undertaking any statistical test or applying a model to the data. The transformation also helps stabilize the variables to be used (Miller & Plessow 2013; Karaca-Mandic, Norton, & Dowd 2012). Lastly, the transformation was done to help the model depict the effect of small changes in the variables (Miller & Plessow 2013; Feng et al. 2013).

4.3. Descriptive Statistics of the Data

Summaries and descriptive statistics of the data set for the two variables under consideration are provided in the table below. The summaries and descriptive statistics are provided for the log-transformed data.

	OMX	BENT CRUDE
Mean	7.081177	4.333389
Median	7.138716	4.349245
Maximum	7.410976	4.835409
Minimum	6.299721	3.547892
Std. Dev.	0.263609	0.342424
Skewness	-0.722727	-0.313878
Kurtosis	2.811190	1.907692
Jarque-Bera	10.53639	7.869936
Probability	0.005153	0.019546
Sum	842.6600	515.6733
Sum Sq. Dev.	8.199800	13.83602
Observations	119	119

Table 1. Descriptive statistics of the dataset

The table above presents the computed descriptive statistics of the log-transformed dataset. As indicated, the mean value of both OMX index and Bent Crude are 7.081177 and 4.333389 respectively. Based on their mean values, the increase on OMX Nordic 40 Index has been larger than that of the bent crude oil over the sample period. The data also demonstrate positive mean values which indicate somewhat large positive increases. With a standard deviation of 0.342424, the Bent Crude oil futures clearly demonstrate a high level of volatility as compared to the OMX index which has a standard deviation of 0.263609. The Jarque-Bera statistics for the bent crude oil future is 7.869936 with a probability value of 0.019546 indicating that the log-transformed data is normally distributed. However, for the OMX index, the data is slightly normally distributed given that its Jarque-Bera Probability is slightly above 0.05. The summary of the crude bent oil future indicates Skewness and

Kurtosis of -0.313878 and 1.907692 respectively indicating the data is normally distributed. With Skewness and Kurtosis of -0.722727 and 2.811190 respectively, the summary statistics also indicate that the data for OMX index follows a normal distribution.

5. METHODOLOGY

The current section outlines the preferred methodology that will be used to complete the empirical investigations. The choice of the methods, procedures, and techniques to be applied were informed by the research problem and their ability to test the research hypotheses. The choice of the methodology was also based upon the previous empirical studies on the same or similar problem as found in the literature. It is essential to note that all statistical analysis presented in this paper were carried out using a software package known as Eviews.

5.1. Correlation Analysis

Correlation was undertaken as a preliminary analysis to determine the co-movement between the oil prices and Nordic stock market indices. This type of statistical analysis is essential for determining the direction and strength of the existing association between two variables that are continuous, in this case, oil price and stock market index. It was used in the preliminary just as an indicator of the likely effect of oil prices. A negative value indicates that an increase in one variable causes the other to decrease and vice versa in the case of positive correlation coefficient.

5.2. Unit Root Tests

Because time series data is being used, the first step would be to determine if the dataset meets the necessary stationarity condition for all the variables. For a time series analysis, the data should be stationary, which means its distribution does not depend on time. As explained by Tong (2012) and Shin (2017), this is essential because it follows a common assumption in time series analysis that the data is stationary. According to Chatfield (2016), Shin (2017), and Box et al. (2015), the main properties of a stationary process is that the data has an unchanging mean, variance, as well as autocorrelation structure over time.

The major reason for ensuring that the data is stationary is the requirement for constant mean and variance in forecasting. Another essential reason for requiring stationarity of the dataset is to ensure that the data can provide meaningful sample statistics for each variable being used (Leamer & Stern, 2017; Nerlove, Grether, & Carvalho, 2014; Brockwell & Davis, 2013). As explained by Shin (2017) and Tong (2012), such statistics are essential in describing the behavior of the variables. If the test statistics show that the data is not stationary, they are transformed by either differencing or taking natural logarithms, which stationaries them (Kitagawa & Gersch, 2012; Brockwell & Davis, 2013).

To determine whether the dataset is stationary or not, *Unit Root Test* will be used. As explained by Durbin and Koopman (2012) and Box et al. (2015), the test determines the presence of unit roots in the dataset. The dataset is considered non-stationary if unit roots are detected (Kitagawa & Gersch, 2012; Akaike & Kitagawa, 2012). The literature pointed out several methods available for testing the presence of unit roots in the dataset, for example, DF-GLS test, Augmented Dickey-Fuller (ADF), Wayne Fuller, Peter Phillips, and Pierre Perron among others (Young, 2012; Akaike & Kitagawa, 2012; Brockwell & Davis, 2013; Leamer & Stern, 2017). Despite the availability of several options, the thesis will only focus on the use of Augmented Dickey-Fuller (ADF) test to determine the presence of unit roots in the dataset. As explained by Shin (2017), the test was introduced in the 1970s by two researchers namely Wayne Fuller and David Dickey. According to Durbin and Koopman (2012), Box et al. (2015), and Tong (2012), the Augmented Dickey-Fuller (ADF) is appropriate for testing stationarity in models with complicated dynamics. In this test, the general approach is to implicitly assume that the data can be written in the form

$$y_t = D_t + z_t + \varepsilon_t$$

where,

- D_t is the deterministic component (trend, seasonal component, etc.)
- z_t is the stochastic component.
- ε_t is the stationary error process.

The next task is to determine the presence of unit root in the stochastic component z_t . The process can be transformed into;

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t$$

Where $\gamma = \rho - 1$. The test is thus completed with a null hypothesis stating that the data is non-stationary, that is;

$H_0: \gamma = 0 \text{ and } H_1: \gamma < 0.$

5.3 Cointegration Test

After testing for stationarity, the next step will be to determine the cointegration of the dataset. As explained by Chatfield (2016) and Durbin and Koopman (2012), cointegration is a property of a collection of variables that integrate data to a certain order called the order of cointegration. The data of a collection of the variable is said to be cointegrated if it is of order zero (Leamer & Stern, 2017; Nerlove, Grether, & Carvalho, 2014). Cointegration is essentially an important property in time series analysis due to the presence of trend, which is either stochastic or deterministic. As explained by Montgomery, Jennings, and Kulahci (2015), many economic data are cointegrated. Alternatively, the time series data is said to be cointegrated if there exists a stationary linear combination of variables (Young, 2012; Akaike & Kitagawa, 2012; Kitagawa & Gersch, 2012).

According to Chatfield (2016), Shin (2017), and Box et al. (2015), cointegration tests are designed to assess the non-stationary time series. In essence, the test analyses processes whose variance and mean varies over time (Kitagawa & Gersch, 2012; Nerlove, Grether, & Carvalho, 2014). It allows the long-term equilibrium parameters to be established with unit root variables. As explained by Durbin and Koopman (2012), the cointegration tests essentially determine the stable long-term relationship between sets of variables. Several statistical tests can be sued to determine cointegration the main ones being Johansen test, Phillips–Ouliaris, and Engle–Granger among others (Rao & Gabr, 2012; Granger & Hatanaka, 2015; Young, 2012).

For the current study, the Johansen test will be applied to analyze the cointegration between the OMX Nordic 40 Index and Brent Crude Futures variables. As explained by Montgomery, Jennings, and Kulahci (2015), the test was developed by Johansen and Juselius in the year 1990, and as explained by Chatfield (2016) and Rao and Gabr (2012), the test essentially checks for any common stochastic trend in the variables. The advantage of using the Johansen test is that it avoids the issue of choosing the dependent variable which enables it to detect multiple cointegrating vectors. The framework provided by the Johansen test allows testing of several cointegrating vectors in the dataset. In this test, the number of cointegrating vectors is determined by two test statistics namely the max-eigenvalue and the trace statistics (Chatfield, 2016; Rao & Gabr, 2012; Granger & Hatanaka, 2015). They are given by the equations below;

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} \ln(1-\hat{\lambda}_i)$$

$$\lambda_{max}(r, r+1) = -T \ln(1-\hat{\lambda}_{r+1})$$

Where r and g are the cointegrating vectors and the number of variables respectively.

5.4. Vector Autoregressive Model

The next step is to choose the best model for analyzing the data. In line with most related past empirical studies, the unrestricted Vector autoregressive (VAR) was chosen as the preferred model for analyzing the data. In essence, most researchers in stock markets, economic activity, as well as oil price shocks have used the VAR model (Durbin & Koopman, 2012; Rao & Gabr, 2012; Granger & Hatanaka, 2015; Box et al., 2015). In particular, the model will be sued to study the relationship between oil prices and stock market index. As explained by Rao and Gabr (2012), the model was introduced by Sims in 1980 and has been used by several researchers in different fields. The model was chosen for this study because it has a greater ability in capturing the dynamic relationship between different variables of interest (Shin, 2017; Durbin & Koopman, 2012; Chatfield, 2016).

Granger and Hatanaka (2015) considered VAR as one of the most successful and flexible statistical methods for analyzing multivariate time series data. According to Brockwell and Davis (2013), Young (2012), and Montgomery, Jennings, and Kulahci (2015), the model is particularly useful for describing the behavior of various financial as well as economic time series data. In addition, it enhances the forecasting of times series data. Another advantage of the model is that it effectively captures the linear interdependencies between variables (Box et al., 2015; Rao & Gabr, 2012; Durbin & Koopman, 2012). The model is developed from the univariate autoregressive model by allowing for one variable to evolve in the process based on their respective lagged values (Shin, 2017; Chatfield, 2016).

As explained by Granger and Hatanaka (2015) and Rao and Gabr (2012), the VAR model produces a system of equations expresses each variable under consideration as a linear combination of its lagged values and lagged values of the remaining variables. The model is essentially developed for a particular order denoted by p where p is the number of lags. The model describes the evolution of k endogenous variables in a given period t where t = 1, 2, ……. T. A p-th order VAR model is denoted VAR (p) and is expressed by the equation;

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t,$$

This, a VAR model of order p including k variables is given by

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-1} + u_t$$

Where p denotes the number of lags, $y_t = [y_{1t} \dots y_{kt}]'$ denotes the column vector of observations while A_0 and A_i denotes column vectors of intercepts and coefficients respectively. The error terms have zero mean and unit standard deviation and are considered to be independent white noise processes (Tong, 2012; Box et al., 2015). They are also assumed to be uncorrelated.

5.4.1. Lag Length Selection

As explained by Nerlove, Grether, and Carvalho (2014) and Akaike and Kitagawa (2012), the length of lag needs to be specified when using the unrestricted VAR model. In addition, as explained by Young (2012), when using this type of model, it is essential to ensure that all the variables use the same number of lags (Tong, 2012; Shin, 2017). According to Granger and Hatanaka (2015), the maximum number of lags in a VAR model can be determined using certain information criteria. As suggested by Young (2012), the optimal lag length can be determined using either *Schwarz's Bayesian information criterion* (BIC) or *Akaike's information criterion* (AIC). The two statistics provide an appropriate measure that determines the optimal lag length thus either can be used.

The Akaike information criterion (AIC) is given by the following equations;

$$AIC = log\frac{1}{N}\sum_{i=1}^{N} e_i^2 + \frac{2K}{N}$$

The Schwarz Bayesian information criterion (BIC) is given by the following equation;

$$BIC = log\frac{1}{N}\sum_{i=1}^{N} e_i^2 + \frac{K}{N}logN$$

In this study, both the BIC and AIC criteria will be used to determine the appropriate lag length for choosing the suitable VAR model. The objective is to choose the number that minimizes the value of the information criteria. To achieve this, the VAR model with the lowest AIC or BIC will be preferred, and its lag length was chosen as the appropriate for modeling the impact of oil prices on the stock market index. Both BIC and AIC criteria were chosen in order to compare the results in choosing the most approached number of lag for the model. Nonetheless, as explained by Kitagawa and Gersch (2012), Nerlove, Grether, and Carvalho (2014), and Akaike and Kitagawa (2012), BIC favors models that are parsimonious while AIC tends to be more efficient and preferable for small samples.

5.4.2. Impulse Response

As explained by Nerlove, Grether, and Carvalho (2014), it is essential to measure the responsiveness of the endogenous variables on the model. The impulse response function provides a particular measure of examining the responsiveness of the variables in the VAR model to shock on the model (Nerlove, Grether, & Carvalho, 2014; Tong, 2012). As asserted by Brockwell and Davis (2013) and Leamer and Stern (2017), the techniques apply a unit shock to the error term, and its effects on the VAR model is examined over a given period. A shock on any given variable will certainly have a direct effect on the same variable, which is also transmitted to other variables in the model. As explained by Shin (2017), Kitagawa and Gersch (2012), and Akaike and Kitagawa (2012), the shock will gradually die away if the model is stable.

5.4.3. Variance Decomposition

As illustrated by Brockwell and Davis (2013) and Nerlove, Grether, and Carvalho (2014), when using VAR models, it is essential to perform variance decomposition. Leamer and Stern (2017) consider variance decomposition as an essential test for interpreting the VAR models. As explained by Shin (2017), Box et al. (2015), and Kitagawa and Gersch (2012), the process gives a clear proportion of the co-movement of all the endogenous variables in the model that are caused by their shocks as compared to other variables. The essentiality of a variance decomposition is to provide evidence of the relative significance of each random innovation and variables affecting the VAR model. As explained by Leamer and Stern (2017), self-generated shock explains a larger proportion of the variance forecast error in the VAR model.

5.5. Section summary

The technique and methodology that was used to test the hypotheses and answer questions being investigated has been outlined in the current section as presented above. The main method of analyzing the data in order to answer the research question is VAR model. In essence, the technique was used to help determine whether the impact of oil price shock is significant in the Nordic stock market. However, before constructing the VAR model, data was tested for seasonality as well as congregation. The VAR modeling also included analysis of the impulse response as well as the decomposition of the variance for each variable.

6. RESULTS

The chapter presents the results of the statistical analysis that was undertaken using the pre-specified methods in order to answer the research questions as well as test the hypotheses. The main goal of the analysis is to determine how oil prices directly influences the derivation of stock market indexes using data from the Nordic country, which will provide empirical evidence of the situation of stock markets in this region. Based on the methodology specified in the previous chapter, the main statistical analyses that were considered include unit root tests, cointegration test, vector autoregressive models, analysis of impulse response, as well as decomposition of variance.

6.1. Correlation Analysis

To test the first hypothesis, a correlation analysis was undertaken which determined whether there is any significant correlation between oil price movements and the stock index in Nordic markets. An ordinary correlation analysis was done using Eviews and the results presented in the matrix below.

Correlation t-Statistic Probability	BRENT CRUDE	OMX
BRENT CRUDE	1.000000 ----- -----	
OMX	-0.324466 -3.710379 0.0003	1.000000 ----- -----

Table 2. Correlation matrix

The table above provides the correlation that exists betwixt oil price and Nordic stock market index and as indicated in the table, the correlation coefficient is -0.324466, which is small indicating nearly weak correlation. In essence, Nordic stock market index and oil prices have no statistically significant correlation. In addition, the correlation is negative indicating that shocks in the price of oil have negative impacts on the stock index in the Nordic markets. The result of the correlation analysis presented above rejected the first hypothesis with a conclusion that there is no significant correlation between oil price and the stock index in Nordic markets.

6.2. Unit Root Tests

As illustrated earlier in the previous chapter, in order to test whether the data is stationary as required for time series analysis, the ADF test was applied on the log-transformed data set. The test determined the presence of unit roots in the data set, and it was done independently for each variable, and the results are presented as follows.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BRENT CRUDE(-1)	-0.055179	0.022887	-2.410903	0.0175
C	0.271170	0.105744	2.564397	0.0116
@TREND ("2009M01")	-0.000476	0.000230	-2.068026	0.0409

Table 3. ADF test results for Brent Crude

The table above provides a summary of the ADF test results for Brent Crude while the complete results are attached in Appendix A. As indicated in Appendix A, the probability value is 0.3721, which is more than 0.05, the critical alpha indicating the presence of unit roots. In essence, the ADF test indicates that the Brent Crude variable has unit roots thus it must be differenced before analysis by VAR model. In the table above, the probability value of the differenced Brent crude is 0.0175, which is less than 0.05 indicating the absence of unit roots. Thus, the transformation will remove the unit roots in the variable as desired.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OMX(-1)	-0.099871	0.037202	-2.684570	0.0083
C	0.684594	0.247847	2.762168	0.0067
@TREND("2009M01")	0.000506	0.000287	1.763824	0.0804

Table 4. ADF test results for OMX

The table above provides a summary of the ADF test for the OMX variable while the complete output of the result is attached in Appendix B and from the appendix it can be seen that the probability value of the variable is 0.2450, which is more than 0.05 indicating the presence of unit roots in the dataset. Hence, the data should be first differenced to remove the unit roots before analysis using the VAR model. In the table above, the probability value of the first-differenced OMX variable is 0.0083, which is less than 0.05 indicating lack of unit roots. Thus, first differencing the variable help remove the unit roots as desired. In summary, for all the variables, the data have unit roots. Thus they must be first differenced before undertaking the analysis using the VAR model.

6.3. Johansen Cointegration Test

The next step is to determine the existence of cointegration of the dataset, which was done using the Johansen test. As explained earlier, the test determined the long run association between the two variables of the study and the output of the results be presented in Appendix C while the table below summarizes the main test statistics.

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.127158	18.19108	25.87211	0.3312
At most 1	0.023294	2.686970	12.51798	0.9115

Table 5. Johansen Cointegration Test

The “None” variable hypothesized lack of cointegration, and as can be seen from the table above, its probability value is 0.3312, which is greater than 0.05, the critical alpha value. Since the value is greater than 0.05, we conclude the presence of cointegration in the data set, that is, the variables have a long-term association. Similarly, following the same approach, the absence of utmost one cointegration is rejected because the probability value of 0.9115 is greater than 0.05.

6.4. Vector Autoregressive Model (VAR Model)

VAR was the chosen model for determining how Nordic stock market index and Brent Crude, the two variables under consideration, relates with each other. Before employing the VAR model, the variables were differenced in order to remove the seasonality elements detected using the ADF unit root test. The seasonal factors were removed by simply getting the first difference of each variable in the series. Hence, in this section, we are estimating the model: VAR [dlog (BRENT CRUDE), dlog (OMX)]. This ordering assumes that Brent crude is the independent variable while OMX being the dependent variable. This implies that the Brent crude variable is assumed to have a contemporary effect on the stock indices, which is measured by the OMX variable.

6.5. Lag selection

Before developing the VAR Model, it is essential to determine the lags that is appropriate for the model given the data being used, which was determines using both the BIC and AIC criteria. The table below summarizes the BIC and AIC criteria for different lag values. Several different lags were tested using Eviews, maximum eight lags, and the table below compiles the results.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	326.9242	NA	9.32e-06	-5.907713	-5.858614	-5.887798*
1	328.8977	3.839293	9.67e-06	-5.870867	-5.723568	-5.811122
2	335.0235	11.69465*	9.30e-06*	-5.909518*	-5.664019	-5.809942
3	338.9570	7.366396	9.32e-06	-5.908309	-5.564611*	-5.768903
4	341.8183	5.254470	9.52e-06	-5.887606	-5.445709	-5.708370
5	342.3765	1.004712	1.01e-05	-5.825027	-5.284931	-5.605961
6	343.3739	1.759027	1.07e-05	-5.770434	-5.132139	-5.511538
7	344.3641	1.710384	1.13e-05	-5.715711	-4.979216	-5.416985
8	346.9552	4.381244	1.16e-05	-5.690094	-4.855400	-5.351538

Table 6. Lag selection criteria

The table above compiles the computed value of different criteria for selecting appropriate, but we are going to focus on only Akaike AIC and Schwarz SC information. The best lag is provided by the value that minimizes Akaike AIC or Schwarz SC or both. As indicated in the table, the Akaike criteria have selected a lag order of 2 while the Schwarz criteria have selected a lag order of 3. Ideally, we should choose a lag order that minimizes the value of Akaike AIC and Schwarz information. However, since the two test does not agree on the same lag value, we test the residual autocorrelation for both lags in order to determine the appropriate one, and the table below combines the summarized results.

	Lag 3		Lag 2	
	LM-Stat	Prob	LM-Stat	Prob
1	13.398	0.0095	9.2048	0.0562
2	6.9102	0.1407	9.5651	0.0484
3	12.164	0.0162	5.9155	0.2055

Table 7. Autocorrelation LM Test for lag

The table above compares the results of the autocorrelation tests for VAR models based on lags 2 and three respectively, and as indicated, the probability value for lag 3 is 0.095, which is less than 0.05 indicating the presence of autocorrelation. However, for lag 2, the probability is 0.0562 which is greater than 0.05 indicating lack of autocorrelation. Thus, we chose lag 2 for the VAR model to be developed. Lag 3 has a probability value of 0.0562, which is more than 0.05 indicating the presence or first-order autocorrelation, which is not desired.

6.6. The VAR model results

To proceed with the VAR model, we assumed that both the Brent crude and OMX data were stationary as required by the model. The unit root test indicated that the data is not stationary, so the analysis of was done on a first differenced data, which is stationary. Also, the lag selection criterion had advised us to take up to 2 lags in the VAR model to be the optimum lags. The data was first differenced in order to remove stationarity as required for a VAR model. A lag 2 VAR Model was then estimated using Eviews, and the output of the results is attached in Appendix D while the table below presents on a summary of the main statistics.

	D(BRENT CRUDE)	D(OMX)
D(BRENT CRUDE(-1))	0.127640	0.029303
	(0.09466)	(0.05267)
	[1.34836]	[0.55631]
D(BRENT CRUDE(-2))	0.112056	-0.056898
	(0.09308)	(0.05179)
	[1.20382]	[-1.09855]
C	0.001204	0.008584
	(0.00742)	(0.00413)
	[0.16220]	[2.07873]

Table 8. *VAR model* results

The table above summarizes the results of the two lag VAR model that was constructed. The values in [ ] brackets represents t-statistics while those in ( ) brackets represents standard errors. From the table above and looking at the oil price (Brent crude), it seems to have a significant influence on itself, going by the t-statistics of 1.34836. In essence, the past realization of oil prices is associated with 12.764% of its own shock. Similarly, for the lag of oil price, the t-statistics of 1.20382 indicates that it has a strong influence on itself. For the second lag, variations in oil prices are caused by 11.2056% of its own shock.

On the other hand, going by the t-statics of 0.55631, it seems oil price have insignificant influence on the Nordic stock market index. The results above indicate that oil prices can explain approximately 2.9303% of variations in the Nordic stock market index in the first lag. However, under the second lag, the results indicate that it explains about 5.6898% variations in the Nordic stock market index. Further and more insightful interpretation of the VAR model results is aided by the impulse response as well as decomposition of variance as presented in the following sections.

6.7. Impulse Response

To interpret the VAR model results accordingly, an impulse response system was adopted. To complete the impulse response analysis, the Cholesky Decomposition method was adopted and the results summarized by the figures below.

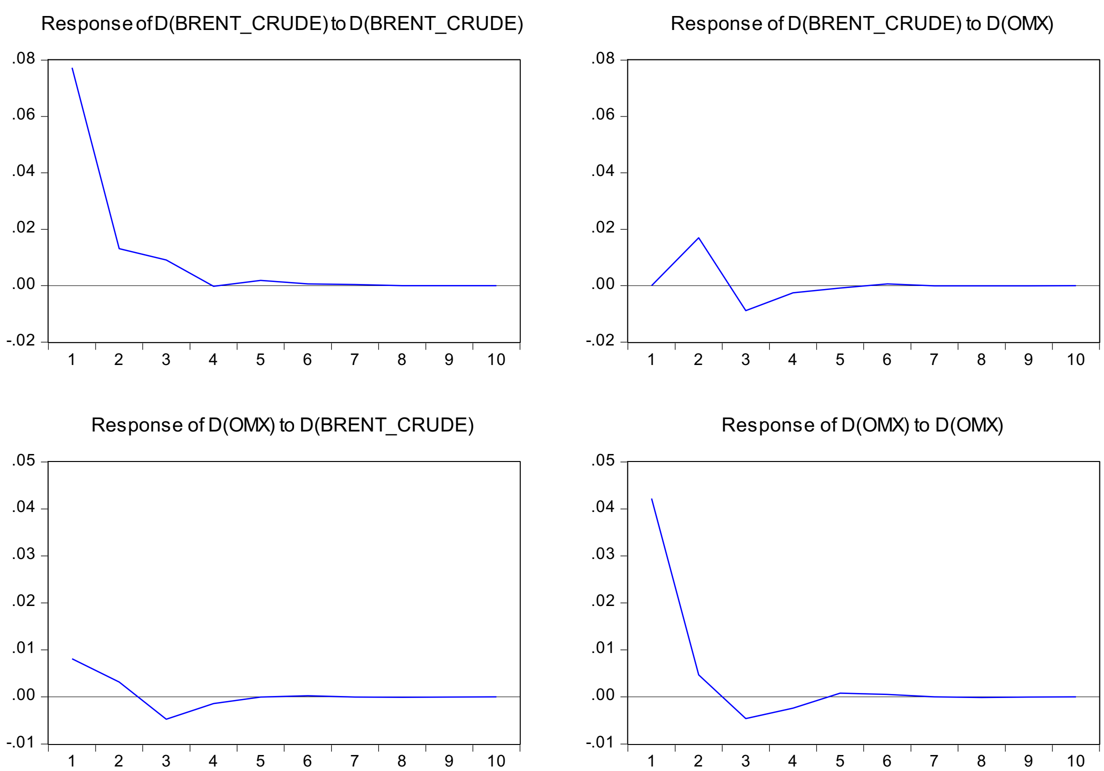

Figure 4. Response *to Cholesky Decomposition*

The charts above show the level of response to shocks in either oil price or stock market index. As can be seen from the first chart, there is a positive response, which is immediate, to shock in the Brent crude oil. The second last chart also indicates that stock price respond immediately and positively to shock in the Brent crude oil. However, the response turns to negative before gradually stabilizing at a neutral value. Similarly, Brent crude oil also responded positively to shock in the stock market index. However, the response is gradual and not almost immediately. In essence, shocks to the stock market index seem not to significantly move the oil prices while shocks in the oil prices significantly and immediately move the stock market index.

The result confirms that price of oil moderates the stock market index in the Nordic market, which directly answered the second hypothesis of the current research study. In essence, the oil price positively affects the Nordic stock market, that is, a positive change in oil prices increases the index's value. However, the impact will revert towards zero and die out after some time, not long (within the fourth period or month). This implies that the impact on the Nordic stock price index does not last more than four months. However, before the fourth month, the impact often turn negative, that is, reduces the value of the stock market index.

6.8. Variance Decomposition

The variance decomposition was estimated on the developed VAR model, and an output of the results is presented in Appendix E while the table below summarizes the results for the shock caused by the oil prices.

Period	S.E.	D(BRENT CRUDE)	D(OMX)
1	0.077253	100.0000	0.000000
2	0.080175	95.51957	4.480435
3	0.081179	94.43654	5.563463
4	0.081218	94.34510	5.654901
5	0.081244	94.33768	5.662324
6	0.081249	94.33201	5.667993
7	0.081250	94.33212	5.667876
8	0.081250	94.33202	5.667978
9	0.081250	94.33196	5.668036
10	0.081250	94.33196	5.668037

Table 9. Variance *decomposition of Brent Crude*

The table above indicates the results of the variance decomposition of Brent Crude variable on itself and the Nordic stock market index (OMX). As indicated in the table above, in the short run, that is, period 2 (second month), the impulse or shock to the Brent crude accounts for 95.51957% of the variation of fluctuation in Brent crude (oil price), that is, own shock. In the third month, the shock in oil prices causes 94.43654% of its own variation, which tends to stabilize around this figure for the remaining months that followed. However, in the short run, shock in the value of stock market index can cause only 4.480435% variation in the oil prices, which is a considerably small effect. In the subsequent months, the variations tend to stabilize at about 5.6%. In essence, in the long run, the shock to stock market index causes only about 5.6% variations in the oil prices. The results indicate that shock to stock price index cause little variations in the oil price. However, shock in oil prices causes moderate own variations. The table below summarizes the variance decomposition of the Nordic stock market index (OMX).

Period	S.E.	D(BRENT CRUDE)	D(OMX)
1	0.042986	3.547692	96.45231
2	0.043358	4.020119	95.97988
3	0.043861	5.096879	94.90312
4	0.043948	5.182573	94.81743
5	0.043955	5.181053	94.81895
6	0.043959	5.183482	94.81652
7	0.043959	5.183617	94.81638
8	0.043959	5.183786	94.81621
9	0.043959	5.183810	94.81619
10	0.043959	5.183811	94.81619

Table 10. Variance *decomposition of OMX*

The table above indicates the results of the variance decomposition of Nordic stock market index (OMX) variable on itself and the Brent Crude. As indicated in the table, in the short run – the first month, a shock to oil prices causes about 3.547692% of variations of the Nordic stock market index. In the second month, it causes approximately 4.020119% of variations in the stock market index and conversely, in the first month, a shock to Nordic stock market index can explain about 96.45231% of its own variation. In the second month, the value is 95.97988%. The figure above implies in the short run, shocks to oil prices do not cause huge variations in the value of the Nordic stock market index.

In the long run, however, shocks to oil prices cause 5.183811% variations in the value on the Nordic stock market index. In comparison, the shocks have a greater impact in the long run. Also, in the long run, shocks to oil prices causes approximately 94.81619% of its own variation (own shock), which is considerably high. In essence oil price shocks tend to have a lasting effect on itself. In essence, the level of the impact is almost the same in both the short and long run. In essence, the result of the variance decomposes directly tested the third hypothesis with a conclusion that there is no significant effect of oil price shocks in the long run.

6.9. Chapter Summary

In summary, the chapter has provided the results of the statistical analysis that were conducted using the pre-specified methodology to answer the research questions. VAR was the main model chosen for analyzing the impact of oil price changes have on the Nordic stock market index, which was measured by Brent crude and OMX respectively. However, before VAR modeling, data was to be tested for seasonality and cointegration. The ADF test indicated the presence of unit roots while Johansen test indicated the presence of cointegration. Thus, data were first differenced to remove seasonal factors before applying the VAR model, which indicated a moderate positive effect of oil prices. In-depth discussion of the results obtained is presented in the next chapter.

7. DISCUSSION

This section presents an insightful discussion of the results of the statistical analysis providing the empirical evidence as outlined in the previous section. In discussing the results, the aim is also to put them into context with the results of other related previous studies as outlined in the literature review section. Lastly, this chapter tries to assess the main reason for the results that have been established.

The VAR model has clearly indicated that there is a moderate effect of shocks in oil prices to the Nordic market. Going by the percentage change, the magnitude of the impact is not huge though it is immediately felt in the market. In essence, the analysis has indicated that shock on oil prices immediately causes an increase on the Nordic stock market index which subsequently changes to negative before reverting to zero. Unlike the results above, other previous researchers such as Cunando and Perez (2014), Papapetrou (2001), Brose and Henriz (2014), and Park and Ratti (2008) established negative impact of oil prices on the stock market return. However, there is a notable difference between our study and these researchers because they focused on stock market return instead of the stock market index as we did here. Also, they did not use data from the Nordic market - all these factors could explain the difference in the results.

The positive effects on the Nordic stock market index were also found to be consistent with the results of previous studies by researchers Papapetrou (2001) and Chen (2010). Using data from the China stock market, Cong et al (2008) found that it has unstable positive effects on the market return, which was measured using the market index. Sadorsky (2012) on the other hand established a positive correlation between prices of oil and stocks in selected companies from the energy and technology sector. The results of these past studies potential give further support for the findings of the current study that has been established. Notably, there were few studies that have directly used the stock market index as the variable under consideration, which might greatly limit the comparability of the current results.

Notably, the current study did not find the effects on the Nordic stock market to be statistically significant - it is barely a moderate effect that does not greatly moves the market. Similar to the present study, researchers Brose and Henriz (2014), even though using stock market returns, found that oil prices do not have a statistically significant impact on the sample period. They investigated how oil impact the stock market returns from selected five Europe markets namely Spain, Italy, Ireland, Portugal, and Greece and established the same results. Notably, they used the same methodology, that is, VAR model, to investigate how oil affect these five stock markets. They also established slight positive effects. Other researchers such as Apergis and Miller (2009) also found slight positive effect using the same methodology and sample period 1981-2007 but focused on eight different stock markets.

One of the possible causes of the statistically insignificant results could be the model estimations. In essence, the model estimation may not have been optimally achieved. As explained by Brose and Henriz (2014), as Apergis and Miller (2009) and Chen (2010), the two elements namely decomposition of variance and impulse responses are very sensitive to the ordering of the variables. Thus, the ordering of the variables may have caused some level of divergence ion the significance of the impact. As explained by Cunando and Perez (2014) and Papapetrou (2001), altering the system of equations in the VAR model could also cause divergence in the significance of the results. Variable bias might also have occurred when deciding which variables to use and why. In addition, there is the possibility of measurement errors which might also affect the results significantly.

The positive impact of oil OMX index can be explained by the fact that all the Nordic countries are net importers of oil. This is possible because some researchers such as Reboredo (2012), Ajmi et al. (2014), and Brose and Henriz (2014) have shown that there is a positive impact of oil importation on given markets. In essence, the stock market responds positively to the shocks in the importation of oil. In another related study, Sadorsky (2012) also showed that the response of the stock market depends on the relative importation of the country in the global oil market. Other researchers such as Park and Ratti (2008), Chen (2010), and

Cunado and de Gracia (2014), have also argued that in oil-importing countries increments in oil prices is translated to higher costs which subsequently affect the stock markets.

In the variance decomposition analysis, it was established that in short, the shocks in the oil prices contributes the highest percentage (95.51957%) of variation to itself. Likewise, the variation in the Nordic stock market index caused by shocks in the oil prices in the short run is 4.480435%, which is relatively small. In essence, shocks in the oil prices cause only small variations in the value of the stock market index in short run but the size of variation tends to increase in the long run. In essence, the results imply that shocks in oil prices tend to have lasting effects in the Nordic stock market index. The results tend to conform to the finding by Apergis and Miller (2009) who established that oil price shocks tend to last for close to one year on the stock market.

8. CONCLUSION AND RECOMMENDATION

In this thesis, the primary goal was to determine the impacts of oil prices on stock market indexes using empirical evidence from the Nordic stock markets. There are five countries that make up the Nordic regional economic bloc namely Norway, Finland, Denmark, Iceland, and Sweden and they have their own stock markets. From these countries others than Norway are included in OMX Nordic 40 Index (althought no Icelandic companies currently feature) and the impact of oil prices on their respective stock markets have not been greatly investigated.

The main methodology of the study was the VAR model, which was chosen to help determine the nature and strength of the impact on the Nordic stock market index. Before modeling the data using the VAR method, the data were tested seasonality and cointegration using the ADF test and Johansen Cointegration tests respectively. Lastly, the BIC and AIC criteria were applied to determine the appropriate lag for the VAR model. The test indicated that lag of order 2 is appropriate for the model. To complete the VAR model, the variance decomposition and impulse response were also considered.

In the preliminary analysis, the dataset was found to have unit roots which are not desired for time series analysis such as VAR Model. In essence, the VAR model is only constructed on the non-seasonal dataset. Thus, data was first transformed by getting the first difference in order to remove the seasonal factors. In addition, the Johansen test indicated the presence of cointegration of the data.

After completing the statistical analysis Using VAR model, the results established found little evidence as to the impact on the Nordic stock market index. In essence, the study has established that there is a moderately positive impact, which essentially confirmed the second hypothesis of the study. The study found little linear relationship between the two variables which essentially answered the first hypothesis, that is, there is a correlation between oil price and the stock index in Nordic markets and even though a co-movement was identified, the impact is not statistically significant.

In addition, the study established that even though the effect is positive, that is, shocks in the oil prices increases the value of the Nordic stock market index, it subsequently changes to positive before finally reverting to zero. In essence, shocks in the oil prices first increase the OMX then decreases it and finally neutralizing at zero level or effect. In addition, it was established that the short-term effect of the oil does not last more than four months, in essence, by the fourth month, the short-term effect has reverted to zero. However, oil price shocks tend to have more significant long-term effects and the analysis also found that oil price shocks tend to have more significant effects on its own variations as compared to the variations in the Nordic stock market index.

8.1. Recommendations for Future Research

For the future research direction, it is essential to consider other specifications of oil prices that can provide a comparative analysis of the situation. For instance, it is essential to use other specifications such as the WTI oil price and compare the results with the Brent crude in order to determine whether one measure gets more significant results as compared to the other. This is possible because of the variation in oil prices caused by the different specifications of the oil.

Another recommendation for future research is to consider asymmetric specification of the oil price. This would enable the researchers to determine the effects of increases and decreases in oil prices independently. Such as asymmetric specification, it would be possible to compare the effects caused by the increase in oil prices and a decrease of oil prices. With the current specification of the variable, it was not possible to make such comparisons, yet the effects might be different depending on whether the oil prices either increased or decreased.

Another recommendation for future research is the decomposition of shocks in the oil prices in terms of factors driving it such as supply and demand among others. The present study did not consider the influence of factors causing shocks in the oil price yet they might play a significant role. In essence, future research studies in this field should incorporate the influence of factors causing fluctuation in oil prices. In particular, the influence of supply and demand for oil should be greatly considered. It is also essential to include the oil exportation level of every country as another essential influencing factor.

In addition, it is essential to consider the Nordic stock markets independently because the impact of shocks of the oil prices might vary significantly per country. Every country might have different influencing factors determining the nature and size of effects of shocks in oil prices. Therefore, treating each Nordic stock market independently would help provide a basis for comparing the effects in each country.

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APPENDICES

Appendix A: ADF test results for Brent Crude

Null Hypothesis: BRENT CRUDE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.410903	0.3721
Test critical values:	1% level	-4.037668	
	5% level	-3.448348	
	10% level	-3.149326	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(BENT CRUDE)
Method: Least Squares
Date: 11/19/18 Time: 10:45
Sample (adjusted): 2009M02 2018M11
Included observations: 118 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BENT CRUDE(-1)	-0.055179	0.022887	-2.410903	0.0175
C	0.271170	0.105744	2.564397	0.0116
@TREND("2009M01")	-0.000476	0.000230	-2.068026	0.0409

R-squared	0.059152	Mean dependent var	0.003720
Adjusted R-squared	0.042789	S.D. dependent var	0.079486
S.E. of regression	0.077766	Akaike info criterion	-2.245120
Sum squared resid	0.695475	Schwarz criterion	-2.174679
Log likelihood	135.4621	Hannan-Quinn criter.	-2.216519
F-statistic	3.615082	Durbin-Watson stat	1.690277
Prob(F-statistic)	0.030017		

Appendix B: ADF test results for OMX

Null Hypothesis: OMX has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.684570	0.2450
Test critical values:	1% level	-4.037668	
	5% level	-3.448348	
	10% level	-3.149326	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OMX)
Method: Least Squares
Date: 11/19/18 Time: 11:25
Sample (adjusted): 2009M02 2018M11
Included observations: 118 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OMX(-1)	-0.099871	0.037202	-2.684570	0.0083
C	0.684594	0.247847	2.762168	0.0067
@TREND("2009M01")	0.000506	0.000287	1.763824	0.0804

R-squared	0.081504	Mean dependent var	0.007702
Adjusted R-squared	0.065530	S.D. dependent var	0.044097
S.E. of regression	0.042627	Akaike info criterion	-3.447551
Sum squared resid	0.208964	Schwarz criterion	-3.377110
Log likelihood	206.4055	Hannan-Quinn criter.	-3.418950
F-statistic	5.102321	Durbin-Watson stat	1.755629
Prob(F-statistic)	0.007533		

Appendix C: Johansen Cointegration Test

Date: 11/19/18 Time: 11:49
Sample (adjusted): 2009M06 2018M11
Included observations: 114 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: OMX BRENT CRUDE
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.127158	18.19108	25.87211	0.3312
At most 1	0.023294	2.686970	12.51798	0.9115

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.127158	15.50411	19.38704	0.1678
At most 1	0.023294	2.686970	12.51798	0.9115

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

OMX	BRENT CRUDE	@TREND(09M0 2)
-10.47689	-1.426395	0.049568
3.234294	-3.282569	-0.032332

Unrestricted Adjustment Coefficients (alpha):

D(OMX)	0.012967	-0.001849
D(BRENT CRUDE)	0.014124	0.009176

1 Cointegrating Equation(s): Log likelihood 359.9292

Normalized cointegrating coefficients (standard error in parentheses)

OMX	BRENT CRUDE	@TREND(09M0 2)
1.000000	0.136147	-0.004731
	(0.08777)	(0.00093)

Adjustment coefficients (standard error in parentheses)

D(OMX)	-0.135849
	(0.03705)
D(BRENT CRUDE)	-0.147979
	(0.07253)

Appendix D: VAR Model Results

Vector Autoregression Estimates
Date: 11/19/18 Time: 15:05
Sample (adjusted): 2009M04 2018M11
Included observations: 116 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(BRENT CRUDE)	D(OMX)
D(BRENT CRUDE(-1))	0.127640	0.029303
	(0.09466)	(0.05267)
	[1.34836]	[0.55631]
D(BRENT CRUDE(-2))	0.112056	-0.056898
	(0.09308)	(0.05179)
	[1.20382]	[-1.09855]
D(OMX(-1))	0.401994	0.111396
	(0.17045)	(0.09484)
	[2.35842]	[1.17453]
D(OMX(-2))	-0.306129	-0.133680
	(0.17099)	(0.09514)
	[-1.79031]	[-1.40502]
C	0.001204	0.008584
	(0.00742)	(0.00413)
	[0.16220]	[2.07873]
R-squared	0.099833	0.044540
Adj. R-squared	0.067394	0.010109
Sum sq. resids	0.662456	0.205103
S.E. equation	0.077253	0.042986
F-statistic	3.077607	1.293590
Log likelihood	134.9959	202.9973
Akaike AIC	-2.241308	-3.413747
Schwarz SC	-2.122619	-3.295058
Mean dependent	0.003176	0.008251
S.D. dependent	0.079996	0.043205
Determinant resid covariance (dof adj.)		1.06E-05
Determinant resid covariance		9.74E-06
Log likelihood		340.0882
Akaike information criterion		-5.691177
Schwarz criterion		-5.453798

Appendix E: Variance Decomposition

Period	S.E.	D(BRENT CRUDE)	D(OMX)
Variance Decomposition of D(BRENT CRUDE):			
1	0.077253	100.0000	0.000000
2	0.080175	95.51957	4.480435
3	0.081179	94.43654	5.563463
4	0.081218	94.34510	5.654901
5	0.081244	94.33768	5.662324
6	0.081249	94.33201	5.667993
7	0.081250	94.33212	5.667876
8	0.081250	94.33202	5.667978
9	0.081250	94.33196	5.668036
10	0.081250	94.33196	5.668037

Period	S.E.	D(BRENT CRUDE)	D(OMX)
Variance Decomposition of D(OMX):			
1	0.042986	3.547692	96.45231
2	0.043358	4.020119	95.97988
3	0.043861	5.096879	94.90312
4	0.043948	5.182573	94.81743
5	0.043955	5.181053	94.81895
6	0.043959	5.183482	94.81652
7	0.043959	5.183617	94.81638
8	0.043959	5.183786	94.81621
9	0.043959	5.183810	94.81619
10	0.043959	5.183811	94.81619

Cholesky Ordering: D(BRENT CRUDE) D(OMX)