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PERFORMANCE EVALUATION OF THE SEISMIC AND SURF MARKET WITH EMPHASIS ON RELATION TO OIL PRICE

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Master thesis Industrial Economics 2020

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Preface

This thesis completes my master's degree in industrial economics at the University of Stavanger with specialization in investment and finance. The master's degree builds on my previously earned master's degree in marine hydrodynamics from the Norwegian University of Science and Technology (NTNU) and work experience from PGS and Subsea 7 representing two companies in the Norwegian oil-service sector.

The motivation behind the selected topic was raised by colleagues in sales and marketing. Based on a discussion it was found interesting to evaluate the effect of the current crude oil price and the performance of the SURF and geophysical industry. The theme is very relevant given the distress the oil service industry has been in from 2014 to 2020 and also when looking at the potential effects the 2020 Covid-19 virus would have on the oil-service sector with respect to market outlook and performance.

I would like to express gratitude to the people working in Subsea 7 for giving me great support and assistance during this thesis. Also, I would like to thank Janne Haarseth for all the support she has provided at home while pursuing this master's degree. I also want to send my gratitude to my mother, father and my family for supporting and motivating me through the years of studies in Stavanger.

Tore Jacobsen

Tore Jacobsen 10.06.2020

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1 SUMMARY

The commodity price of oil is strongly influenced by supply and demand. Oil service companies which in this thesis have been limited to contain key players from the seismic/geophysical and SURF (**S**ubsea **U**mbilicals **R**isers and **F**lowlines) sector, both have performance indicators that are strongly correlated to the commodity price of oil. The demand for seismic in the short term depends on changes in the oil price and the exploration companies' free cash flow. When oil prices decline and free cash flow is reduced, it is well known in the industry that investment in geophysical exploration is one of the first to be reduced as new petroleum reserves in the short term are perceived as a normal good. In the long run, however, seismic data is a necessity for maintaining oil and gas production and it also required for performance monitoring of existing reservoirs.

In multiple annual reports & capital market presentations by the major geophysical and SURF companies listed on Oslo Børs, vessel continuity and revenues are typically explained by the volatility of the oil price. In this master thesis, this coupling has been tested by extracting share-prices for different companies and comparing them to the Brent oil price. The oil price is as mentioned earlier strongly dependent on the supply and demand dynamics in the market. The geophysical market is often exposed to external market-shocks and due to low alternative use; build-up of excessive short-term overcapacity can occur. Recent developments have shown that geophysical companies have decided to either cold or hot stack several vessels. A similar pattern can also be observed in the SURF industry.

According to the PGS annual report 2019, year 2015-16 saw the most severe downturn in the oil service industry for decades. Supply side significantly reduced through scrapping/retirement and cold stacking of the least efficient vessels and hence the active 3D seismic vessel fleet was reduced by 50%. According to PGS, substantial CAPEX was required (above 50MUSD) to bring stacked vessels into service as seismic equipment/streamers generally had been distributed to other active vessels. In this period, the industry changed significantly and moved toward the Multiclient business model (chapter 7.1). This trend continued in 2018 towards 2020. At the start of 2020, WesternGeco announced a plan to exit the marine

acquisition market and, after the summer, Shearwater acquired their assets. A few months later, CGG communicated their plan of becoming asset light. A similar pattern also occurred in the SURF industry with large mergers and consolidations being formed after 2015 in order to adapt to the market. McDermott (6.1.2) filed for chapter 11 in 2018, and some smaller actors decided to leave the industry. To some investors this was surprising as the oil-price had gradually recovered in the period from 2016 to 2020.

On the positive side on medium term, further offshore exploration is most likely required to meet future demand as there is declining oil and gas reserves (chapter 10). In addition, cost reductions of the industry have decreased break-even oil price (Equinor ASA, 2018) and when combined with high oil-prices, E&P companies are generating substantial available cash flows and are well positioned to increase spending giving that demand in the long-term increases. Intuitively the oil business is strongly impacted by the price of oil because the price of oil is the main driver for increased revenue by oil service providers. However, oil service providers do not typically influence the oil-price and therefore it is not given that also stock prices rise with increased oil-price. In the case of E&P companies, they typically pay dividends to investors and it can therefore be argued that an oil-price increase will create expectations for higher dividends due to higher probability. Therefore, the relationship between the stock price of a E&P company and the oil-price should be stronger compared to oil-service providers.

However, in the long term, there is uncertainty about the need for seismic and subsea developments in light of technological and structural shifts to alternative energy sources. The speed of the "green shift" means that geophysical and SURF companies 'long-term growth potential by many are considered to be limited. In this thesis it sought to show that both geophysical and subsea contractors stock-price in many cases can be directly correlated to the development in the oil-price. However, as mentioned capacity restrictions can potentially shift the correlation on a case-by-case basis.

2 INTRODUCTION

According to (Cooper, 2003) (Beidas-Strom & Pescatori, 2014) and the annual reports of PGS and Subsea 7 from 2018-2019; companies in the geophysical & SURF industry face market risks such as currency exchange risk, credit risk, liquidity, commodity price and interest rate risk. Typically, a company will have a mixture of fixed and floating interest rates and use financial instruments (hedging) to manage risk of interest rate and currency exchange variations. Commodity risk can be substantial for geophysical and SURF companies as they typically are directly exposed to fuel price variations and it can also be assumed that the clients of the two sectors investment budgets are correlated to the oil price. Regarding the fuel-price, as stated in PGS annual report 2019, a 10% increase in fuel prices would increase the total fuel costs by $3-10 million per month. Companies are therefore constantly seeking to forward fuel price risk to customers on contract work.

Demand for geophysical products and services & subsea field developments, depend on E&P company's budgets on hydrocarbon-resource exploration, field development, and production. Spending levels are heavily influenced by oil and gas prices and the current business key focus areas. In addition to the risk of less demand, companies face risk as increased competition, changes in governmental regulations affecting the markets, technical downtime, licenses and permits to work, and operational hazards such as weather conditions. Contracts for services are occasionally modified by mutual consent and in certain instances may be cancelled by customers on short notice without compensation. The latter is more common the geophysical industry than in the SURF industry as geophysical contracts typically are less in duration and magnitude (chapter 7).

Most researchers studying the relationship between stock-prices and oil price, have similar conclusions – many stock prices are correlated with oil-price, even though the indexes, methods and segments are different. The magnitude of correlation depends whether a country is an exporter or importer of oil and some authors (Thenmozhi & Srinivasan, 2016) conclude that the oil price and stock indexes of the big oil-importing countries are affecting each other in the long- and medium-terms, but not over short periods. Contrary, Phan, Sharma and Narayan (2016), argue that stocks react much faster to oil price changes than consumers of oil. Also, they found that if the firm's size increase, the sensitivity to crude oil price became stronger. (Patton, 2016) argues that relationship between oil price and company stock price are statistically significant and is more sensitive than companies which are less related to oil production.

(Asche & Dahl, 2017) conclude that the price of oil has a much bigger impact on Norwegian oil companies belonging to the Operator or drill-and-well sectors, but other Norwegian companies operating in the oil service industry will feel much less impact. In addition, the same author concluded that it seems that whether the oil price negatively or positively influences countries' stock price indexes, depends on whether the countries are net-producers or consumers of petrochemical products. The E&P producer stock prices are impacted positively by oil price, but the magnitude (Segal, 2011) of the positive correlation depends on which oil segment company operates within. In this thesis only companies listed on Oslo Børs that are Oil service providers are examined, but it should be noted that the companies further described in this report are international companies with operations and developments all across the world.

In this thesis the correlation of major oil-service providers within the geophysical aspect and subsea field development (SURF) aspect will be compared to the oil-price. Also, the E&P company Equinor has been included for further reference where the objective is to establish relationships on stock closing prices obtained by selecting a portfolio of representative companies listed on the Oslo Børs stock exchange. To be able to perform a comparison, this thesis is split into a description of the historical behavior of crude oil prices (chapter 3), an introduction to seismic acquisition (chapter 4), the supply aspect of the geophysical market (chapter 5), introduction of the SURF business segment of the oil-service market (chapter 6) and then a comparison on stock-price development compared to the oil price are given in chapter 8 & 9 by the use of Python scripting.

3 CRUDE OIL PRICES

The majority of financial analytics generally agree that price of stocks and crude oil can relate to each other in some respect, but there are arguments on whether the oil price has positive, negative and sometimes neutral impact on the economy or stock market value. Many authors state that the trend direction of correlation depends on the country's economic relationship to oil production (Wang, Wu, & Yang, 2013). Typically for companies listed on Oslo Børs, this hypothesis can be examined as many companies have a strong relationship to the E&P industry.

When it comes to the fluctuations in oil price, Figure 3-1 below can be useful to plot the behavior as function of key global events in the duration from 1985 to 2012.

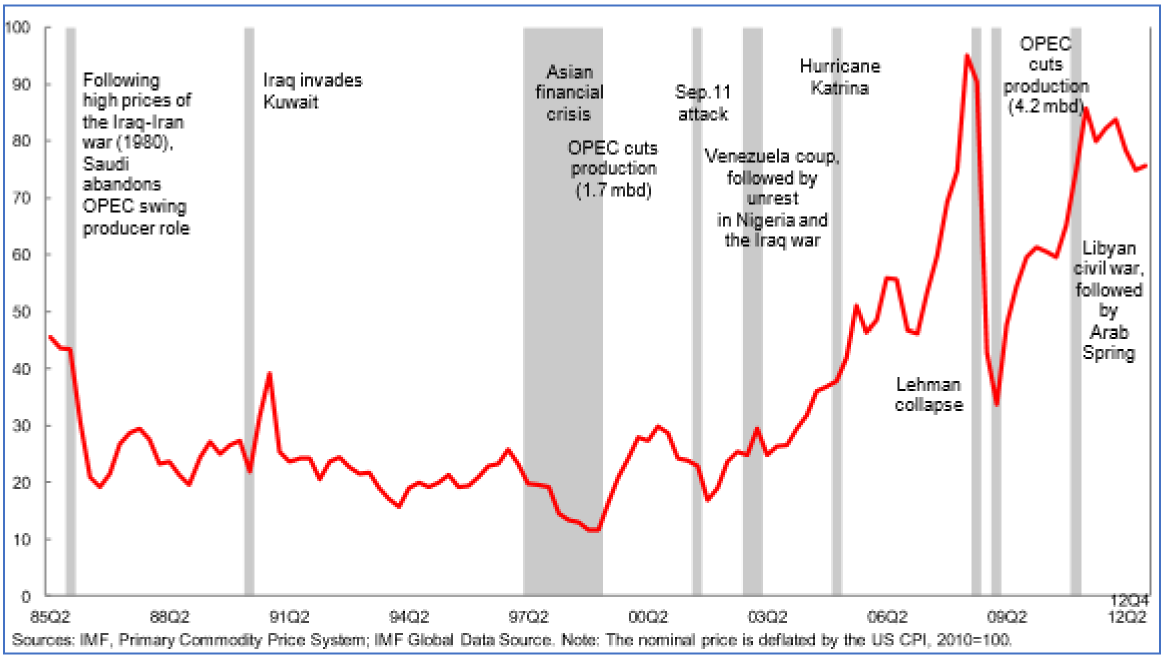

Figure 3-1 Oil-price behavior as function of major events

From the figure we can see that in the 1980s , there seems to be a strong correlation with global oil price's fast increase or decrease with wars occurring in Iraq and Iran. From the figure it can also be seen that when the financial crisis hit in 2008-2009 the price decreased steadily followed by a large cut in production by OPEC which gave a rise in prices. Unfortunately, the graph did not show the second crash in mid-2014 when prices fell from over $100 per barrel to around $20 per barrel but this is shown in Figure 3-3.

Figure 3-1 show the oil-price as function of key external events, but we should also have a look at the internal supply and demand that affect the market. The figure below shows demand and supply balance until end of 2016. From the figure we can observe that prior to 2014 demand exceeded supply which gave a steadily increasing oil-price Figure 3-3 in the same period. When supply started exceeding demand in the period from 2014 to 2016 the oil price started to decline.

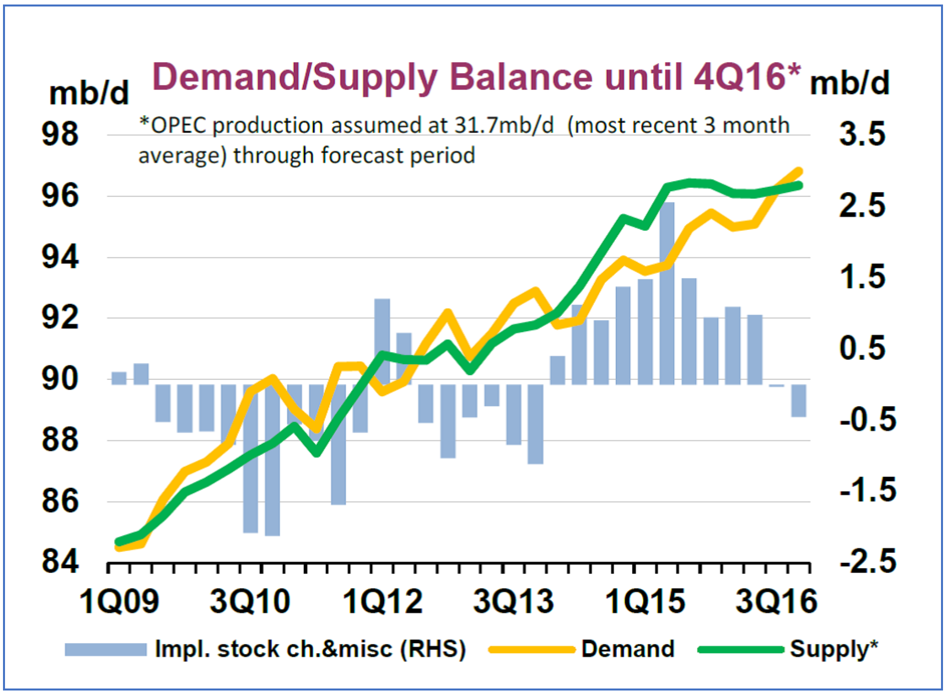

Figure 3-2 IEA ((The International Energy Agency, 2015)) demand and supply balance of Oil

Figure 3-3 Crude oil price (USD) from 2009 to 2016

Oil price movement is a key indicator for investors and financial managers due to negative or positive correlation between commodity price and companies stock prices. For instance, it was observed after for the latter period from mid-2014 that the majority of US stock-prices were also falling following the course of the oil price (Ghouri, 2006). This was a development much commented in financial media as it to some extent was unexpected. The usual assumption is that a decline in oil prices is positive for the economy for net oil importers like the united states and china were prior to 2019. An example of this can be seen in the papers provided by Mike Patton. According to (Patton, 2016) the figure below shows oil price volatility and Dow Jones industrial average from December 26, 1990 to January 25, 2016. The data illustrates to some extent whether or not oil price impacts influence the Dow Jones average stock price volatility.

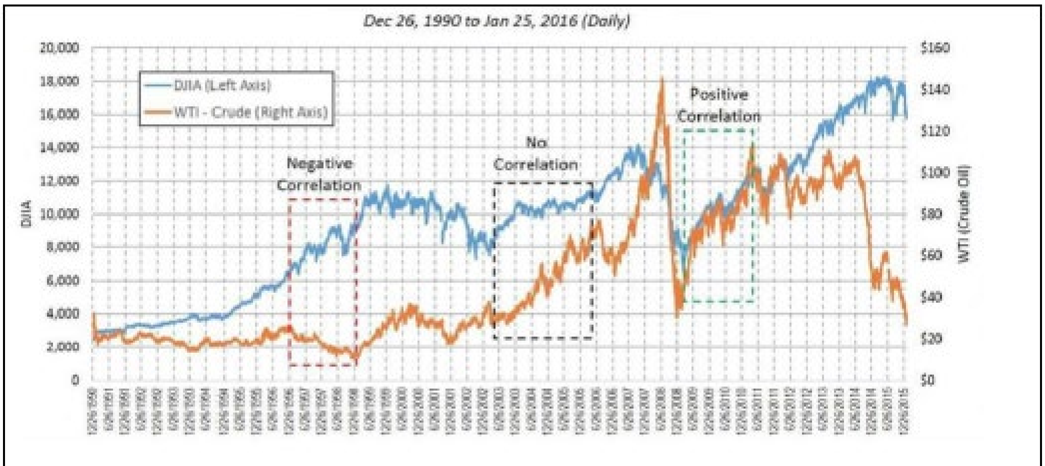

Figure 2. Dow Jones Industrial Average price and Crude oil price

Source: Patton (2016).

Figure 3-4 Correlation between WTI crude and Dow Jones Industrial Average (Patton, 2016)

The above figure shows correlation trends when comparing oil price to the Down Jones Industrial average price. It is hard to determine what impacted the first two correlations, but the last correlation, which shows positive correlation was impacted by oil because of fast oil price increases, increased oil companies' profits and that probably increased company's stock price (Patton, 2016).

4 GEOPHYSICAL SEISMIC METHOD

Seismic exploration are methods for mapping and finding petroleum's resources and can therefore be considered as the first step in the E&P value chain when rock formations are surveyed for possible petroleum deposits. Being the first step in the value chain, the seismic industry is exposed to high volatility .

Occurrence of petroleum starts when a trap allows deposition of gas, condensate or oil. These below ground traps occur where a permeable reservoir rock is covered by some low permeability cap rock. This combination of rock can take several forms, but they all prevent the upward migration of oil and natural gas up through the reservoir rock. Once oil and natural gas are in the reservoir rock, they continue to migrate upwards through the pore spaces of the rock until blocked by some sort of seal with a cap rock the low permeability cap rocks are generally shale or low permeability sandstones and carbonate and these can be found by seismic surveys. The two typical ways of performing offshore seismic acquisition is by using streamers and large offshore vessels, or by using ocean bottom seismic solution.

4.1 Offshore towed streamer acquisition

In an offshore seismic survey, white noise pulses are emitted into the rock formations below the seabed. This involves a large number of people and equipment are deployed to acquire the data. The white noise is generated by seismic canons shooting at intervals of approximately 5-10 seconds. The sound waves are reflected back to sensors that are either placed on the seabed or towed behind a seismic vessel in the form of streamers typically containing hydrophones. Streamer can be 5-10km long depending on the survey location and depth. In 2D surveys only 1 streamer is used, whereas in 3D seismic up to 15 streamers can used according to (PGS, 2018).

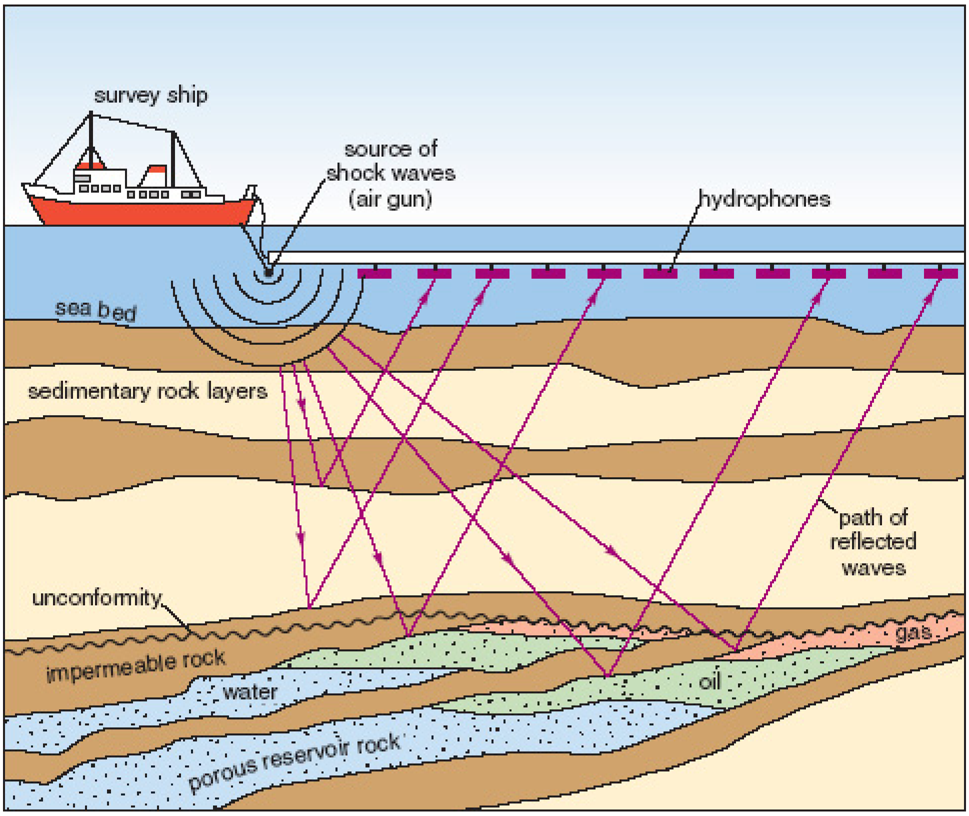

Figure 4-1 Seismic imaging (Courtesy of PGS)

There are several categories of seismic surveys namely 2D,3D and 4D surveys (NPD, 2018).

- In 2D surveys, the data are collected by a single sensor cable. This provides a relatively low-resolution image of the underground and is used for reconnaissance in new exploration areas.
- In 3D surveys, seismic data are collected by several parallel sensor cables, providing a three-dimensional and more detailed image of the subsurface. This is used in the exploration/appraisal phase.
- 4D surveys consist of repeated 3D surveys of the same area in order to detect any changes in a reservoir over time as a result of production or injection. These surveys are conducted in producing fields (the fourth dimension is time).

The collected data is typically processed onshore by the use of large data-clusters and is typically delivered in the tree different ways as described above. 2D seismic gives a coarse image of the subsurface while 3D seismic provides more detail. 4D seismic reveals changes in the subsurface reservoir as a function of time.

Independently of the survey format, the data are collected through a gun-string firing compressed air wave during 5-10 second intervals and streamers collect the reflected wave paths as shown in Figure 4-1 and Figure 4-2.

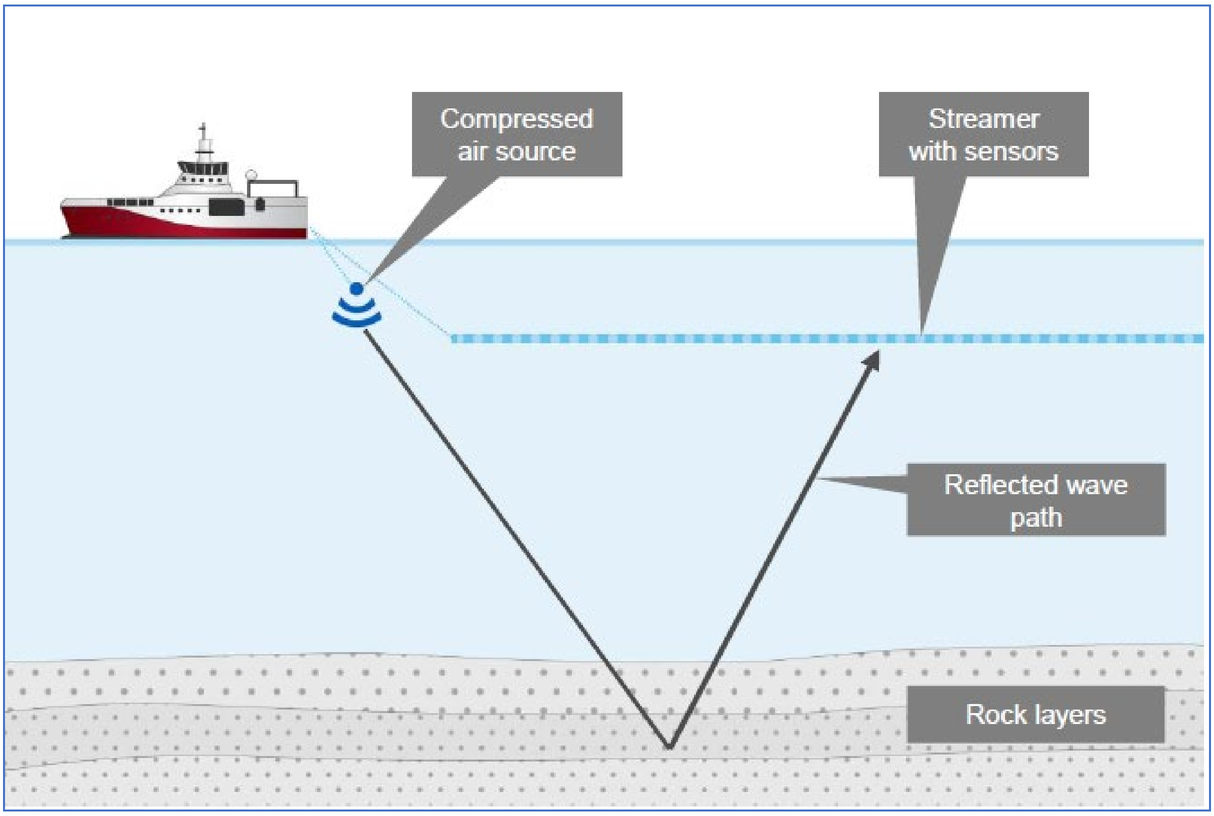

Figure 4-2 Typical setup for an offshore seismic operation with towed gun-arrays and streamers (Courtesy of PGS)

Image quality is a key performance criterion for seismic imaging jobs. The criteria can be based on number of data-points, measurement inaccuracy, number of dimensions and level of detail. Accurate data, rich in both low and high-frequency information, can be used to estimate acoustic properties such as impedance. This allows data scientist to discern the rock properties and fluid content of potential reservoirs. An example of the importance of image quality can be made of the Edvard Grieg discovery (Johan Sverdrup). The exploration team at Lundin believed that the Utsira High in the North Sea had potential. Drilling and exploration had been taking place here since well number three on the Norwegian shelf, with no particular success. But then, Lundin Norway found Edvard Grieg in 2007. With improved seismic imaging, Lundin were able to find Johan Sverdrup with expected resources totaling 2.2 – 3.2 billion bbls of oil. This field is among the largest on the Norwegian shelf and this discovery was partly made possible due to almost half a billion investment in streamer technology which with Broadseis indicated a major oil-trap. A image showing the development in streamer technology is shown in the figure below.

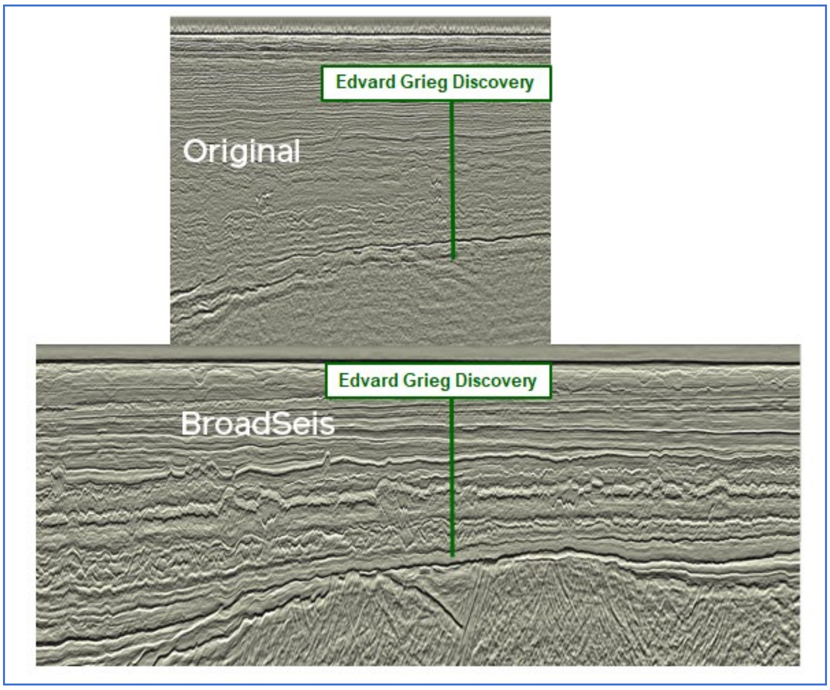

Figure 4-3 Broadseis of Johan Sverdrup field. Courtesy of PGS

Companies like PGS have invested heavily in R&D on further enhancing stream technology. One of the biggest competitors to towed streamer acquisition is Ocean Bottom Nodes (chapter 4.2)

4.2 **Ocean bottom nodes**

Ocean-bottom node (OBN) surveys decouple the source from the receivers (streamers). In other words, these nodes can be put on the seabed and no gun-string needs to be fired as required on streamer surveys. This allows for flexibility in ways surveys are designed and executed and it is claimed that this can also provide better illumination of the seabed. It is also claimed that noise is removed from datasets, high sampling and fold. The fold is the number of traces that are collected within a single subsurface bin and it is sought to make the traces between the source and receiver as wide as possible to improve illumination of the bin.

It is also claimed that OBN acquisition is more flexible in areas of infrastructure as it is not required to navigate a streamer vessel with a long streamer-spread attached to it. This allows for better receiver position and illuminating areas that are typically not reachable for marine streamer acquisitions. Also, efficiency is key in the discussion between streamer seismic and ocean bottom nodes. It is claimed that deployment and recovery of nodes can be more efficient than streamer seismic in many fields as it is known that deploying an offshore streamer set can take several days. However, for larger survey areas streamer seismic will most likely be more efficient. Also, streamer based geophysical companies claim that battery lifetime of nodes can sometimes provide issues for the seismic acquisition.

The key customers of ocean bottom seismic claim that more and more surveys will be conducted with the use of Ocean Bottom Nodes, and both Total and Shell predict that Ocean Bottom Nodes will perform 50% of all offshore seismic within the next 10 years (Walker, 2018). So even though there are some differences between conventional seismic acquisition with towed streamers and ocean bottom nodes, they are present in the same geophysical market.

Figure 4-4 A manta nodes placed on seabed (Seabed Geosolutions)

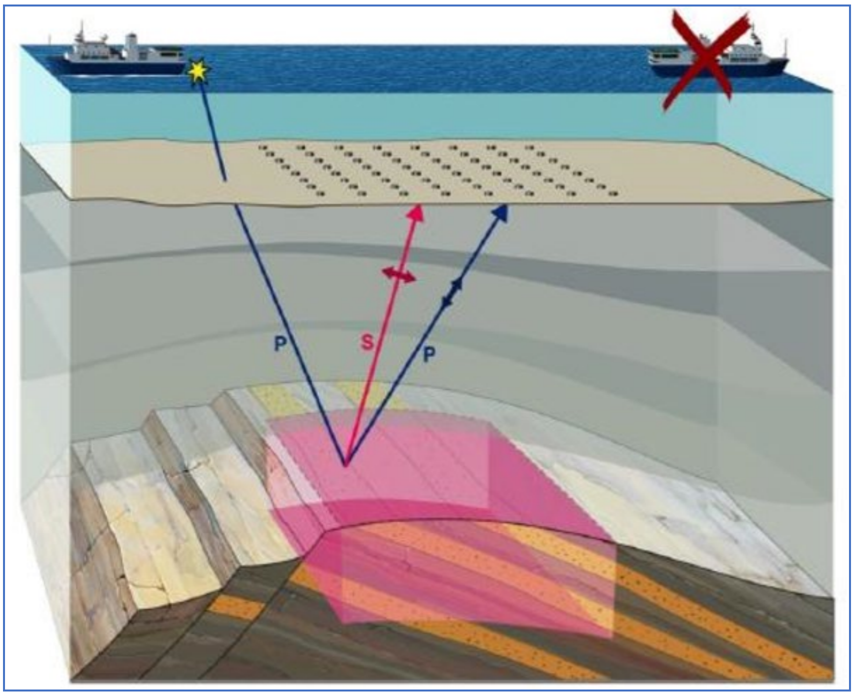

Figure 4-5 Ocean Bottom nodes without need for separate gun-vessel (Geonunes)

5 SEISMIC MARKET

As mentioned earlier, seismic surveys are the primary tool an oil company would use when exploring for new hydrocarbons. Not only does it increase the exploration success thus reducing risk, it allows operators to monitor already discovered reservoirs through time. The principle behind seismic survey is reflective seismology, i.e. a generated shock / acoustic wave that travels into the earth, is reflected by the earths rock and returns to the surface where it is recorded and measured by a receiving streamer (chapter 4). Shock waves are generated by either explosives, specialized vibration vehicles/plates or more commonly air-guns powered by a compressor.

By analyzing the required time for seismic waves to travel between the rock formations and the surface, geophysicist can utilize sophisticated software to allow the creation of subsurface maps. These maps provide an indication of where hydrocarbons may be, as well as provide details on the structural geology of the area explored.

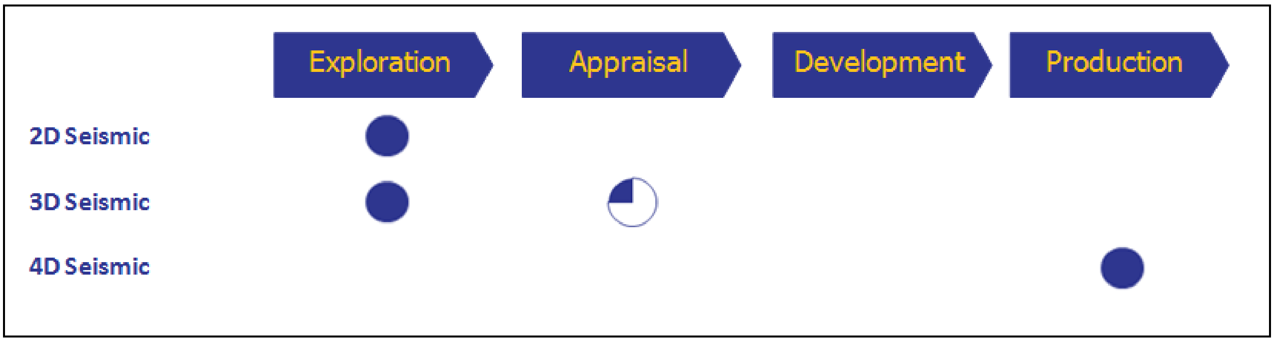

Figure 5-1 Reservoir lifecycle and acquisition method (PGS annual report 2019)

As previously mentioned, seismic could be offshore and onshore in multiple dimensions. The output of 2D seismic is a single graphical representation of the rock. 2D is used when collecting large areas of data and 3D survey is not economically viable. When the data is obtained using 3D seismic, it is displayed as a three-dimensional cube that can be viewed in multiple directions, to allow further detailed analysis of the reservoir. As such, added details helps to reduce the uncertainty 2D seismic surveys present. 4D seismic is a standard 3D survey with time interval as a 4th dimension. Comparing data over time provides increased understanding of the reservoir’s behavior and historical changes and aid to provide clarity on its future conditions and performance.

In all seismic surveys accurate positioning is key to acquiring data (IAGC, 2011). Without knowing the exact time and position from where the data originated, acquired information is of little use. Positioning is done using differential GPS (DGPS) to ensure precise positioning, as well as various software and offset data points.

Conducting offshore seismic surveys in shallow water or transition zones, by far, is the most challenging application (IAGC, 2011). Finding a vessel large enough to accommodate all required equipment and personnel, yet with a small enough draft to operate in the waters is a particular challenge. Using barges or shallow draft vessels reduces stability of the vessel, thus increases inaccuracy / quality of acquired data. This may lead to selection of different equipment or a combination of instruments to conserve space, weight and provide more reliable data.

The methodology of survey largely remains the same, both onshore and offshore. Predefined lines are set at appropriate spaces and lengths and each line is surveyed before moving to the next. For both onshore and offshore seismic acquisition 2D seismic is a relatively low-cost activity costing significantly less than both 3D and 4D seismic surveys.

The seismic market is perceived as cyclic and volatile. Prior to the 2009 financial crisis, when the oil-price was increasing, the majority of companies had a solid revenue and severe plans for future expansion. Post the financial crisis and the oil-crisis in 2014 the majority of companies in the segment experienced a decline in demand and also high financial obligations for the companies owning their own vessels such as PGS.

According to the PGS annual report 2019, 2014-17 saw the most severe downturn seen in the oil service industry for decades. Supply side significantly reduced through scrapping/retirement and cold stacking of the least efficient capacity. The active 3D seismic vessel fleet was reduced by 50%. According to PGS substantial CAPEX is require (above 50MUSD) to bring stacked vessels into service as seismic equipment/streamers generally have been distributed to the active vessels. The seismic equipment is quite comprehensive since both gun-umbilicals and streamers are space and weight intensive. Also, onboard processing equipment is challenging to move from vessel-to-vessel.

In the period after 2014, the industry has changed significantly and moved toward the MultiClient business model (chapter 7.1). This trend continued in 2018 towards 2020. At the start of 2019, WesternGeco announced a plan to exit the marine acquisition market and, after the summer, Shearwater acquired their assets. A few months later, CGG communicated their plan of becoming asset light. Following these strategic moves, PGS is perceived as the only fully integrated offshore seismic company according to PGS (PGS, 2019)).

The decline after the downturn in 2014 can easily be seen by the number of seismic streamers in operation as shown in the plot below. From the figure, it can be seen that the number of seismic streamer capacity are approximately 50% lower than the capacity in 2013.

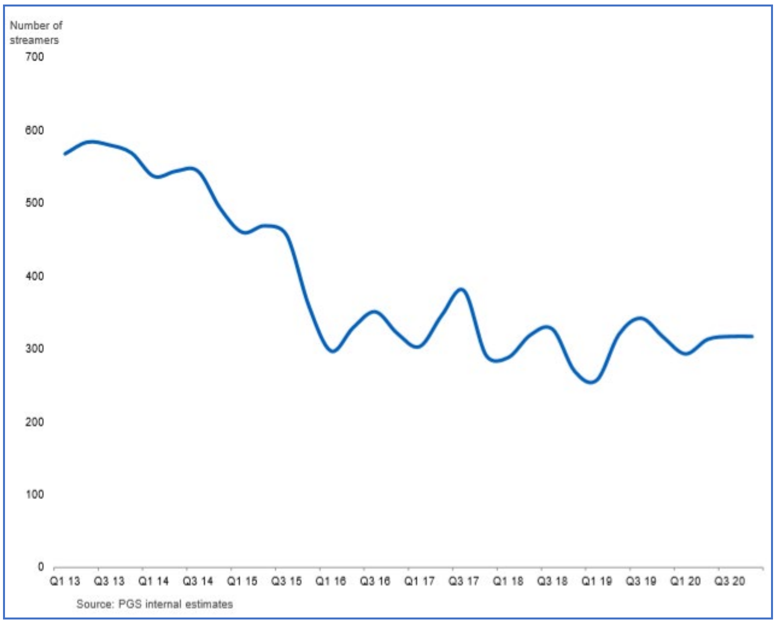

Figure 5-2 Streamer capacity from 2013-2020 (PGS annual report 2019)

5.1 **Key market players**

Both offshore and onshore seismic survey services are dominated by major service companies such as PGS, Shearwater and Polarcus. These companies control more than 90% of the offshore seismic supply. There are less than 50 active vessels operating worldwide, down from circa 140 in 2013, with different capabilities and geographic location. Majority of the vessels are owned by Shearwater and PGS.

5.1.1 Shearwater

Shearwaters is a global provider of geophysical marine acquisition and processing services (Shearwater, 2020). The company was originally established in 2016 as a joint venture by Rasmussen group and GC Rieber shipping, but now also has supportive owners as Schlumberger and Eidesvik Offshore. Schlumberger's WesternGeco was the world's biggest offshore seismic company measured in revenue of multiclient sales and fleet capacity in 2017. Shearwater and CGG entered into an agreement in 2019 to acquire 5 high-end seismic acquisition vessels and in 2020 Shearwater had a fleet of 23 vessels.

Figure 5-3 Shearwater Geoservices vessel Vespucci in transit

5.1.2 Petroleum Geo-Services ASA (PGS)

PGS is a Norwegian geophysical company based on Lysaker and started in 1991 when consolidating Precision Seismic and Geoteam. The company has of 2020 925 employees onshore and 470 employees offshore. The active fleet of PGS consist of eight 3D vessels that are active in both multiclient and contract acquisitions.

The main differentiator for PGS compared to other geophysical companies is based on technology. They are the only seismic company who still has a R&D department and differ quite extensively from Shearwater and TGS who subcontract R&D (PGS, 2019). PGS have also developed their own streamer technology called GeoStreamer which has been very successful.

Figure 5-4 PGS Ramform Atlas

5.1.3 CGG AS

CGG is a French seismic company established in 1931 with approximately 5100 employees. In 2007, when CGG acquired the Veritas group, it became one of the world's leading seismic companies. In the last 7 years, the Group's headcount has fallen drastically from 9,600 people at the end of 2013 to around 5,000. This major and unprecedented industry crisis led to a financial crisis for CGG, resulting in having to enter into chapter 11 proceedings in 2018. In this respect CGG is no longer a key market player related to seismic exploration but still have multiclient sales and imaging capabilities.

Figure 5-5 CGG leasing a Eidesvik vessel for a seismic survey in 2018

5.1.4 Polarcus Limited

Polarcus is based in Dubai, UEA and was listed on the Oslo Børs stock exchange in 2009 with a new-build program of seven new geophysical vessels. As of 2020 the market share of Polarcus is around 20% of the active 3D high-end seismic global fleet and around 500 employees. Multiclient sales consist of typically 20-30% of annual revenue.

Figure 5-6 Polarcus Amani Seismic research Vessel

5.1.5 Multiclient geophysical (MCG)

MCG was founded in 2007 as a company that should specialize in geophysical evaluation of multi-client data. The main business area is 2D and 3D surveys reprocessing data and in the business model the company does not own any vessels. Since the business principle if to buy data and processing capabilities externally, MCG claim that they have a strong business strategy during times of a weakened seismic market.

Figure 5-7 The S/V Nordic Bahari leased by MCG

5.1.6 Magseis Fairfield (MSEIS)

Magseis Fairfield is one of the industry leaders in ocean bottom nodes (Ocean bottom nodes as described in chapter 4.2) . Magseis Fairfield deliver large node counts with automated node handling and deployment/retrieval systems, and tailored source solutions (magseis fairfield, 2020).

Magseis Fairfield is headquartered in Oslo, Norway and has offices in Sweden, USA, UK, Brazil and Singapore. The company has been listed on Oslo Stock Exchange since June 2014. In May 2018 Magseis ASA transferred to the main list on Oslo Stock Exchange, and in December 2018 Magseis acquired Fairfield Seismic Technologies and WGP-Group and changed the company name to Magseis Fairfield ASA (magseis fairfield, 2020).

Figure 5-8 Magseis Fairfield's survey vessel Artemis Athene

5.2 **Technological differentiators in seismic market**

The customers of seismic data utilize the data to reduce the probability of unsuccessful exploration drilling and also to better understand respective reservoirs as function of time. Typically, the success-rate for exploration drilling is around 50 percent (PGS, 2019) so the accuracy and reliability of the acquired seismic data is of high importance. This necessity of high-quality seismic data is evident as the biggest geophysical clients still believe that development in seismic technology is one of the most important technology-enhancers is the E&P value chain.

One example of technological advance in the seismic industry is the PGS GeoStreamer from 2007. This new streamer technology incorporated multisensor broadband fidelity with rich azimuthal illumination. The combination of having low-frequency signals and advanced sensors remove noise and provide a clearer illumination of the seismic image (Tenghamn, Vaage, & Borresen, 2008).

Another example on technology development is on data-processing. The first seismic acquisitions were conducted in the early 1900’s (2D seismic). In 1980 3D-seismic was used and in 2004 4D seismic was used (extra dimension of time). The development of this way of presenting seismic data is considered as a major technology development by the NPD.

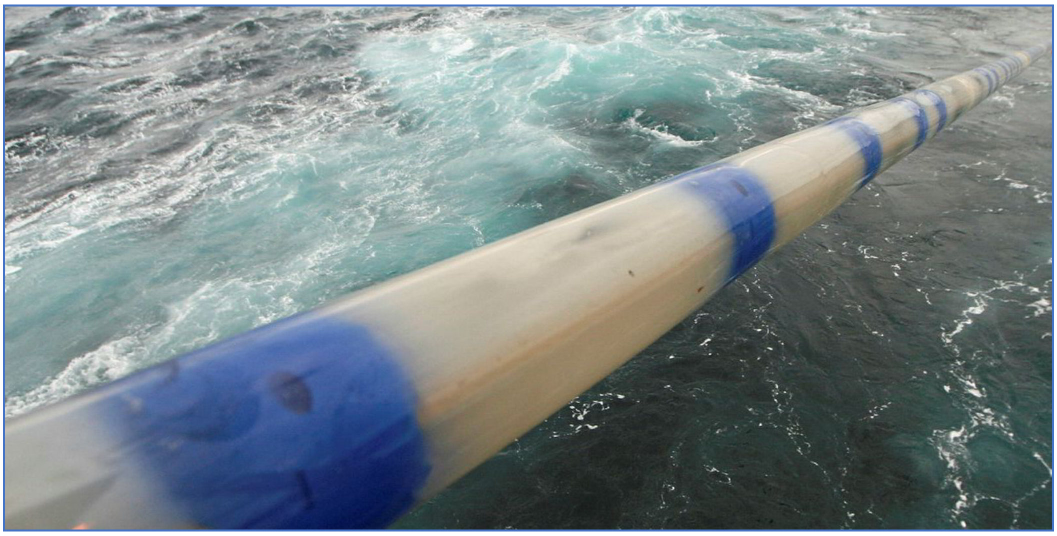

Figure 5-9 PGS GeoStreamer technology for broadband acquisition of seismic data.

Also, the vessels acquiring geophysical data are results of technology development. The PGS fleet is based on Ramform design which is a characteristic shape with a very wide aft deck. The hull shape of the Ramform Class vessels was originally drawn from Marjata, a Norwegian electronic intelligence collection vessel (Haugland, 1995). The curved waterline of Ramform ships allows them to achieve stable motion. The wide aft-deck allows for a high number of streamer and gun-umbilicals and also allows for a broader acquisition width giving higher seismic illumination.

Figure 5-10 PGS Ramform vessel design further developed from Marjata research vessel

Several technology developments have also been targeted into the processing side of geophysical acquisition. Advanced computation algorithms are used to process seismic data often referred to as “big data”. Machine learning has been applied to process a large quantity of information and this is done through advanced visualization and algorithm processes. As an example, PGS partnered with Cognite and Google Cloud in 2019 to utilize cluster computers and improve machine learning processes.

5.3 **Risks & Opportunities**

Correct management of common risks and opportunities can have huge implications for the commercial and technical success of geophysical acquisition. Most common risks are according to (Daleel, 2020):

- **Offshore Weather Window** Selecting the time of the year when to perform the geophysical survey is important. Calm weather will reduce the number of costly weather days, as well as reduce unwanted noise recorded by streamers that will affect the quality of data and subsequent interpretation. Where bad weather is encountered, typically the gun-string is recovered while the streamers are left in the water. If the weather increases to storm conditions (significant wave height above 5 m), also streamer recovery might be required. Typically, a streamer recovery can take up to a week. This can have a significant commercial impact depending on the length and number of streamers in operation.

- **Quality** The data-set accuracy is crucial during the seismic operation and has the potential to add significant costs during onshore processing. Experienced QC/QA personnel representing the client onboard the vessel can be required depending on the contract type. An early data Processing Technology now allows early some data processing and analysis to be performed on the vessel in order to verify that data quality is acceptable. This allows adjustments in the acquisition program and hence avoid large costs of re-acquiring data. (Daleel, 2020)
- **Vessel Selection and Availability** With only 4-5 months of available good weather in the North Sea, most cost-effective vessel selection may be limited due to demand. A trade-off between cost and vessel selection where a vessel may be brought in to cope with more adverse weather conditions can sometimes be required. Clever management of survey operations and good market management can help reduce the risk. (Daleel, 2020)
- **E&P production companies cash flow** Another risk that can be mentioned is the available funds in the E&P company to perform seismic exploration. As the cash-flow of a E&P company is strongly related to currency exchange rates and the price of oil, exploration costs can be increased/decreased rapidly and hence this can act as opportunity and risk. (Daleel, 2020)

6 SUBSEA UMBILICALS RISERS AND FLOWLINES (SURF) MARKET

According to (Rystad Energy, 2018), offshore developments have benefited over lower breakeven prices achieved in the time period 2014-2018.This has been achieved through downsizing, simplification, re-design, high-grading effects, unit prices and currency gains. Also, according to Rystad the overall greenfield cost to develop a field in 2015-2017 (normalized by reserves developed) has come down 42% against 2012-2014 numbers, going from $11 per barrel to $7 per barrel for deep-water developments.

A big portion of the cost reductions are claimed to be achieved by E&P companies cost-cutting regimes, but cost-reductions are also helped by the in-balance between supply and demand for services. Rystad Energy estimates that half of the cost reductions are achieved by E&P companies cost cutting regimes (like Equinor's STEP program) where these programs are tailored to encourage re-use of existing solutions, reducing cost contingencies, allowing for standardization and challenging established technical requirements (Rystad Energy, 2018). Also, for field development in oil-driven currencies, where part of the development or operation is supplied locally, significant currency gains can also be attributed to breakeven prices calculated in USD in the later years. Lastly it should be added that allot of the cost-savings that have been made are caused by the possibility to re-visit and optimize existing business-cases and solutions which on for example the Johan Castberg development reduced the required break-even was reduced with 10 billion NOK from re-visiting the conceptual design resulting in a drop of required break even oil price from 85 USD/bbl to 27 USD/bbl (Equinor ASA, 2018).

Figure 6-1 Seven Borealis pipe-layer and heavy lift vessel for Subsea 7

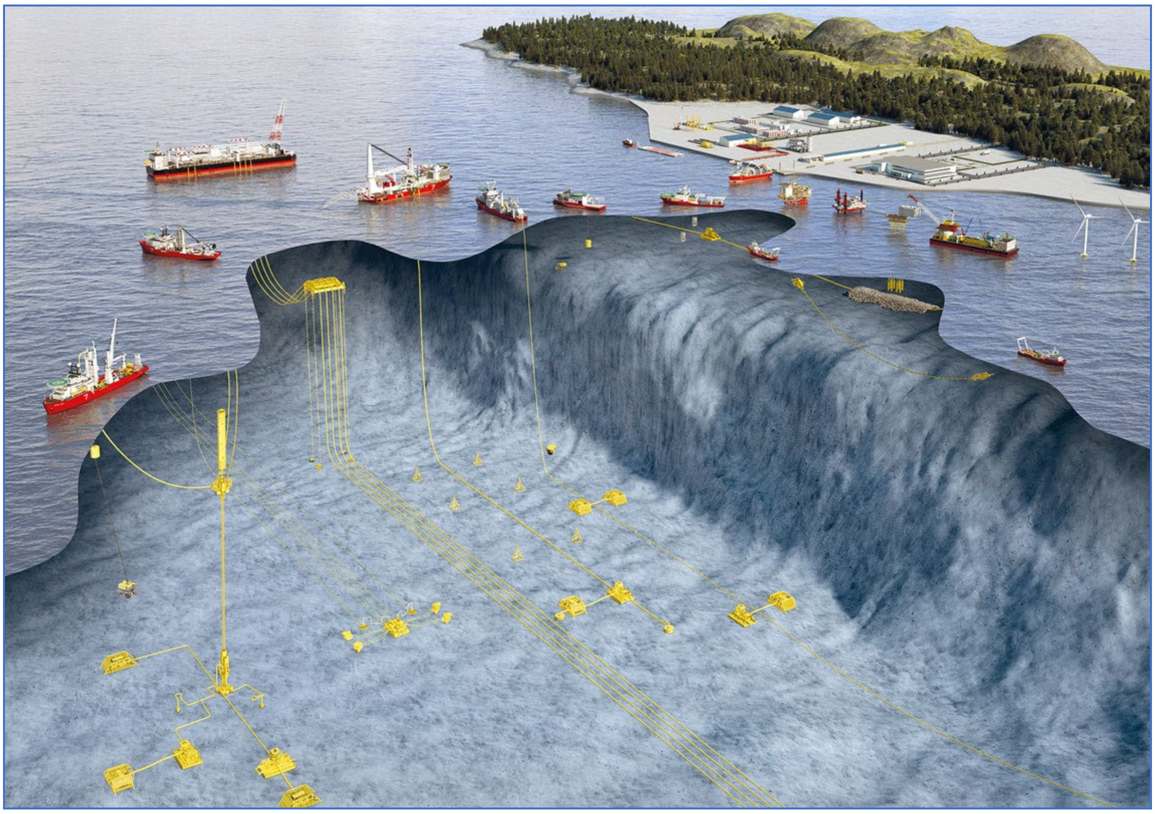

Figure 6-2 The SURF industry contain installation of risers, flowlines, structures, wellheads and control umbilicals (Courtesy Subsea 7)

6.1 Key SURF market players

Similar to the geophysical industry, the SURF industry is dominated by a few key companies where multiple consolidations have occurred in the latter years in the form of alliances and mergers. Key players in the SURF industry are given in the figure below. Subsea 7, Technip FMC and Saipem are the biggest companies in the SURF industry, but also smaller regional and national players exist.

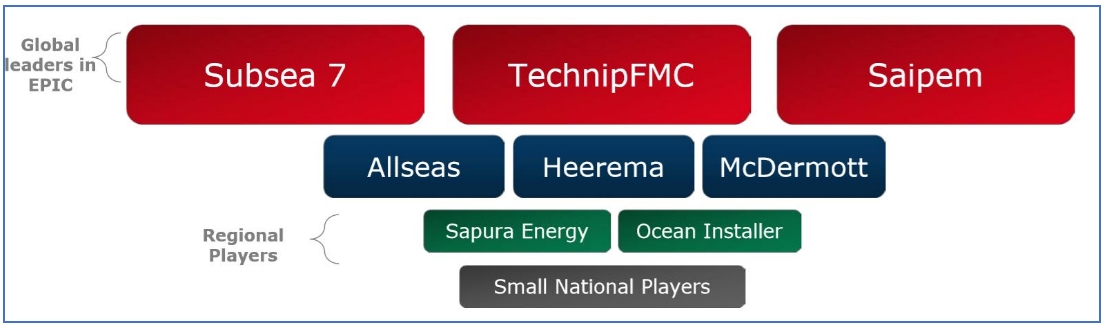

Figure 6-3 Key players in the SURF market

Subsea 7 merged with Acergy in 2011 and Technip and FMC merged in 2018.The figure below shows the alliances, mergers and joint ventures that have been formed in later years. Even though some mergers and consolidations formed in the period of 2010-2012, it can be seen that the frequency of consolidations has increased dramatically post 2015 Figure 6-4.

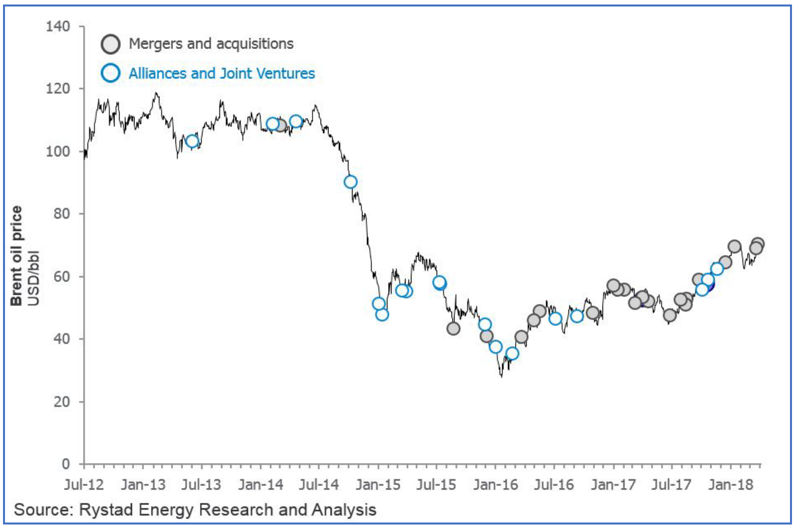

Figure 6-4 Alliances, joint ventures, mergers acquisitions in the oilfield services sector July 2012-march 2018 (Rystad Energy, 2018)

A short description of the top 3 SURF companies are given below as described in Figure 6-3.

6.1.1 Subsea 7

Subsea 7 was established in 2011 by merging the two companies Acergy SA and Subsea 7 Inc. Subsea 7 is a seabed-to-surface engineering, construction and services contractor to the offshore energy industry worldwide. The company provides integrated services and plans, designs and manages the delivery of complex projects from shallow to ultra-deep-water depths. It delivers a full suite of services across all categories of Life-of-Field work, including inspection, maintenance and repair, integrity management, remote intervention and renewables. The company identified four core segments: SURF, Life-of-Field, Conventional & Hook-up. It also has a comprehensive range of mobile assets, including remotely operated vehicles and other construction, survey and diving equipment. The company was founded on January 7, 2011 and is headquartered in London, the United Kingdom. The company was listed on the Oslo Stock Exchange in August 2005 (Subsea 7, 2019).

Figure 6-5 Subsea 7 Seven Vega reel-lay vessel

6.1.2 McDermott

McDermott International, Inc. is a multinational engineering, procurement, construction and installation company with operations in the Americas, Middle East, the Caspian Sea and the Pacific Rim similar to Subsea 7 and TechnipFMC. The company had severe financial losses in 2018 and tried to sell assets with no success and payable invoices were not paid. In 2019 the company posted a loss of $1.9 billion and on 21th of January 2020, the company filed for chapter 11. According to McDermott Chapter 11 is a tool commonly used by companies with global operations to rehabilitate their balance sheets in an orderly manner while continuing day-to-day operations. It is viewed as an effective strategy to strengthen businesses that are unable to meet their current financial obligations (McDermott, 2020).

Chapter 11 refers to the section of the U.S. Bankruptcy Code that governs court-supervised reorganizations of businesses. A company that files for protection under Chapter 11 is generally allowed to continue normal business operations. Chapter 11 provides the company with breathing room – and protection from its creditors and debtholders (McDermott, 2020).

Figure 6-6 McDermott DLV2000 pipelay vessel

6.1.3 TechnipFMC

The London-headquartered company, with operational headquarters in Houston and Paris, officially began operating under the TechnipFMC name in January 2017 following the merger of SURF company Technip and subsea production system (SPS) supplier FMC Technologies. The company operates through three business segments: Subsea, Offshore/Onshore and Corporate and has 44000 employees split between the subsea and onshore departments. Similarly, to Subsea 7 the company offer EPCI (integrated engineering, procurement, construction and installation) and engages similarly to Subsea 7 in the fields of project management, engineering and construction for the energy industry. It provides services for basic and detail engineering, procurement, construction and project management.

Figure 6-7 TechnipFMC's deep energy reel-lay vessel

6.1.4 Saipem

Saipem is an Italian oilfield services company which until 2016 was a subsidiary of Eni which still has 30% of Saipem's shares. The company was a pioneer in offshore drilling and pipeline construction and has several pipelay vessel, heavy lift vessels and drilling rigs in operation even today. The company is headquartered in Milano and has over 30000 employees. The company competes with TechnipFMC and Subsea 7 in heavy lift operations and especially for laying larger trunklines (above 20" outer-diameter subsea pipelines) with either S-lay or J-lay. Saipem has a small market share when it comes to installing shorter smaller diameter flowlines and umbilicals and smaller subsea structures.

Figure 6-8 Saipem 7000 capable of lifting 14000tonnes

Figure 6-9 Saipem Constellation pipelay vessel

6.2 **RISK AND OPPORTUNITIES SURF**

The effective management of common risks and opportunities can have huge implications for the commercial and technical success of the category. Most common risks are:

- **Offshore Weather Window** Selecting the time of the year when to perform the subsea installation campaign is important. Calm weather will reduce the number of costly weather days, as well as reduce overall risk of the marine operation. Depending on the contract, weather waiting can be included in the SURF contractor's responsibility matrix and without proper planning this can be costly. Typical marine operations can be carried out in significant wave heights below 3m. If the weather increases to storm conditions (significant wave height above 5 m), weather standby is expected.
- **Safety** The planning and execution of the marine operation is of outmost importance. Critical lifts can be performed over producing wells and infrastructure, and vessels can be positioned close to existing infrastructure. Planning the operation with the mindset of safety and having appropriate barriers in place is therefore very important and there is typically a larger focus on safety in the SURF industry compared to the seismic industry.
- **Vessel Selection and Availability** Similar to geophysical surveys; with only 4-5 months of available good weather in the North Sea, most cost-effective vessel selection may be limited due to demand. A trade-off between cost and vessel selection where a vessel may be brought in to cope with more adverse weather conditions. Typically pipe-lay (reel-lay) vessels are of limited quantities and as they typically also need to be close to a spool-base, proper planning is very important to avoid unnecessary idle and standby.

7 CONTRACT MODEL

7.1 Geophysical industry

E&P companies are typically the biggest clients for geophysical companies. These include but are not limited to Exxon, Total, BP, Shell, Eni and Equinor. The local presence of the E&P companies affects where the geophysical companies are located and traditionally the most important geographical areas are the Gulf of Mexico, West Africa, Brazil and the Norwegian continental shelf.

The biggest competitors in the marine seismic market are TGS, Spectrum, PGS, Shearwater, CGG and Polarcus. These companies deliver seismic data in the forms of contract work and multiclient contract work. A contract type business model is used when a particular E&P company request the seismic company to perform a specific job for a specific area. The oil-company then becomes the sole owner of the data. This can be viewed as an exclusive or proprietary acquisition contract and the E&P pays the full cost of the project which gives zero risk to geophysical company.

The contrary is when an investment is made by the geophysical survey company itself, in building up a library of data that can be sold to multiple clients over time (multi-client surveys). The income from contract surveys are received upon completion of the survey, while the income from multi-client survey can be spread over several years. In this case the geophysical company bears all risk and pays the cost of the project. Financial risk can be mitigated by pre-funding from customers. Multi-client work can be performed in between contract work in order to increase the utilization of vessel equipment. The two different contract formats are shown in Table 1.

Contract business model	Multi-client business model
E&P company pays the full cost of project	E&P company only pays for a license to access desirable data
Geophysical Company and E&P company enter into agreement for acquisition of geophysical data over a pre-determined area (e.g. acreage under lease)	Geophysical company decides on target-area based on market (E&P companies) interests
Provides a service with geophysical data only available to the E&P company	Develops a product with geophysical data available for licensing
Geophysical company provides the vessel and required crew	Geophysical company bears all risk, pays cost of project (financial risk can be mitigated by pre-financing from customers
E&P company owns the acquired data	Geophysical company owns the geophysical data

Table 1 Multi client vs contract business model (definitions based on (IAGC, 2011))

After the downturn in the E&P industry, the majority of E&P producers have leaned toward increasing the use of the multi-client business model since exclusive ownership of data is less important than the interpretation of that data (PGS, 2019). The main driver behind this change has probably been the geophysical industry trying to maximize the vessel utilization in the downturn to avoid cost of stacking vessels, equipment and crew. In accordance with (IAGC, 2011); the multi-client contracts distribute the costs of data acquisition and processing over time and among multiple customers. Under the model, the geophysical company initiates and conducts projects of general industry interest at its own financial risk. Restricted non-transferrable data-user licenses are then sold to individual E&P companies for a fraction of the cost of acquiring and processing the data themselves allowing multiple E&P companies the opportunity to evaluate resource potential in particular area along geological trends that will facilitate higher exploration and development success rates. According to IAGC multi-client contract models can benefit stakeholders in regions with the which fulfill the following characteristics

- Licensing rounds or lease sales are held regularly, on schedule, with pre-determined areas available for licensing or leasing announced well in advance of each licensing round or lease sale
- Smaller area is offered for licensing or leasing, thus promoting greater competition for area
- The confidentiality period for the multi-client geophysical data is a minimum of 15 years, allowing the data owner multiple licensing rounds or lease sales
- At the end of the confidentiality period, only the processed data is available for release to the public.

One can easily see this transmission occurring by looking at the figure below from (IHS Markit, 2020).

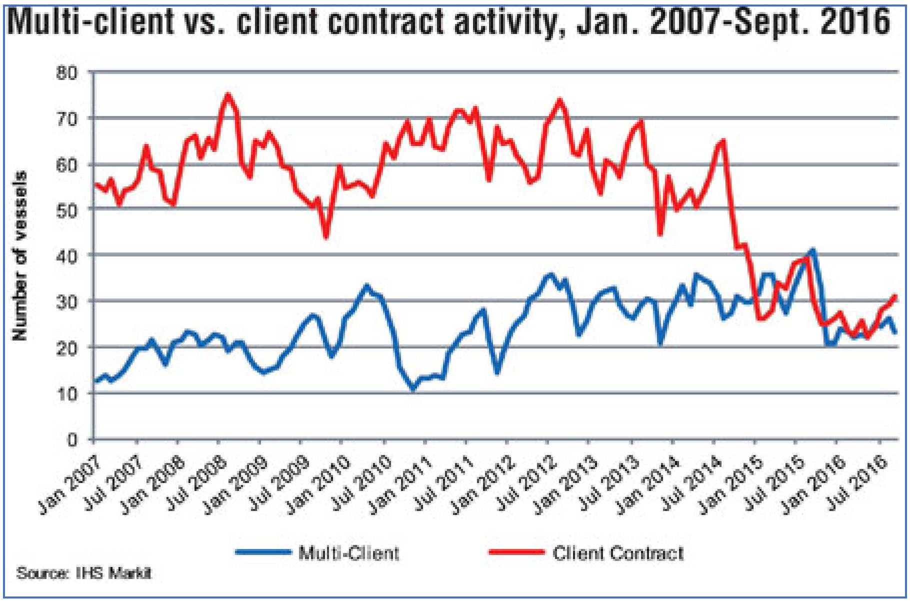

Figure 7-1 Multiclient vs contract business model for geophysical companies.

For both the contract and multi-client model, onshore processing onshore processing may be executed after receival of seismic data from the vessel. This part can be included in the contract model for the geophysical companies that retain this capability. The companies that have this capability in-house are shown in the figure below.

	MultiClient	Contract 3D Acquisition	Contract 4D Acquisition	Multi-Component Streamer	Imaging	Reservoir	Ocean Bottom Seismic
PGS	✓	✓	✓	✓	✓	~	✗
CGG	✓	~	~	~	✓	✓	✗
SHEARWATER	✗	✓	✓	~	~	✗	✓
TGS [2]	✓	✗	✗	✗	✓	~	✗
WesternGeco	✓	✗	✗	✗	✓	✓	✗
Spectrum [2]	✓	✗	✗	✗	~	✗	✗
Polarcus	~	✓	~	✗	✗	✗	✗

Figure 7-2 Top geophysical companies and capability matrix (PGS, 2018))

7.2 **SURF industry contract**

The typical contract format in the SURF industry is standardized and usually the contract form of Norwegian Subsea Contract 05 (NSC 05) is used as the typical request of services are similar. This contract format contains standard conditions developed for contracting within the subsea segment on the Norwegian continental shelf. The operator in the field consortium will typically issue an invitation to tender (ITT) where services are requested by the operator. The ITT contains the operators need for services, obligations of the parties and risk allocation. The contractor will then in its offer include contractual expectations to the operator contract and based on the exception the terms and conditions of the contract are negotiated.

The reimbursements principles will be clearly stated in appendix B in a SURF contract where the two most commonly used compensation formats are lump sum or provisional sum. Lump sum means that the compensation remains fixed where the supplier carries the monetary, schedule and technical risk. In many cases the major flaw of the Fixed Price approach can be misalignment of objectives and inefficient risk allocation. Aligning objectives and ensuring that risks allocated in a way that puts the right party to manage risk is important and specifying a one-sided responsibility can in many occurrences be too simplistic.

For a provisional sum compensation form the company carries the price risk. Comparing this to the contract format used in the seismic market one can see that that there are several similarities. Weather risk is usually an important discussion point during contract establishment for both the SURF and geophysical sector. Also, discussion on rates for variation orders and additional work will be based on unit prices. However, the main difference between the two is that in the geophysical market one usually sells data which is complex to obtain with respect to required vessel days and in the SURF industry one usually sells defined services. Due to the large size of contracts the compensation and contract model for acquisition is usually simpler than the NCS 05 contract used in the SURF industry. Since the capital expenditure in a SURF contract typically has over 60% capital investment related to sub-services and items, these contracts are typically broken down into more subcategories than geophysical contracts.

The three different main type of SURF contracts can be summarized in the table below. Each of the main approaches would have different strategies, risk and scope uncertainty. This implies that the degree of involvement from the client side varies significantly, from a full project owner involvement, to a minimum participation. Selecting the right project delivery strategy has a direct impact on the success rate of the projects.

	Cost reimbursement	Lump Sum	Alliance format
Price attractiveness	Highly competitive	Not competitive	Highly competitive
Risk	High for project owners	High for contractor	Shared
Project size and value	Any	Small	Any, but not less than 100MUSD
Incentives	Few, mainly encourages wasteful behavior	None	High for all parties
Cost to operator	Medium to high	High	Low to medium
Scope uncertanity	Low	High	From low to high
Predictability of total expenditure	Low	Low	High for all parties

Table 2 Typical SURF contract formats

Especially the alliance format has become common in bigger SURF contracts in the after the market downturn after 2014 which was natural based on Figure 6-4. Due to the alliance of the major SURF contractor Technip and FMC (6.1.3) Subsea 7 (6.1.1) for instance formed alliances with Schlumberger (OneSubsea) and AkerSolutions to be able to deliver both SURF project services and subsea production system hardware. In addition, Subsea 7 and Technip formed alliances with clients resulting in a common risk base and increased predictability on total expenditure (TOTEX). TechnipFMC currently have an alliance with Neptune Energy, and Subsea 7 have alliances with AkerBP and Spirit Energy.

7.3 Market drivers and correlation to oil price for seismic and SURF

In order to be able to identify the market drivers in the geophysical industry, we need to evaluate the value-chain in the oil-and-gas business segment. As mentioned earlier in chapter 4, seismic exploration is at the very start of the value-chain due to the fact that typically before drilling, production and other down-stream activities petroleum resources need to be discovered. Hence one of the biggest drivers for geophysical companies market outlook will be E&P investments in future exploration.

In the short term the budgeted E&P investments are made annually based on the recent oil-price trends and company revenue made at the end of the financial year. Due to the high volatility of the oil price, this will induce large volatilities also in the geophysical market as the E&P companies will increase revenue in the short term by reducing exploration CAPEX. On the contrary if market is increasing, E&P companies will increase exploration costs rapidly when new projects are sought for. In other words, it is plausible that the geophysical market is directly correlated. Below is a figure showing multiclient sales and oil-price and one can see some degree of correlation in the graph.

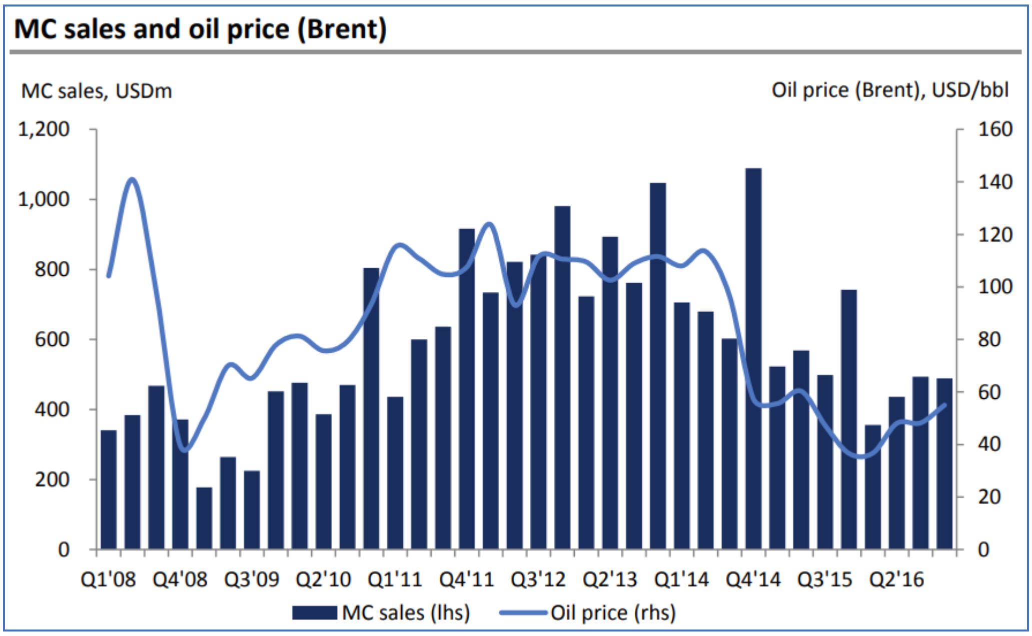

Figure 7-3 Multiclient sales and oil-price (PGS, 2019)

However, the changes in oil-price cannot solely explain the change in multi-client sales. As demand increase, there will typically be a driver for E&P producers to increase their portfolio on reserves. The relationship between short-term and long-term demand in the seismic market is important due to the fact the E&P producers quite quickly adopt to the demand in the market and the associated cost with acquisitions. As a consequence, the seismic industry has by many be claimed to be one of the most cyclical industries in the E&P value chain.

Supply and demand on petroleum resources can hence be claimed to not be direct drivers for revenue in the seismic industry in the short term. For the long-term however their revenue will be directly linked to the exploration investment-level of E&P companies.

7.3.1 Supply of hydrocarbons

To further elaborate of the supply side of Oil as earlier shown in chapter 3, a figure of the oil-price (Brent) is shown in the figure below. The figure shows a steady increasing trend with some exceptions. In 1990 the large increase in the oil-price can be explained by the Gulf War when Iraq invaded Kuwait. There was a supply shock when these two major OPEC members stopped exporting oil which gave a drastic increase in price from 20 to 40$ per barrel. Later there was a steady increase in oil price from 1999 to 2008 linked to events such as war in the middle east, natural disasters and increased global demand. In 2008 the oil-price peaked at 140$/barrel and then decreased during the financial crisis. After recovery the oil demand and price gradual increased until the development of shale-oil flooded the supply side of the market and also reduced the overall price. The price steadied at around 60$/barrel and plummeted again in March 2020. At the time of writing this thesis, the combination of the Corona Virus and failure of mutual agreements within OPEC reduced the oil price from 60 to 20$/barrel.

Figure 7-4 Oil-price supply

This figure showing the supply side of Oil is closely linked to the demand side of the market shown in chapter 7.3.2 below.

7.3.2 Demand of hydrocarbons

The demand after oil and gas have increased in annual (average) between 1 to 2 percent and is linked to the economic development in the world. Increased industrial production and wealth contributes to this development. For the period of 2017 to 2019 we can see that there has constanly been a oil-supply inbalance in the global oil market

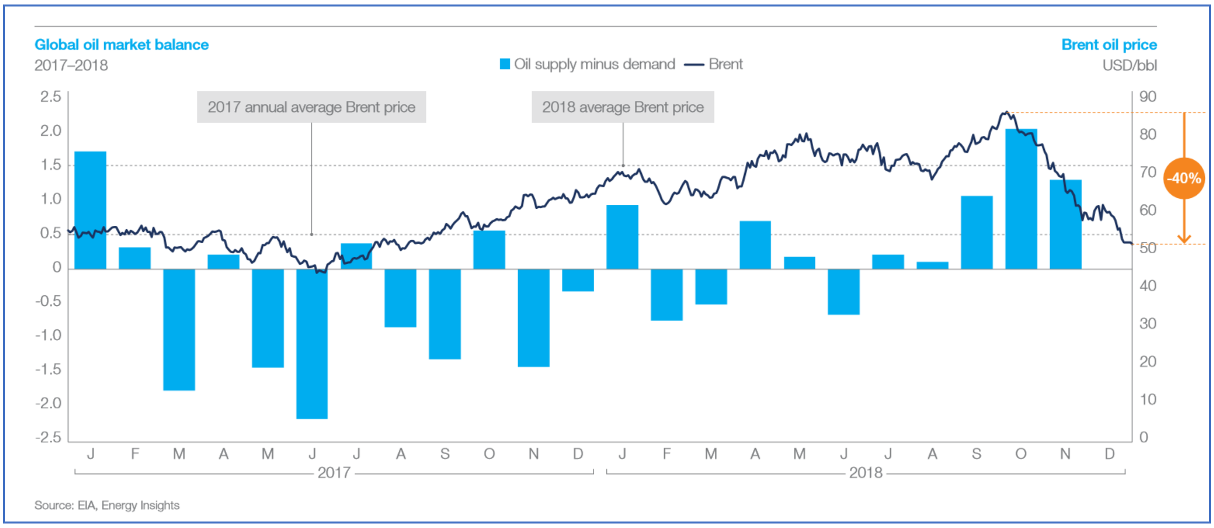

Figure 7-5 Demand side of oil from EIA

The supply-elasticity is as commonly known typically dependent on the marginal cost for the different production segments. From Figure 7-7 it can be seen that there is a substantial difference in break-even for the different segments. Lowest break-even is for producing field typically in the middle east, and the highest is for oil sands. There are ongoing shifts for the supply side as described in the chapters above and according to (Rystad Energy, 2018)

Tight oil – such as onshore shale has had an development in recent years. In 2015, shale was as the second *most expensive* resource according to Rystad Energy's global liquids cost curve in Figure 7-6, with an average breakeven price of $68 per barrel. This has recently dropped to below $50 per barrel marginally behind the giant onshore fields in Saudi Arabia and other Middle Eastern countries. Also, the average payback time for different Brent scenarios (Figure 7-6) is very low for oil sands. This means that if oil-prices increase above 60 $/bbl, oil sands will influence the supply side of the market.

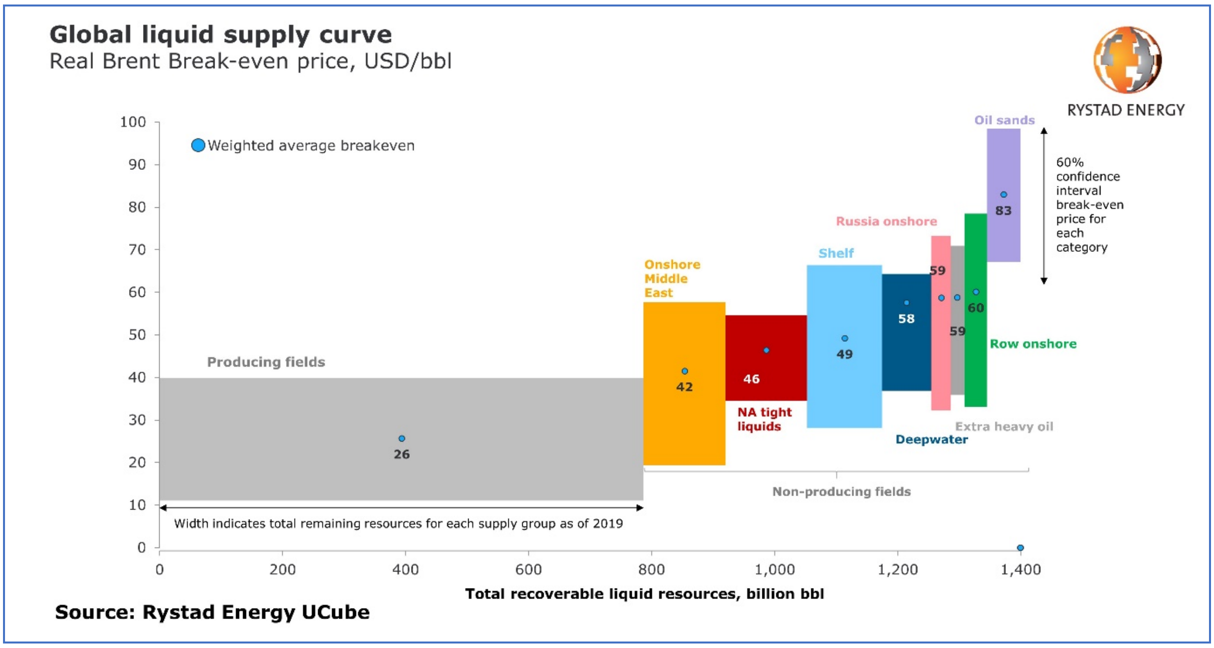

Figure 7-6 Global oil supply curve as function of field type

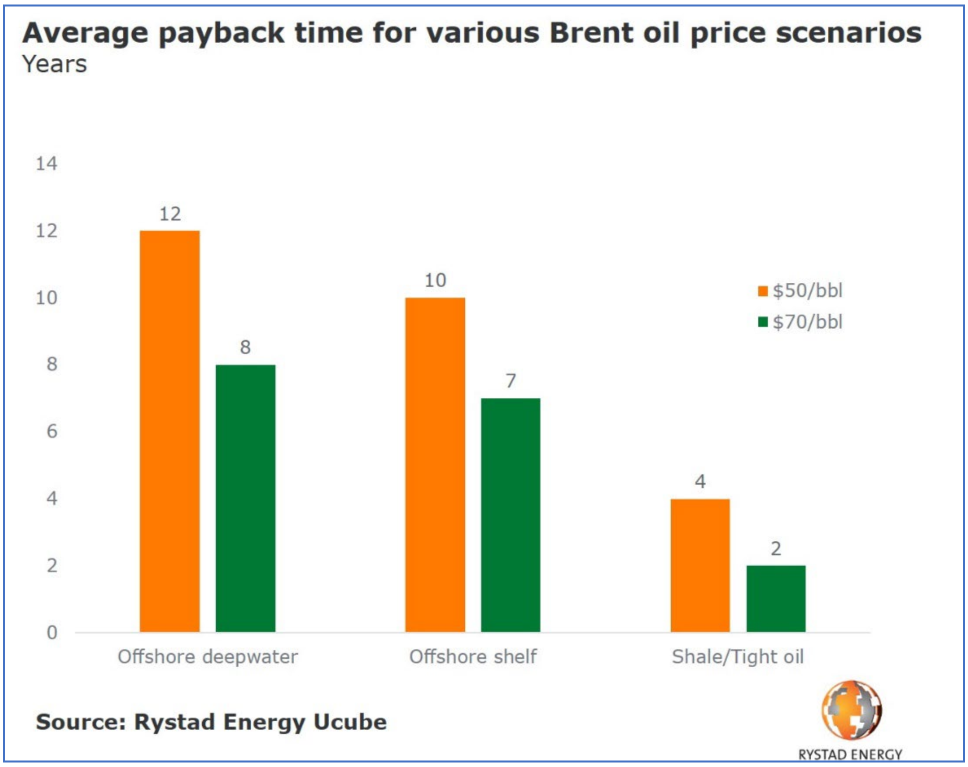

Figure 7-7 Average payback time for various Brent field

Combining the findings from Figure 7-4, Figure 7-5 and Figure 7-6 one can conclude that different mechanism will influence the oil-price given an increase or a decrease in global demand and it is therefore not a linear relationship between supply and demand in the global oil market. This will influence the market outlook for both the geophysical (chapter 5) and SURF market (chapter 6) and provide scenarios that need to be analyzed in detail.

8 STOCK DATA ANALYSIS IN PYTHON

8.1 Oslo stock exchange

Oslo stock exchange was open in April 1819 were its main purpose was to enable trade of foreign exchange. Almost a 100 years later it became and exchange also for commodities and in 1881 a list of 16 bonds and 23 shares was published and is regarded as the date of origin of the Norwegian equity market. The Oslo exchange benchmark- Total return index (**OSEBX**) functions as an indicator of the performance of the Oslo stock-exchange and has a base value of 100 given from December 1995. From Oslo Børs the closing prices of selected stocks further outlined in this thesis is extracted and evaluated in the general-purpose programming language Python.

Figure 8-1 Oslo Børs stock exchange

The stock exchange is typically divided into groups called sectors. The energy sector approximately contains half of the Oslo Stock exchange value and is therefore very important in Norwegian economy. In the energy sector we find amongst other E&P companies, drilling, seismic and SURF companies. When estimating the effect of a change in oil price on the Oslo Stock Exchange, it is important to know how large the proportion of companies related to the oil industry is. The **OBOSX** Oil service Index is a free float adjusted total return index (dividend adjusted) composed of the most liquid shares within the Oil Service sector. Only companies that are members of both the OBX Index and the OSE101010 Energy Equipment & Service Index are included. The selection is therefore currently limited to BW Offshore, Subsea 7 and TGS-Nopec geophysical company. Even tough indexes are not directly comparable, these two indexes (OBOSX and OSEBX) are plotted below in python.

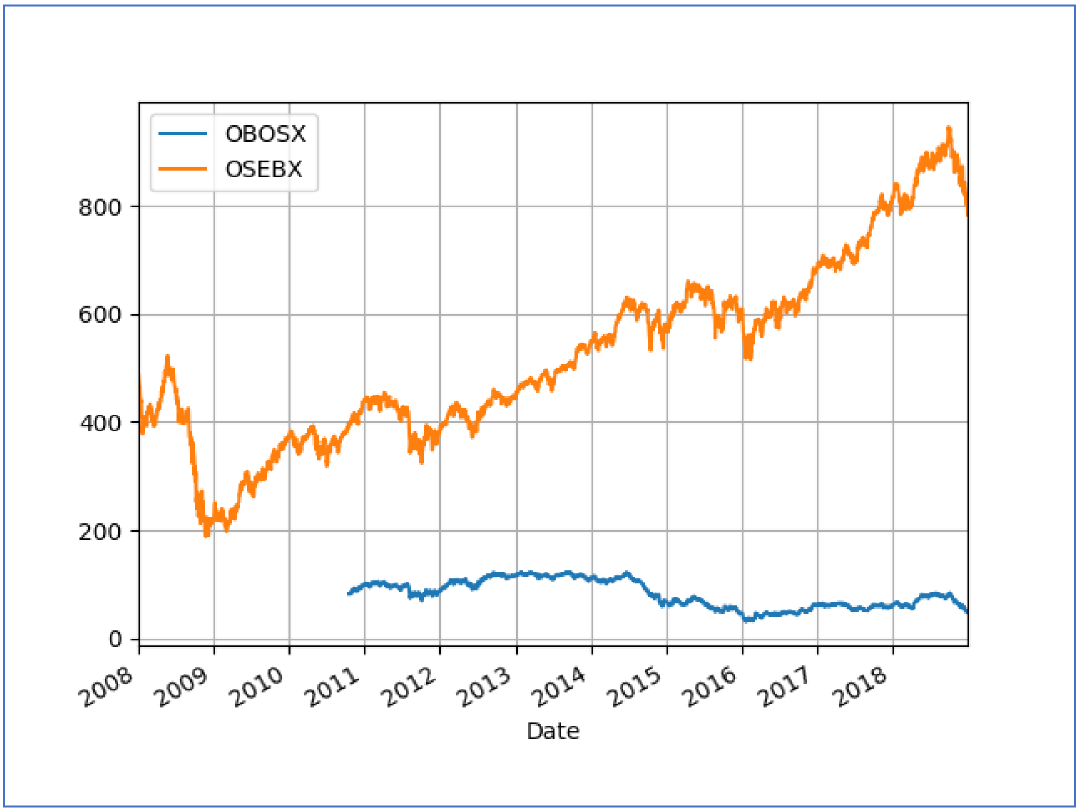

Figure 8-2 Oslo main exchange (OSEBX) and Oslo Oil service Index (OBOSX)

From the figure we can see that OSEBX has increased steadily since 2010 while OBOSX has remained fairly constant with a slight increase in the later years. However, when plotting OBOSX versus crude oil price in the figure below, it seems that there is a strong correlation between the index and the commodity price (Figure 8-3).

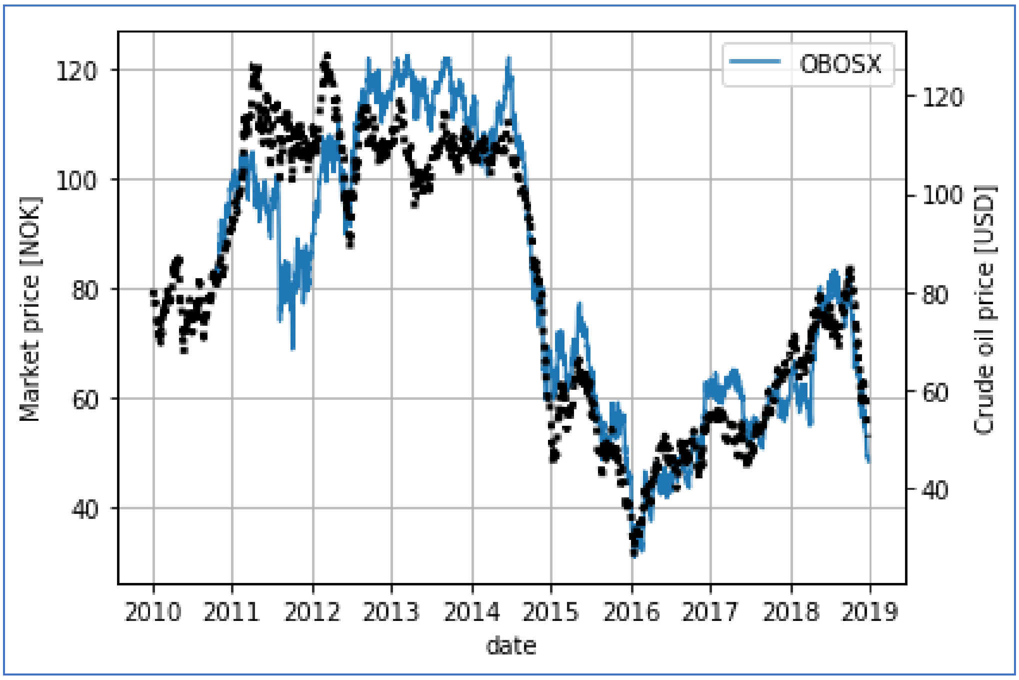

Figure 8-3 OBOSX plotted against crude oil price

From the figures above it can be seen that the Oslo Børs stock exchange and in particular OBSOX most probably is influenced by the oil price. This can also partially be justified by looking at the policy rate (Figure 8-4). The policy rate is Norges bank main instrument for stabilizing inflation and developments in the Norwegian Economy.

A common economic theory stipulates that increasing interest rates increase manufacturers and consumer costs, which again reduces demand for oil which again can cause oil prices to drop (inverse correlation). Following the same theory, when interest rates drop, consumers and companies are able to borrow and spend money more freely, which drives up demand for oil. The greater the usage of oil, which has OPEC-imposed limits on production amounts, the more consumers drive the price upwards. To some degree this can be examined by the figure shown below.

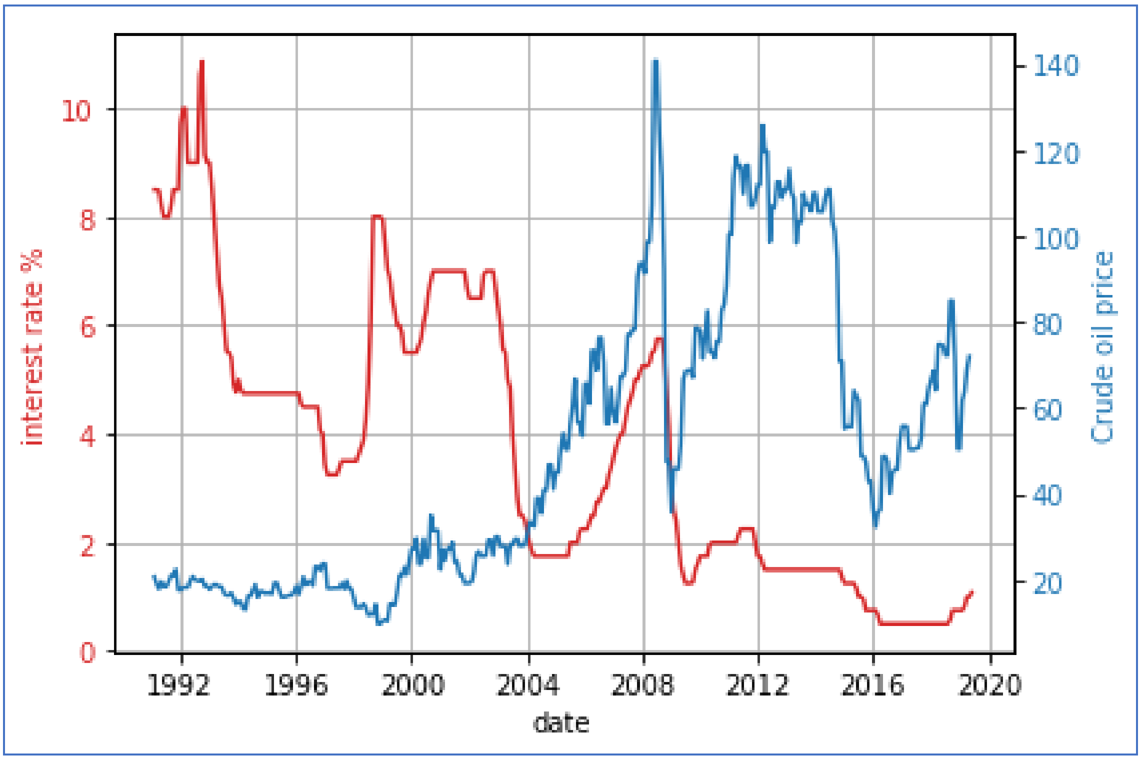

Figure 8-4 Crude oil price versus Norges bank interest rate

According to the central bank of Norway the interest rate is designed to ensure a stable and low inflation close to 2.5% annually. Adjustment of the inflation rate is made to ensure a stabilized production and employment rate and hence when the economy is growing often an increased interest rate is used to dampen inflation. If the Norwegian economy was isolated and solely correlated to the oil price, it would therefore in theory be an inverse correlation shown in Figure 8-4 above, however we can see that this is not fully the case. However, we can see that there is a large inverse correlation again emphasizing the strong influence the oil price has on Norwegian economy and industry.

8.2 **Stock analysis**

As previously mentioned in chapter 8, Share price data has been pulled out of the Oslo stock exchange listed companies Subsea 7 (S7 chapter 6.1.1), PGS (PGS chapter 5.1.2) , Magseis Fairfield (MSEIS chapter 5.1.6), Multiclient Geophysical (MCG chapter 5.1.5) and the oil-price (Brent chapter 3) in USD. Oil price is shown with the purple line below and it can be seen that there is a strong correlation between the Subsea 7 share-price and the oil-price. For the seismic companies PGS, MSEIS and MCG this correlation seems to be weaker. However, it should be noted that the timeline on the graph below is between 2015 and Q2 2019 where the Oil and Gas-industry experienced a severe downturn and the reasons for the low correlation in the seismic industry can be that the market is still recovering during this time period.

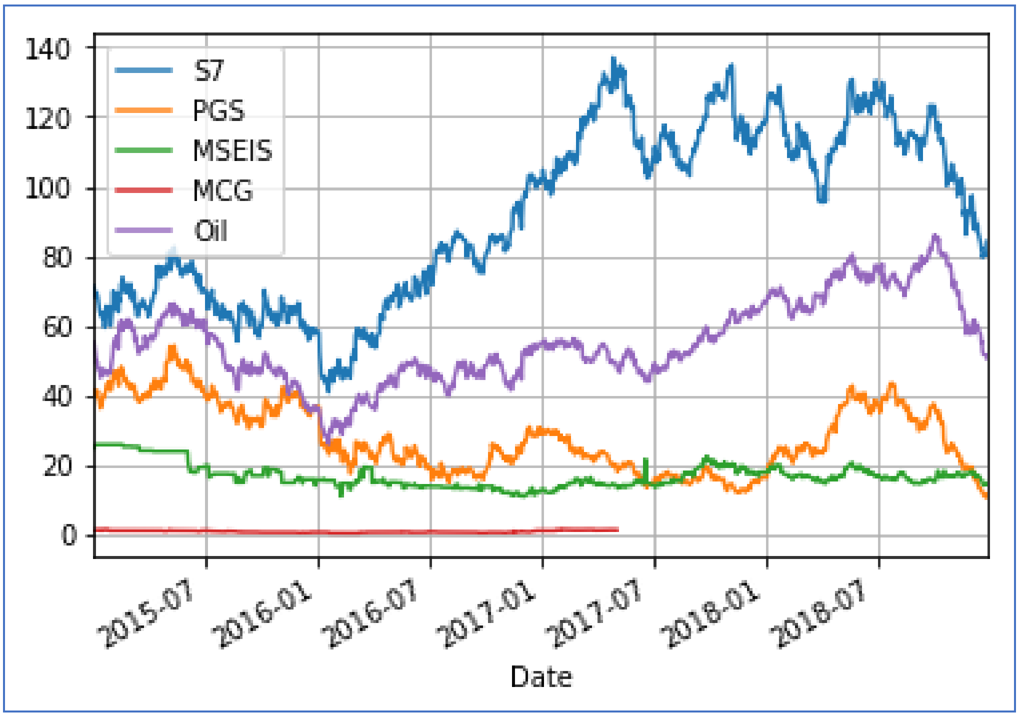

Figure 8-5 SURF and Seismic industry plotted against price of Brent between 2015 and 2019

Going further back in time and also introducing the new companies TGS and Spectrum, there seems be a direct correlation between the oil price and the share-prices. This can probably be explained that during a longer up-turn in the oil-and gas market as the one seen after the financial crisis in 2008, the lag in the market eventually fades and increased spending by E&P companies are directly transferred to both surf and the seismic industry. Comparing Figure 9-1 and Figure 9-2 this affect can be observed in the figure below.

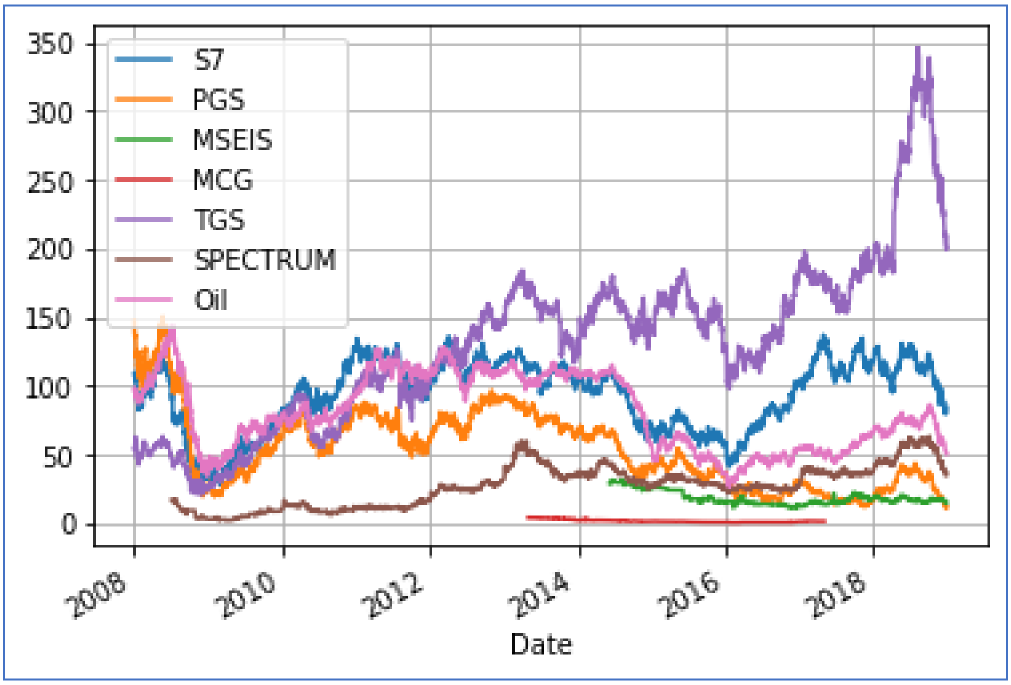

Figure 8-6 SURF and Seismic industry plotted against price of Brent between 2008 and 2019

We can also plot the stock prices as moving averages. A moving average is the mean of the **n** last closing prices. A common approach in stock theory is to present 20 days which represent the number of trading days in a month. In general, the shorter the number of days, the more sensitive the moving average will be to price changes. Hence if we select a bigger number of days, the short-term fluctuations will be smoothened by the indicator. However, if we select the number of days to wide, we may miss some information as well. The graphs (Figure 9-5 to Figure 9-8) below show the moving averages of the representative stocks. It can also be mentioned that financial analysist and investors can sometimes use moving averages to analyze price trends and predicting coming changes. During a price uptrend, price will be higher than moving averages and opposite in a downtrend. When closing price cross the moving average, investors can interpret this a potential change in the price trend.

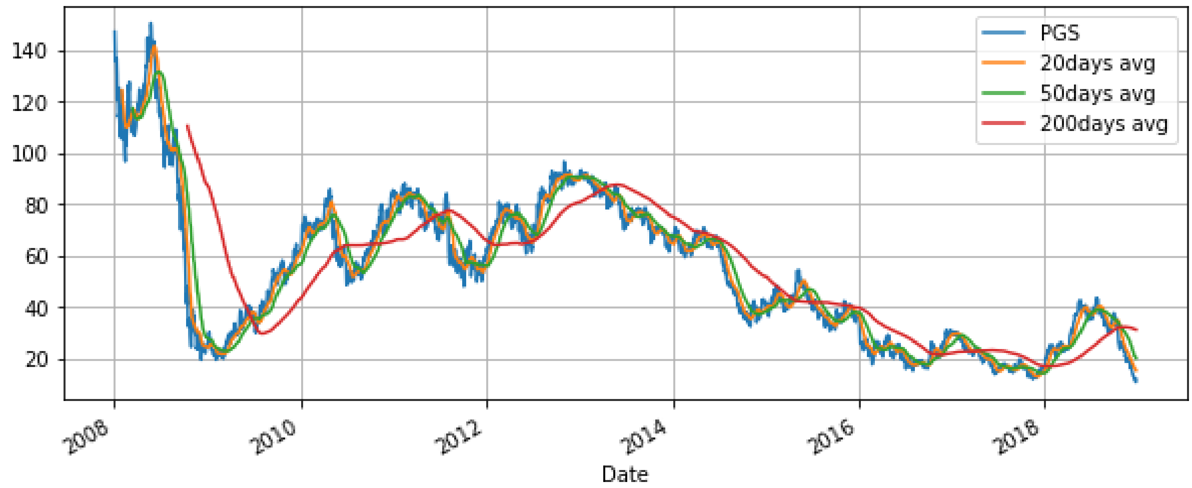

Figure 8-7 Moving averages of PGS stock

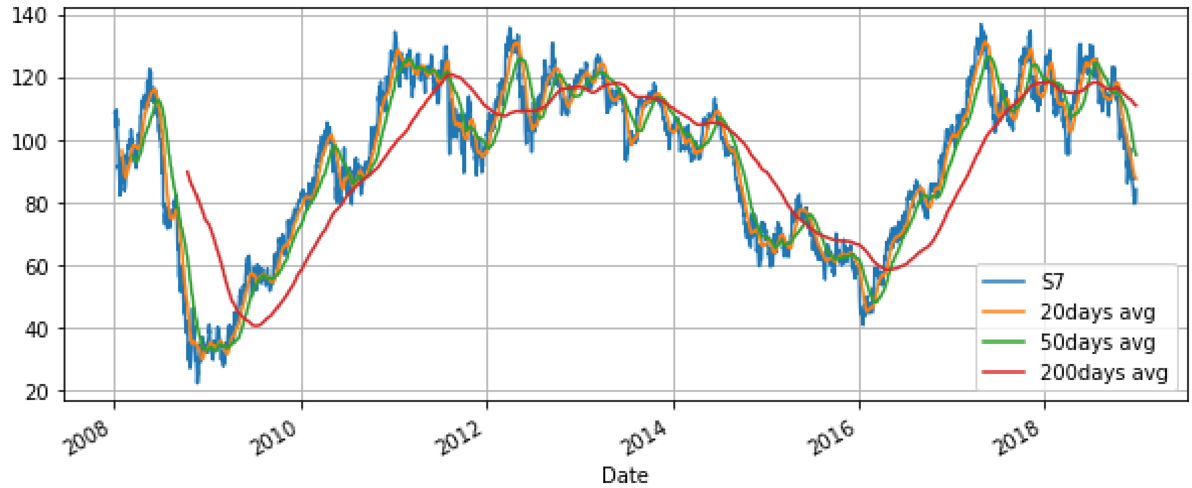

Figure 8-8 Moving averages of Subsea 7 stock

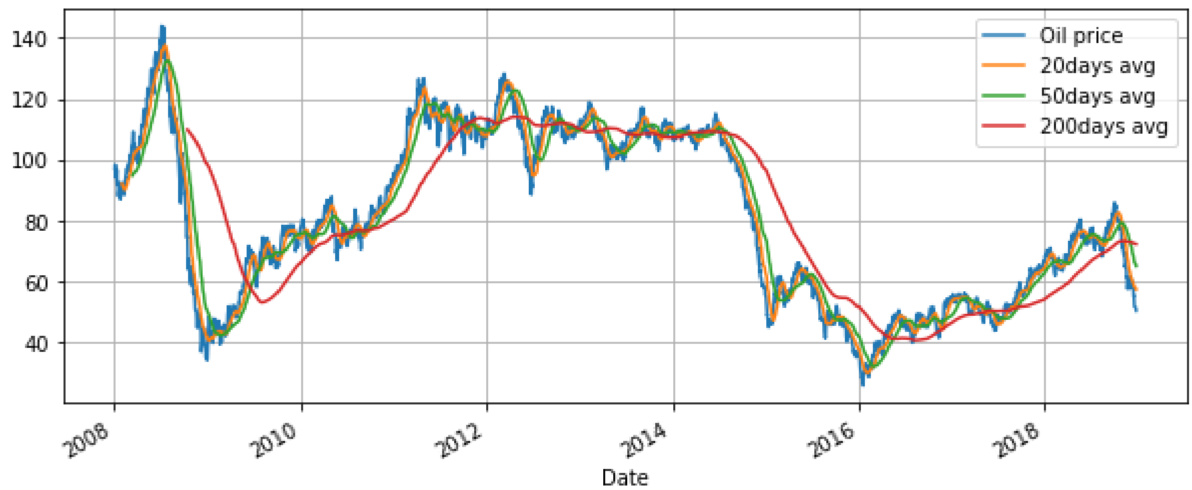

Figure 8-9 Moving averages of Brent Oil price

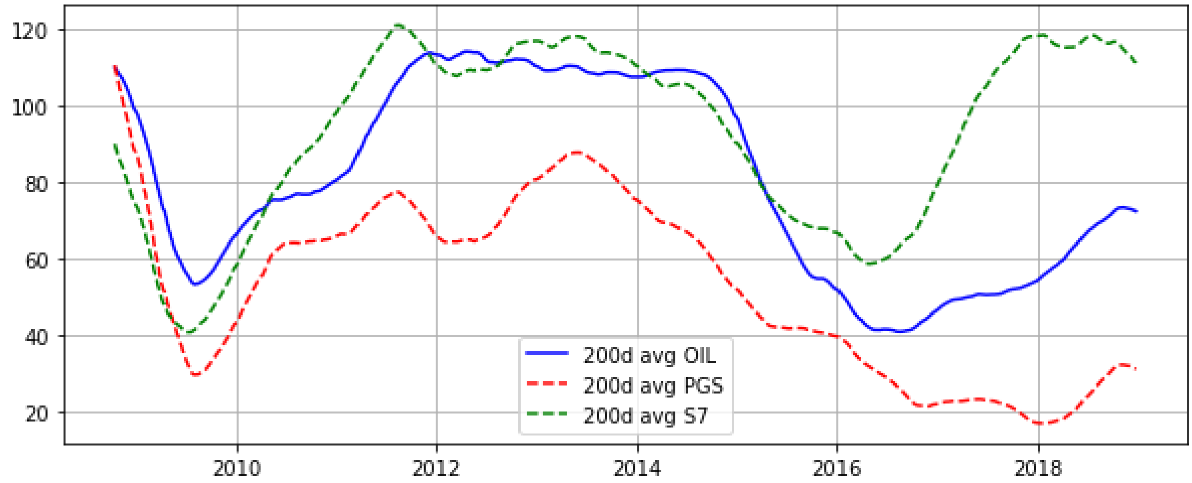

Figure 8-10 Comparison 200day average Oil, PGS and Subsea 7

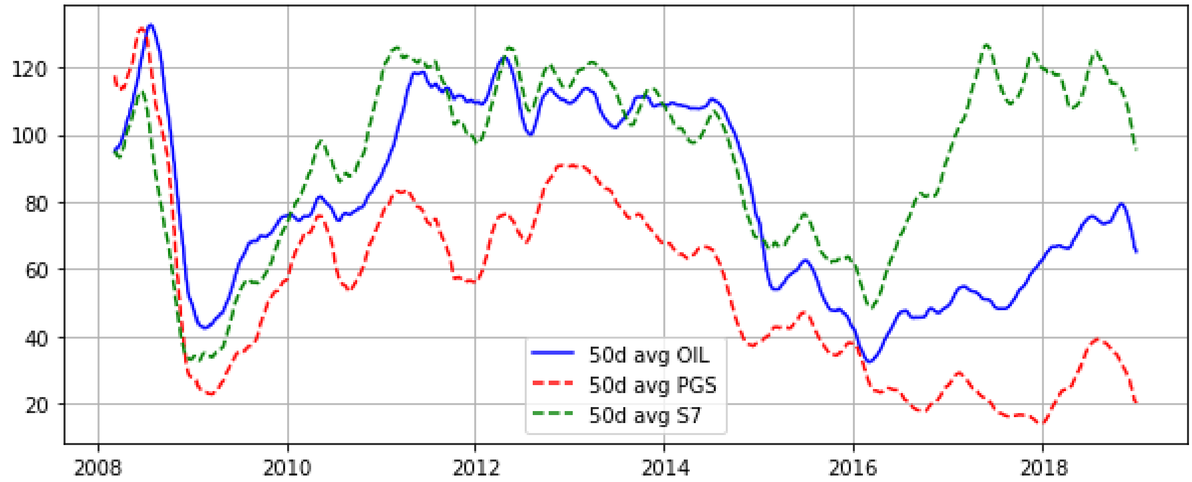

Figure 8-11 Comparison 50day average Oil, PGS and Subsea 7

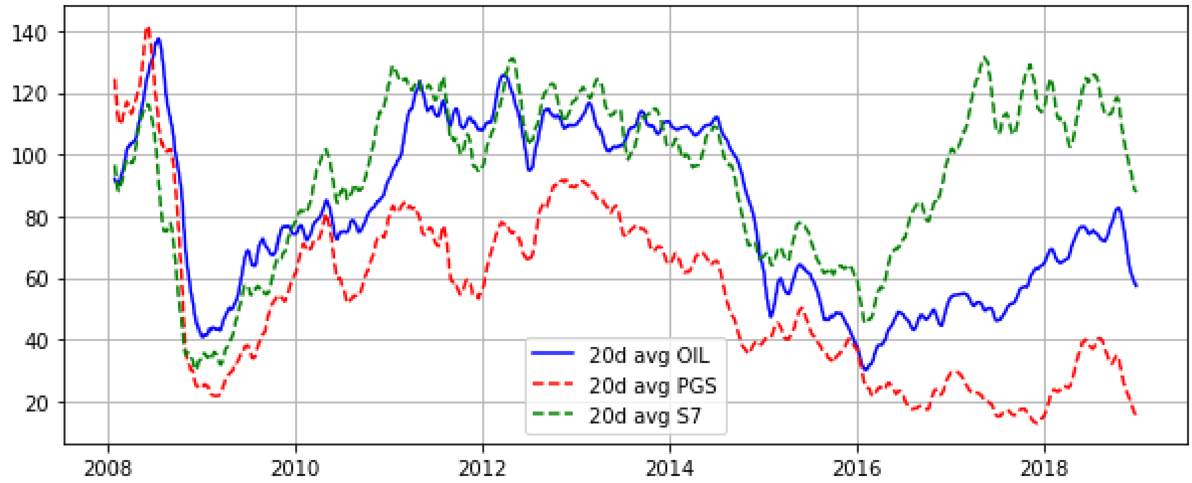

Figure 8-12 Comparison 20day average Oil, PGS and Subsea 7

From the figures above, especially for the 200d moving averages it can be seen that there seems to be a direct correlation between the moving averages of oil price (Brent) and the two representative stocks. This again reinforces the hypothesis mentioned earlier.

One point of interest is the 20d average of the PGS stock after 2016. Even though the oil price gradually recovered from 2016-2019, this was not captured in the PGS stock. One explanation of this was that internal financing was challenging after delivery of the Ramform Tethys in 2016 and Hyperion in 2017 combined with a weak multiclient and contract market due to E&P companies still being reluctant to perform new seismic exploration.

Figure 8-13 Ramform Tethys (2016) and Ramform Hyperion (2017)

However, it can be argued that looking at stock-data an oil price in the same graph can be misleading as the one is not comparing against the same reference level. Therefore, it can be interesting to calculate the daily percentage change on closing price of the stocks/commodity. The daily percentage change is the change in the value of a stock over a single day of trading when comparing closing and open prices.

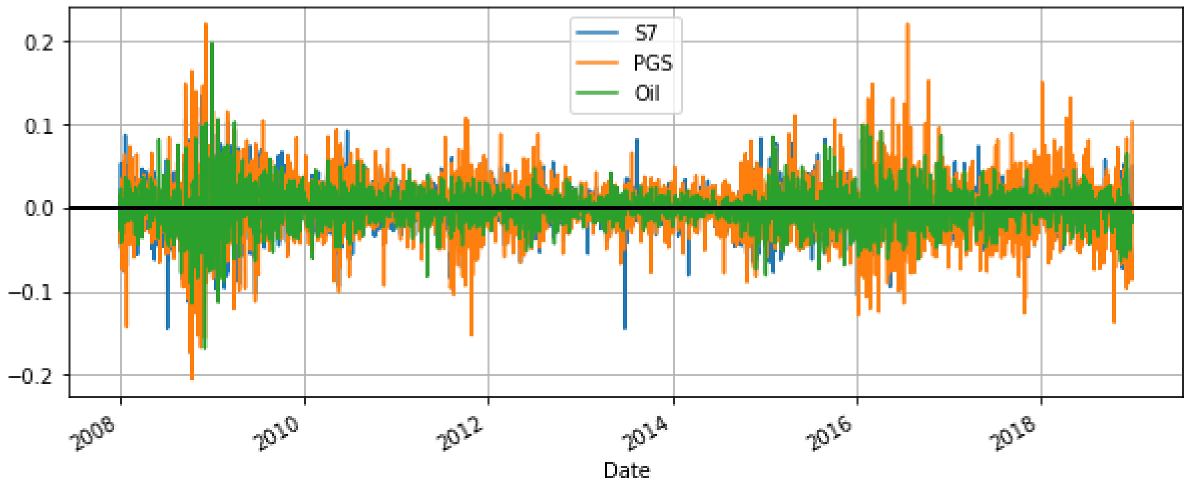

Figure 8-14 Daily percentage change of Subsea 7 and PGS compared to oil price (Brent)

From Figure 9-3 it can be seen that the daily percentage change of oil seems to be correlated to the PGS stock. Also, it can be seen that the PGS stock by far is more volatile than S7 and the price of oil. By including all the companies described in the sections above we get Figure 9-4 and we can see the same trend. From this plot we also see that the daily percentage change of MCG and MSEIS which are smaller companies are larger as expected.

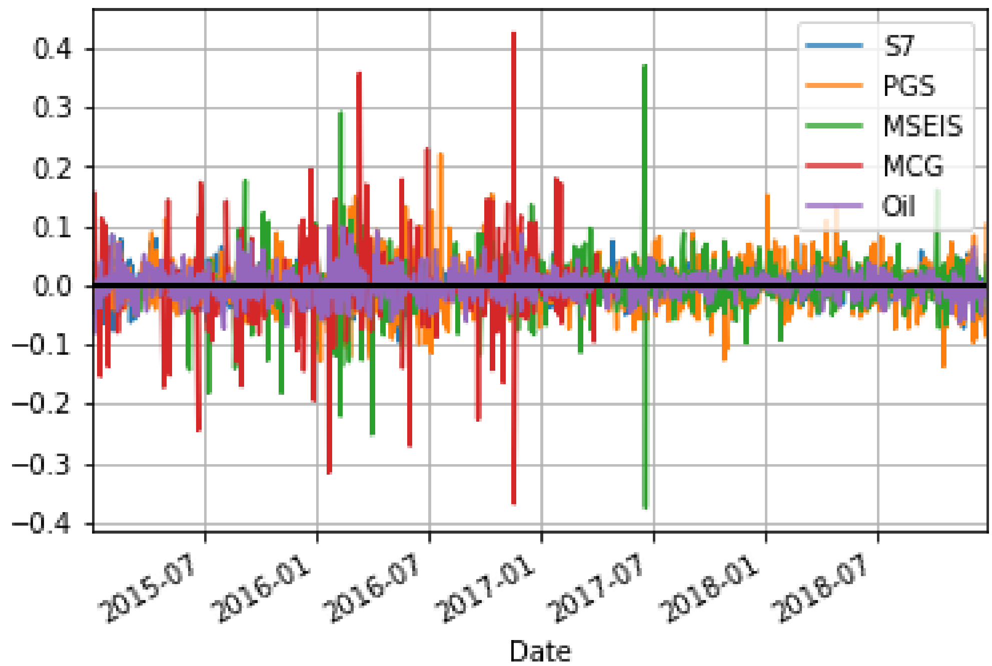

Figure 8-15 Daily percentage change of multiple stocks compared to oil price (Brent)

8.3 Volatility and correlation of stocks

The volatility of a stock is a metric that measures the amount of change of variance in the stock-price over a specific time-period. It is common to compare the volatility of a stock to another stock to get a feel for which may have less risk, or to a stock market index. It is commonly said that if a market rises and falls more than one percent over a sustained period of time, it can be called a "volatile" market. Generally, the higher the volatility, the riskier the investment is in that segment or stock (Heydt, 2015).

Volatility is typically calculated by taking a rolling-window standard deviation on the percentage change in a stock (Wooldridge, 2009). The standard deviation is the square root of the variance. The size of the window is important as it will affect the overall results. Typically, a wider a window will give a lower quality estimate of the volatility. As the window narrows, the result approaches the standard deviation. Therefore, it can be quite hard to pick the correct window size.

For looking at the relative volatility of a stock, one can calculate the beta β. The beta is a measure that approximates the overall volatility of a stocks return against the returns of a relevant benchmark. For oil service providers as described in the chapter above it would typically be related to the OBOSX benchmark. As an example, a stock with a beta of 0.8 has historically moved 80% for every 100% move in the underlying index.

The procedure to calculate the volatility of a closing price on a stock is to first evaluate the variance. To find the variance on typically follows this procedure (Wooldridge, 2009)

1. Find the mean of the dataset
2. Calculate the difference between each data value and the mean. This is the deviation of the data points
3. Square the deviations which eliminates negative values
4. Add the squared deviation and dived the sum of squared deviations with the number of data values.

If the stock price is to be considered as random samples from a normal distribution, then 68% of all data values will fall within one standard deviation. 95% of data values will fall within two standard deviation and 99.7% of all values will fall within three standard deviations. Assuming one standard deviation is typically used by traders as a simplification. However, we know from experience that distribution of extreme price movements are not as seldom as the normal curve would predict.

To be able to see if the closing prices of the companies presented in this thesis follows a normal distribution, we use Equation 1 and results from Figure 9-10 and Figure 9-11. From this we can use Python and sort the daily percentage change as shown in Figure 9-12. It is important to mention that a kernel density estimation method (Yang & Marron, 1999) is use which is a non-parametric way to estimate a PDE (probability density function) of a random variable. This implies that since we have a finite data sample from the available stock database, data smoothing errors are expected. In practical terms this means that from the presented normal distribution, one can misunderstand that the tails are relatively thin which means that price-shocks are infrequent. However, we know from the real world that this assumption might not be correct.

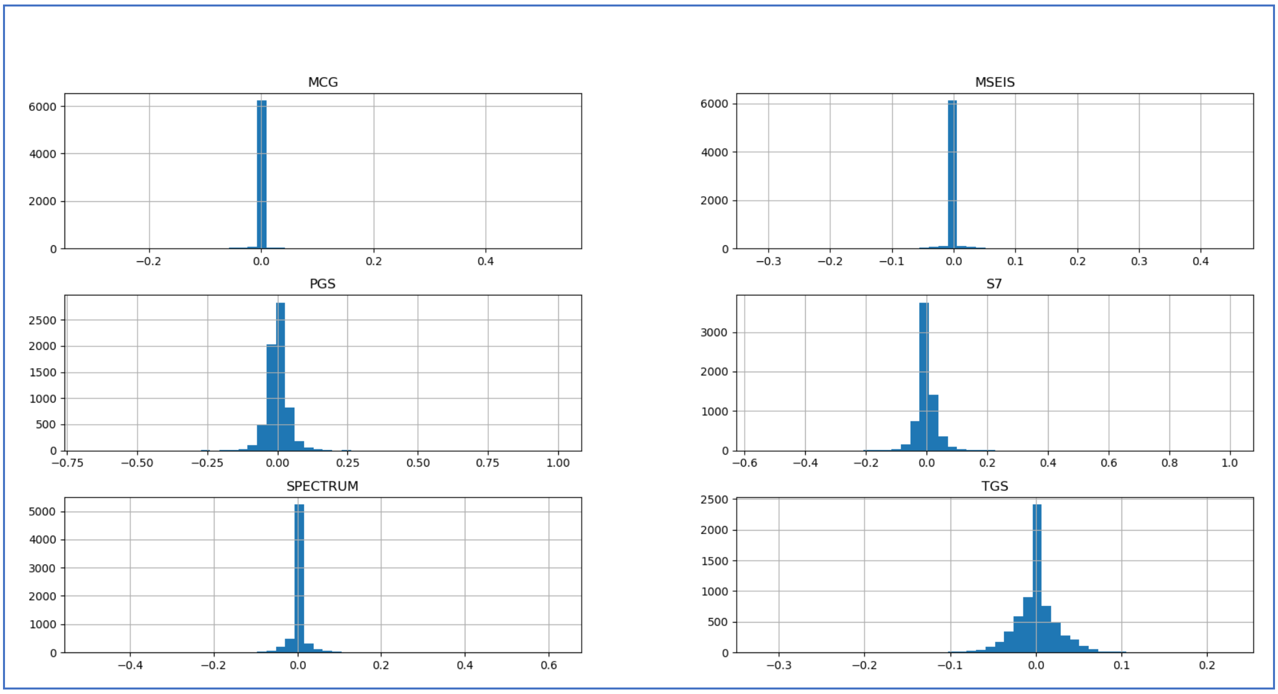

Figure 8-16 Distributions of daily percentage change on closing prices of oil-service stocks (MCG, MSEIS,PGS, S7,SPECTRUM,TGS from 2000-2019)

However as seen above for the stock data presented in this thesis, the distributions seem to fit a bell-curve and are symmetrical and normally distributed. The daily changes center around 0 and it is seen that especially the TGS stock is symmetrical around the center. Also introducing Equinor (E&P) into the graphs produce we can produce Figure 9-13.

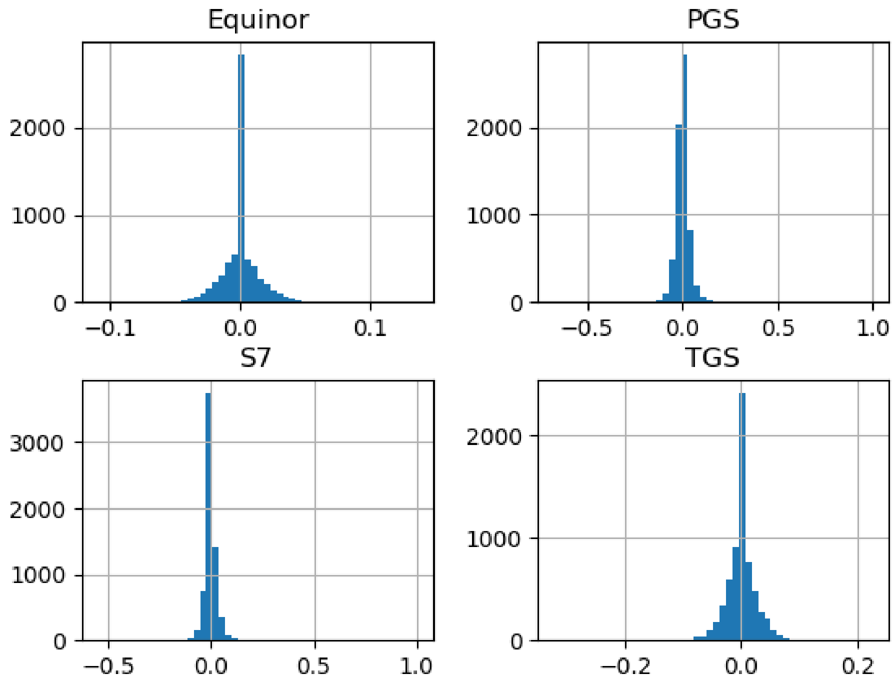

Figure 8-17 Key oil-service stocks and Equinor distributions

From Figure 9-17 above it can also be seen that the E&P company Equinor which is one of the biggest buyers of services from PGS, Subsea 7 and TGS also follows a normal distribution and seem to be symmetric around 0. When the distributions are known another useful graphical representation to determine if the closing price of the stocks are correlated is a scatter matrix. A scatter matrix can be used to determine if correlation is positive or negative and is a estimation of the covariance matrix (Leonard & Papasouliotis, 2006). With the probability distributions of Figure 9-17, we can establish the covariance matrixes in python and plot them as a matrix in Figure 9-18.

From the matrix in Figure 9-18 the diagonal shows the distribution of the 4 numeric variables of stock-prices. In the other cells of the matrix we have scatterplots (correlation plots of pairs of variates) of each variable combination within the data frame. In the first row we see correlation between Subsea 7 and PGS, TGS and Equinor. From the bottom row of the plot where Equinor is plotted one can see that both the Subsea 7 (S7), PGS (PGS) and TGS (TGS) stock shows a linear relationship with the closing price of the Equinor stock which is as expected and shown in the chapters above. However, we see from the PGS stock that there is not strong correlation and this can partially be explained by the stock-price movements post 2016 when the company had significant debt related to the weak market and the vessel rebuild program (Figure 9-3) The diagonal again seem to be normally distributed but this is strongly dependent on the bandwidth selection. Bandwidth selection is important as it is a free parameter which exhibits strong influence on the result and when assuming a gaussian basis function, the optimal bandwidth is typically the one that minimize the mean integrated square error (Chen, 2015).

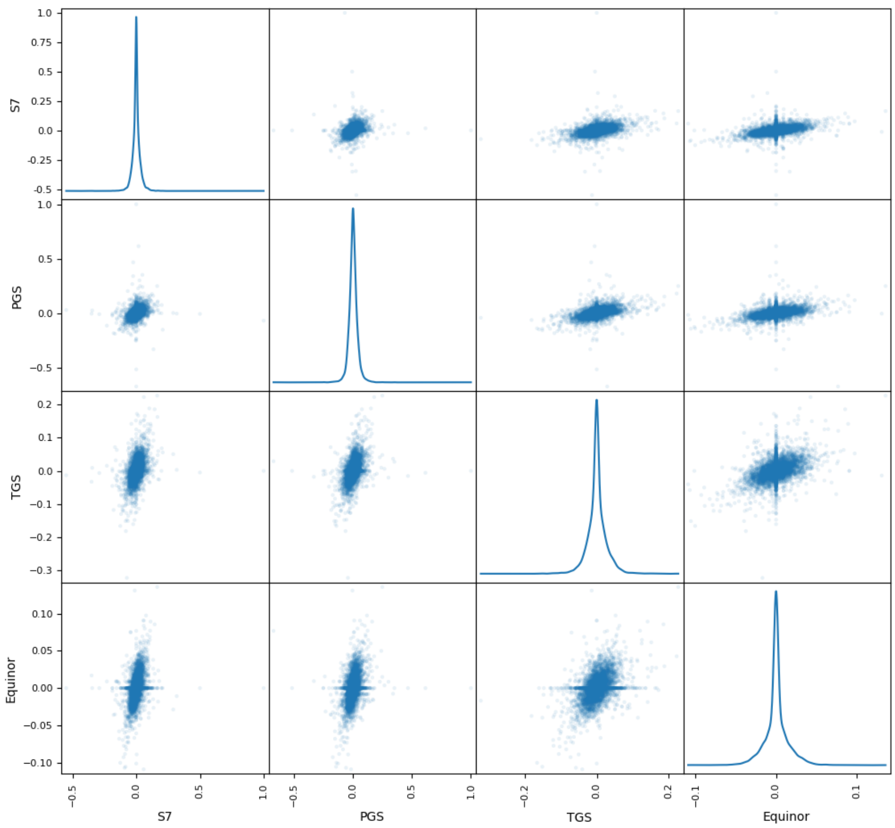

Figure 8-18 Scatter matrix of oil-service providers and Equinor

Also introducing the oil-price into the scatterplot gives us Figure 9-15 where the same trend as described above can be observed.

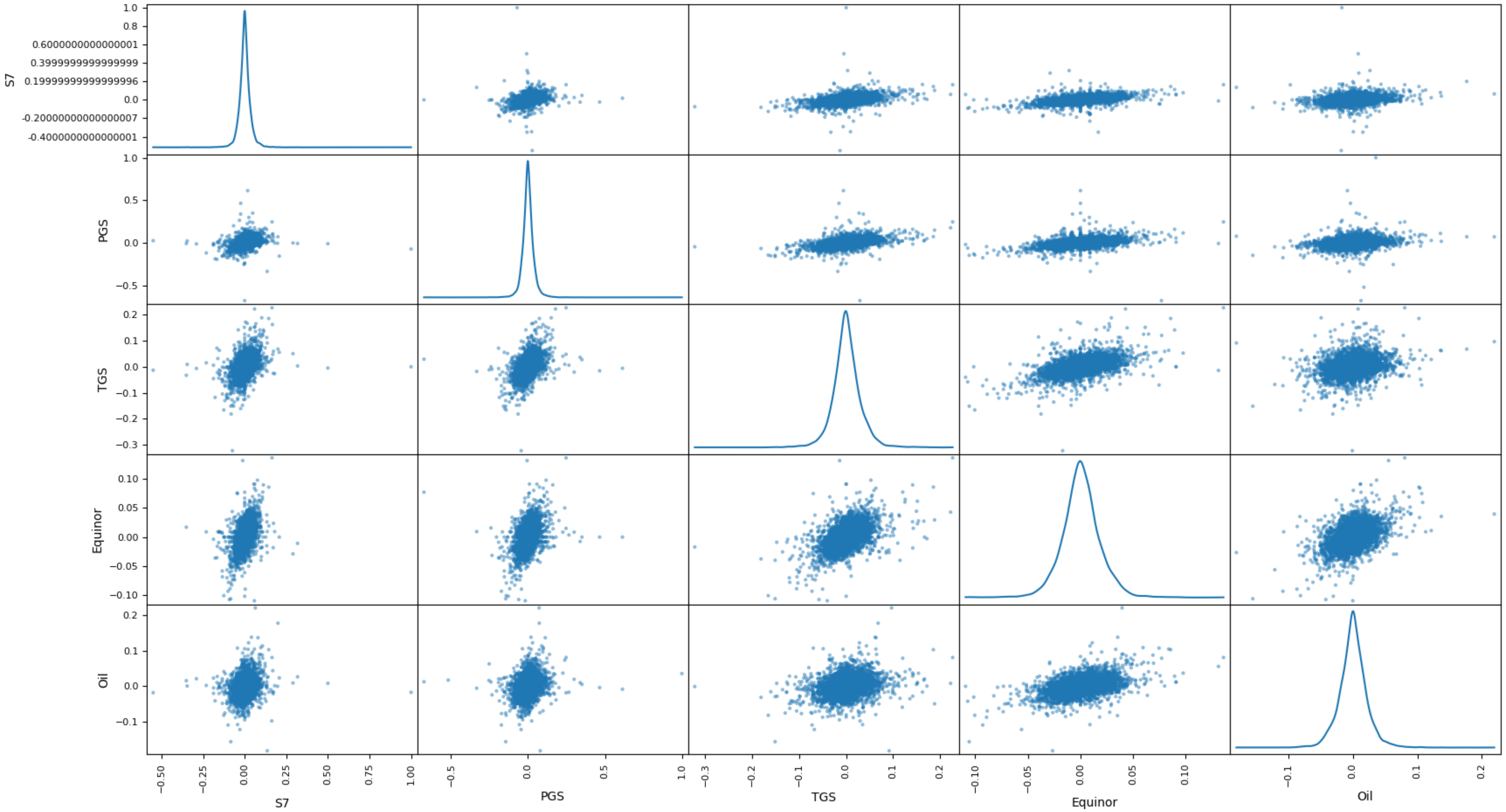

Figure 8-19 Scatter plot of oil-service providers, Equinor and Oil-price

The same scatter plot can also be made with logarithmic scale instead of raw closing price which add the benefit of normalizing the closing price value. Normalization is known to be a typical requirement for many multidimensional statistical analyses when the variables are both measured in percentage (Davison, 1983). From this we see that the matrix changes slightly, but the conclusion remains similar.

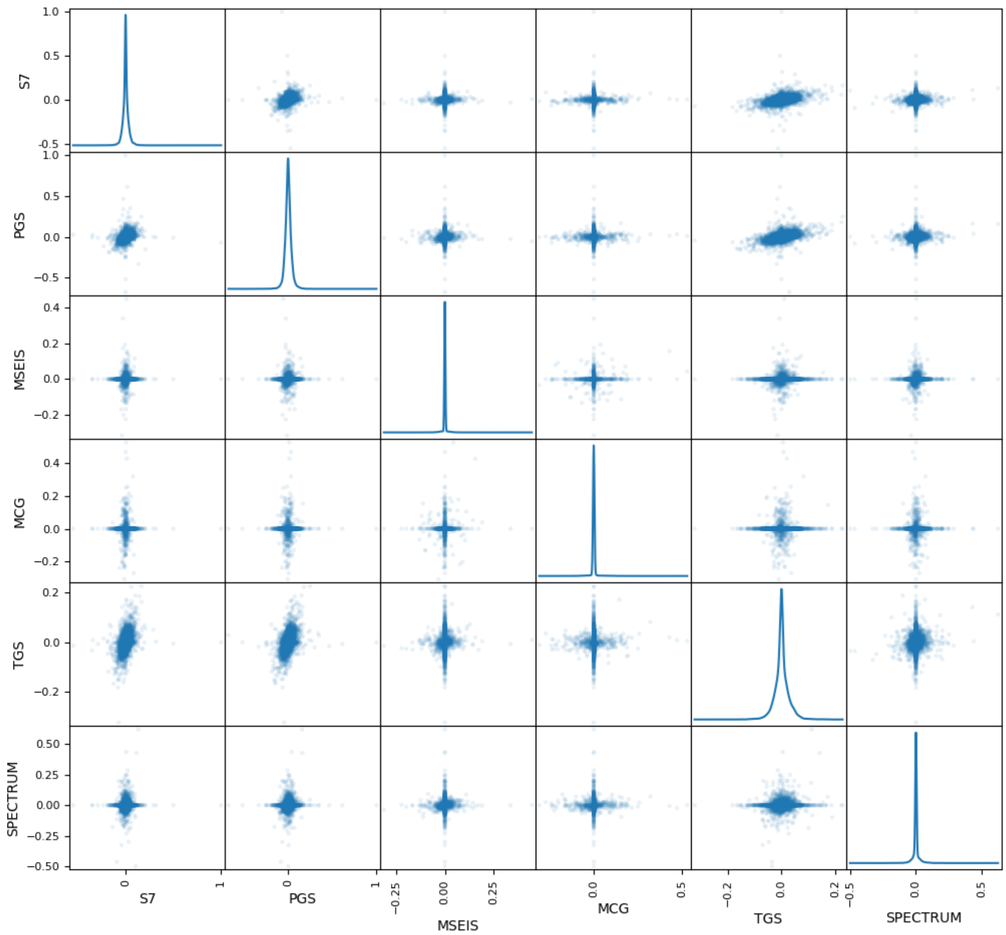

Figure 8-20 Logarithmic price on scatter-plot matrix

As mentioned above the scatter-matrix plot is a nice visual tool for observing correlation in variate and multivariate distributions. However, to test the hypothesis that oil price and stock price of the selected oil-service companies mentioned above are positively correlated, a hypothesis test can be performed. From (Wooldridge, 2009) we know that in order to perform a hypothesis-test we can assume a linear relationship exist between the depend and predictor variables. To some extent we see that this is the case from the figures presented above.

Linear regression is a model that predict a relationship of direct proportionality between the dependent variable (plotted on the vertical Y-axis) and predictor (plotted on the horizontal X-axis). If linearity exists, we should have a straight line (Wooldridge, 2009). As we note that the correlation for the PGS stock seem to be weaker (as can be seen from Figure 9-6) than for the remaining oil-service companies presented in this thesis a simplified regression analysis is performed on this stock.

Equation (2)

$$\partial PGS_{share} = \beta_1 + \beta_2 Oil\_price$$

For our dependent variable, I will use Stock data for PGS and Equinor, which measures price of the respective stock. For our predictor variables we will use the oil price. We also know from (Wooldridge, 2009) that in statistics, ordinary least squares (OLS) is a type of linear lest squares method for estimating the unknown parameters in a linear regression model. In this context it is important to be aware of the ordinary least squares (OLS) assumption which should be BLUE (Best Linear Unbiased Estimate) which from (Wooldridge, 2009) are given below:

1. **Linearity**: A linear relationship exists between the dependent and predictor variables. If no linear relationship exists, linear regression isn't the correct model to explain our data. In other words, the model is built by linearly adding terms together where the betas (β) are the parameters that the OLS estimates. Epsilon (ε) represents the random error.

Equation (3)

$$y_i = \beta_1 + \beta_2 x_{1i} + \beta_3 x_{2i} + \ldots + \beta_k x_{(k-1)i} + e_i$$

2. **No multicollinearity**: Predictor variables are not collinear, i.e., they aren't highly correlated. This is not relevant in our case as we have only one predictor variable, however in the case of multiple variables, avoiding multicollinearity is important.

In the case of multiple variables, the violation of this assumption is not very usual, it only occurs when the model is inaccurate (Wooldridge, 2009). It is important to point out that there should in most cases be some correlation between the independent variables, only that it should not be perfectly correlated. According to (Wooldridge, 2009), If there would be any correlation between the independent variables, then multiple regression would not have been used sufficiently in a time series analysis. Since we only include one predictor, this assumption should be valid.

3. **Zero conditional mean**: The error terms account for the variation of the dependent variable that the independent variables fail to explain. In other words, in this context it would mean that the independent variable here given as oil-price have been impacted by unknown variables, which we did include in our model.

By only including one independent variable we might violate this condition as there might be other variables influencing the stock price such as currency, OPEC decisions, politics etc. However, this is not further included here as this is a simplified assessment.

4. **Homoskedasticity**: The certainty (or uncertainty) of our dependent variable is equal across all values of a predictor variable; that is, there is no pattern in the residuals (same variance in their errors). In other words, the residuals are homoscedastic meaning that they have the same variance.

Equation (4)

$$Var(e_i) = \sigma^2$$

5. **No autocorrelation (serial correlation)**: Autocorrelation is when a variable is correlated with itself across observations. The error terms are said to be autocorrelated if and only if the errors of response variables are uncorrelated. The failure of this assumption is very common among stock price because a previously growing stock price could influence current stock price. This kind of situation creates a failure for the fourth assumption which can give misleading results. This can be a

typical problem which can be solved with Durbin-Watson test were one test two hypothesizes.

H0: No autocorrelation, ρ=0

H1: Autocorrelation ρ > 0

Durbin Watson-statistic

Equation (5)

$$DW = \frac{\sum_{i=2}^{N}(\hat{e}_i - \hat{e}_{i-1})^2}{\sum_{i=1}^{N}\hat{e}_i^{\,2}} = \frac{\sum_{i=2}^{N}\hat{e}_i^{\,2} + \sum_{i=2}^{N}\hat{e}_{i-1}^{\,2} - 2\sum_{i=2}^{N}\hat{e}_i\hat{e}_{i-1}}{\sum_{i=1}^{N}\hat{e}_i^{\,2}} = \frac{\sum_{i=2}^{N}\hat{e}_i^{\,2}}{\sum_{i=1}^{N}\hat{e}_i^{\,2}} + \frac{\sum_{i=2}^{N}\hat{e}_{i-1}^{\,2}}{\sum_{i=1}^{N}\hat{e}_i^{\,2}} - 2\frac{\sum_{i=2}^{N}\hat{e}_i\hat{e}_{i-1}}{\sum_{i=1}^{N}\hat{e}_i^{\,2}}$$

$$\approx 1 + 1 - 2\hat{\rho}$$

$$= 2(1 - \hat{\rho})$$

By using python and the script developed in the appendix we get the following results when testing equation (2).

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    PGS   R-squared:                       0.163
Model:                            OLS   Adj. R-squared:                  0.163
Method:                 Least Squares   F-statistic:                     439.5
Date:                Thu, 11 Jul 2019   Prob (F-statistic):           2.61e-89
Time:                        11:59:32   Log-Likelihood:                 4660.8
No. Observations:                2258   AIC:                            -9318.
Df Residuals:                    2256   BIC:                            -9306.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -0.0002      0.001     -0.270      0.787      -0.001       0.001
Oil            0.7149      0.034     20.965      0.000       0.648       0.782
==============================================================================
Omnibus:                      363.287   Durbin-Watson:                   2.111
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2162.649
Skew:                           0.617   Prob(JB):                         0.00
Kurtosis:                       7.633   Cond. No.                         52.7
==============================================================================
```

Figure 8-21 OLS regression results of PGS stock versus oil

Adjusted R squared of 0.163 indicated that 16.3% of the PGS stock price can be explained by our present predictor variable (Brent oil price). This is expected as we know that the PGS share price is not solely dependent on oil price and especially when observing the stock closing price after 2016 we would expect a lower correlation as shown in Figure 9-3.

The regression coefficient represents the change in the dependent variable results from a unit change in predictor variable when all other variables are kept constant. Since we have logarithmic returns, we need to be cautious. An increase of 1% in oil price increases PGS stock price with 0.71 percent.

The P-value mentions that with an increase of oil price which gives a PGS share price increase of 0.75 is 78% . when performing the Durbin-Watson test to autocorrelation we see that should some serial correlation as the value is close to 2.1. The model can therefore be concluded to not represent a strong model due to the occurrence of the collapse of the seismic market post 2016. Results presented here are therefore only indicative assuming OLS can be used to predict the PGS stock-price reaction based on Oil-price.

Regression plots of the remaining stocks can be produced as shown in Figure 9-18 to Figure 9-21. From the residuals versus oil we can also observe that they are more severely spread for the PGS stock compared to the other stocks including Equinor stock price.

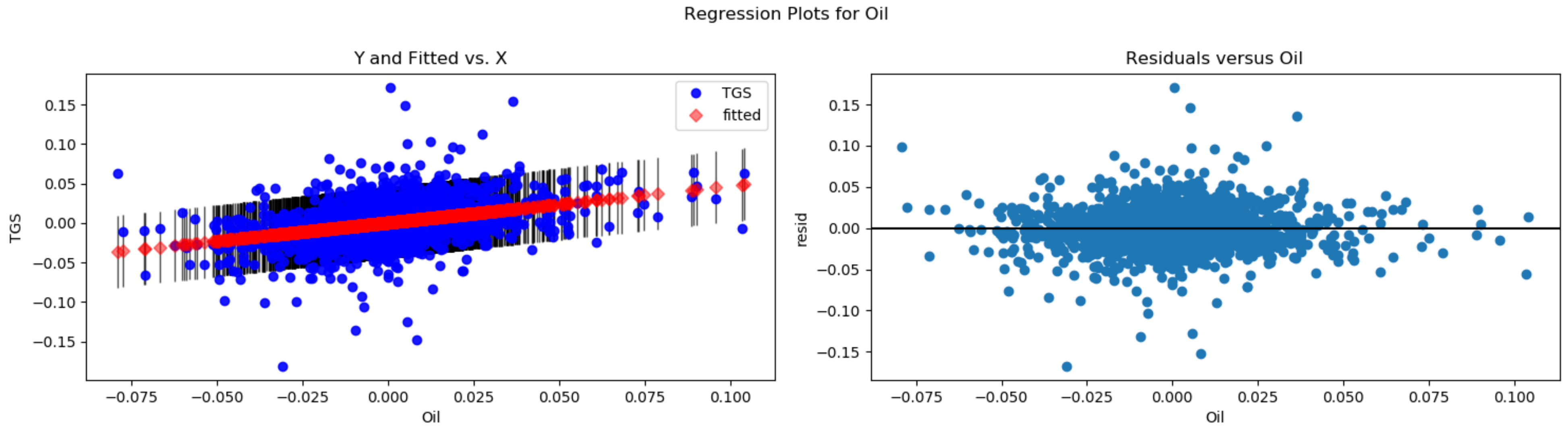

Figure 8-22 Regression plot of TGS versus oil

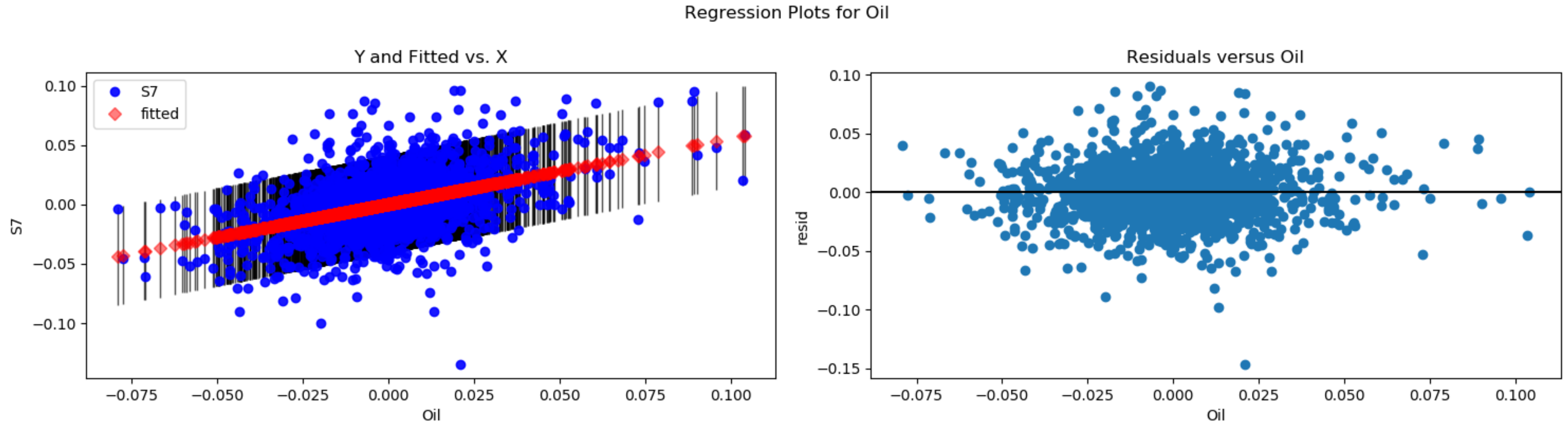

Figure 8-23 Regression plot of S7 versus oil

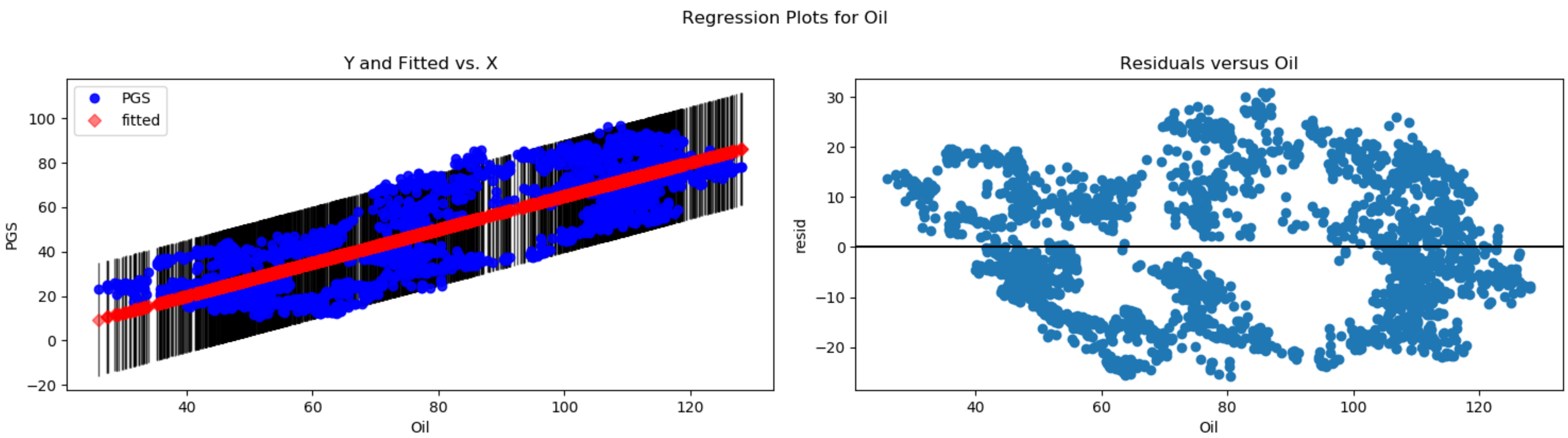

Figure 8-24 Regression plot of PGS versus oil

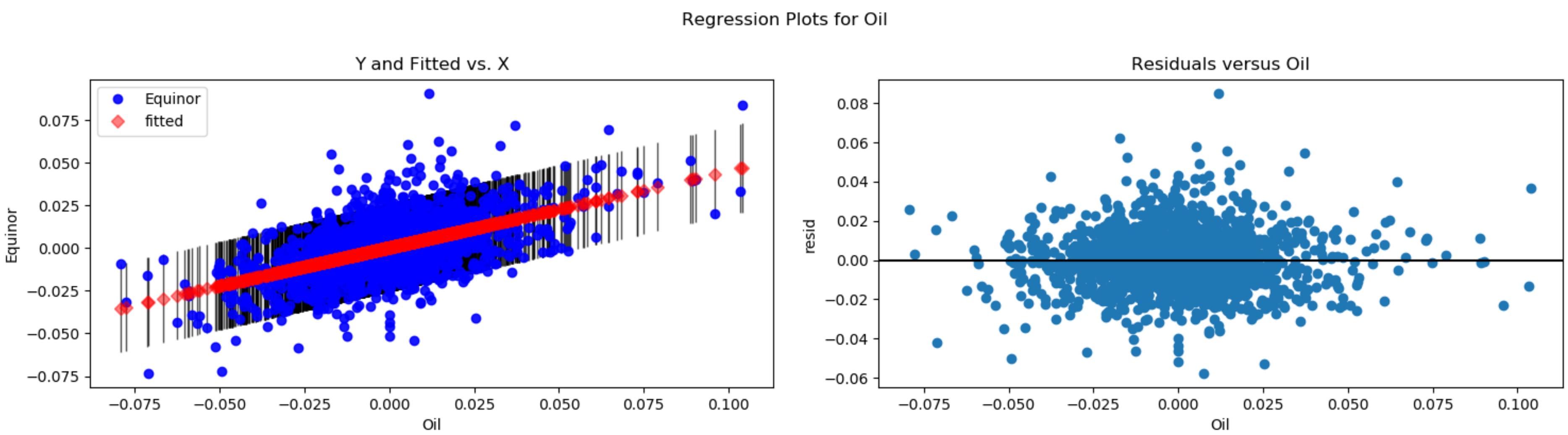

Figure 8-25 Regression plot of Equinor versus Oil

9 EXPLORATION AND SURF INVESTMENTS MEASUREMENT FOR THE FUTURE

A reserve Replacement Ration (RRR) is the amount of oil added to a company's reserves divided by the amount extracted for production and is a metric used by investors to judge an oil company's operating performance. Reserve-replacement ratio of 100% indicates that the company can sustain current production levels and if it is less than 100% it implies that the oil producer will deplete it resources. If this ratio has been low over a period of time, it traditionally has implied high investment activity for exploration and also for SURF. For 2017 and 2018 the RRR has been very close to 0 due to the fact that investment in E&P after the market crash in 2014 has been significantly reduced.

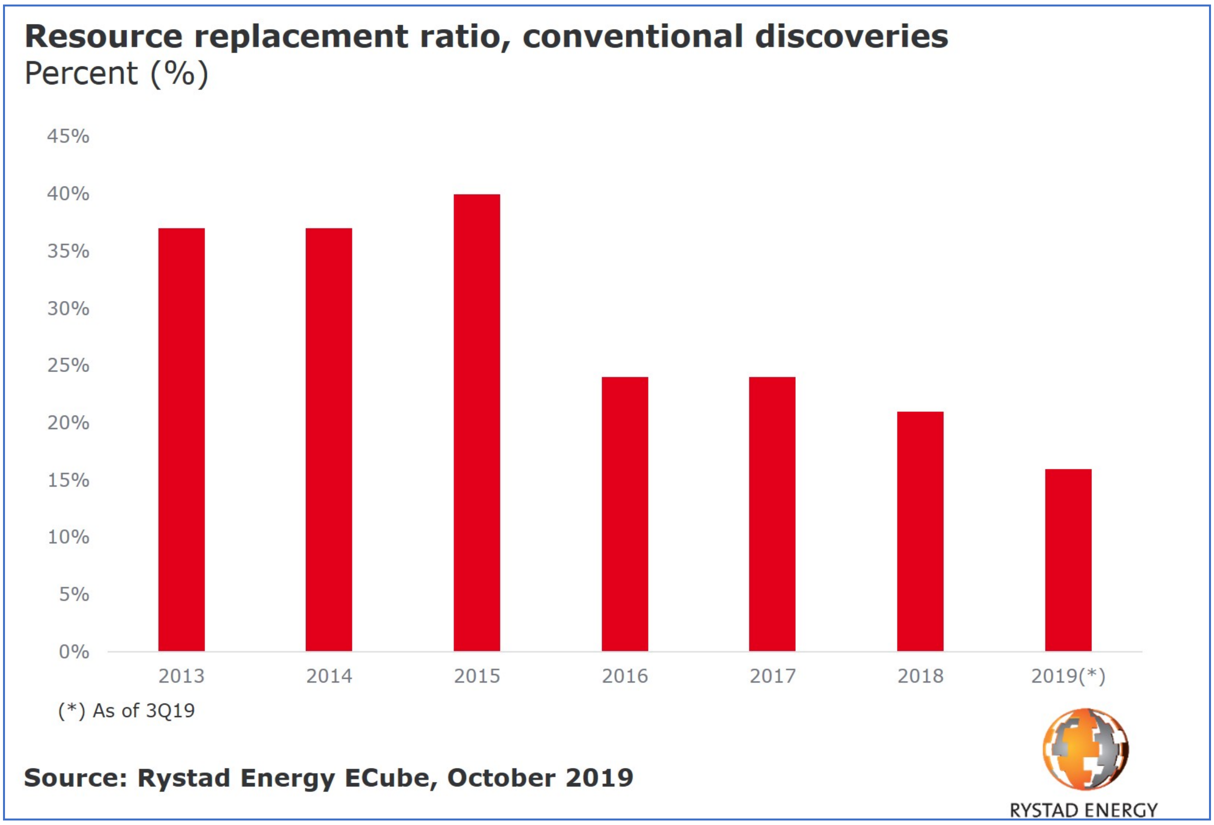

Figure 9-1 Resource Replacement Ration according to Rystad Energy ECube 2019

From the figure above it can be seen that RRR has been less than 1 in the period from 2013 to 2019. This implies that production levels cannot be withheld in a period of 10 years given no extra resources from extended exploration. This has been a trend the latter years and could potentially be an indication that both the geophysical and SURF market will recover in the future. However, dependent of the speed of the “green-shift” in energy production going from hydrocarbons to renewables this perception might be optimistic.

10 CONCLUSION

It is well known that the commodity price of oil is highly volatile and strongly influenced by supply and demand equilibrium dynamics. Oil service companies which in this thesis have been reduced to contain key players from the seismic and SURF (Subsea Umbilicals Risers and Flowlines) have performance indicators that are strongly correlated to the commodity price of oil and it is known that the demand for seismic in the short term depends on changes in the oil price and the exploration companies' free cash flow. When oil prices reduce and free cash flow is reduced, and it is well known in the industry that investment in geophysical exploration is one of the first to be reduced as new petroleum reserves in the short term are a luxury normal good for oil producers. Between geophysical exploration and SURF development, there typically exist a lag, and hence a similar coupling is hence also applicable for the SURF industry. In the long run, seismic data is a necessity for maintaining oil and gas production and it also required for performance monitoring of existing reservoirs. In all annual reports by the major geophysical companies listed on Oslo Børs, vessel continuity and revenues are explained by the volatility of the oil price. This coupling has in this master thesis been tested by extracting share-prices for different geophysical & SURF companies and comparing them to the Brent oil price and in general a positive correlation is found for both the geophysical and SURF industry.

However, from 2015 to 2020, experience have shown that geophysical companies have decided to either cold or hot stack several vessels. Because ships and crew are among geophysical companies most important input factors, the companies in the geophysical business are often found taking advantage of the available capacity, despite the declining demand. This has created a large imbalance between geophysical supply and demand. For the geophysical company PGS, it can be seen that post 2015 the closing price of the share has not been directly correlated with the increasing oil-price and there has been a phase-lag in the closing price of the company. On the other hand, the surf industry shows a more direct positive correlation without the same magnitude on the phase-lag.

This work has been written in a limited period of time, resulting in a limited amount of sensitivities being performed. It is found that in general the geophysical and SURF industry is positively correlated to the oil-price where the commodity price has been the only variable. In practice it is known that market analysts seldom solely refer to the oil price to predict market development in the medium and long term. In the geophysical industry it is common to examine reported budgets in E&P exploration for the top E&P producers to predict market movements. For the SURF industry it is common to evaluate oil & gas supply and demand and also access databases with subsea well (trees) procurements. It is known that every subsea tree will need a subsea pipeline, and hence databases with this type of information can be very useful to increase accuracy of future SURF market predictions. An example of the subsea tree procurement can be observed from the figure below from (Rystad Energy, 2017).

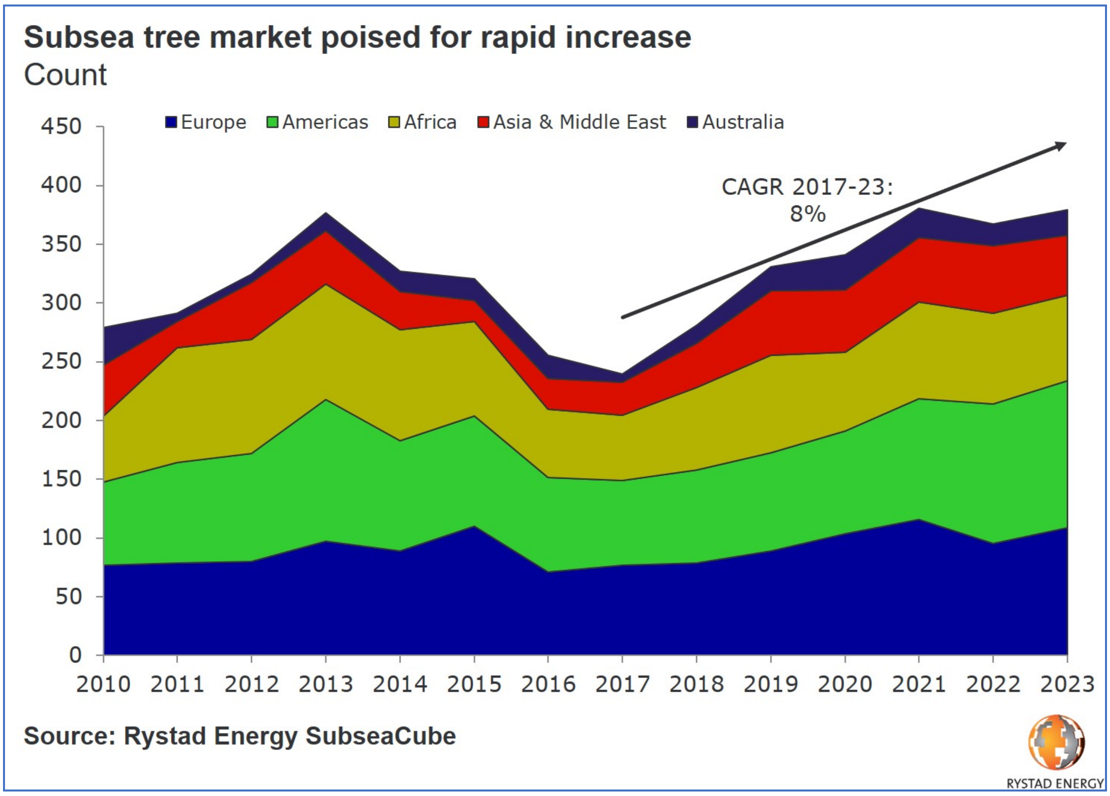

Figure 10-1 Example of Subsea tree marked count (2017) relevant for SURF

For further work, it would be of interest to quantify the relationship between share closing price and quarterly oil price & subsea tree marked count. Typically, it will be multiple years of procurement time of a subsea tree prior to a SURF contractor is awarded the installation contract. Also it would be of interest to evaluate the closing price of respective stocks compared to the reserve replacement ratio in chapter 9 and test for correlation and quantify magnitude of a potential phase-lag.

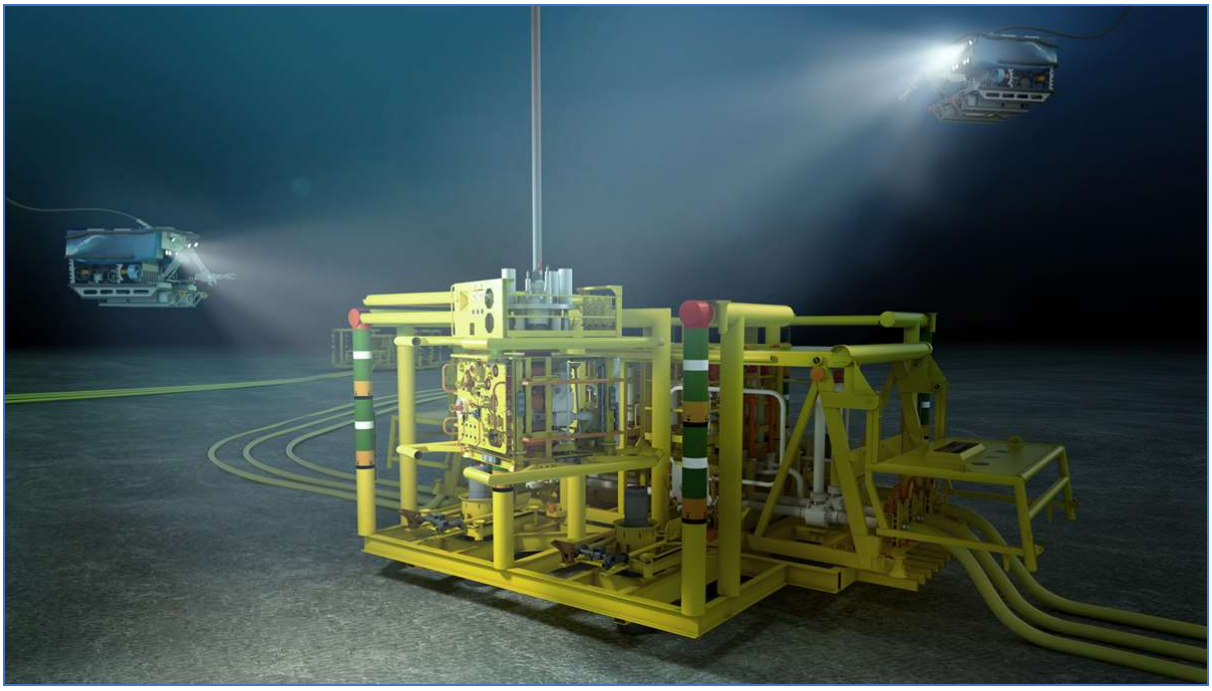

Figure 10-2 AkerSolutions subsea tree

Appendix Python scripts

[1] Python script 1

```python
# -*- coding: utf-8 -*-
"""
Created on Tue Jul  9 08:41:48 2019

@aut No documentation available
"""  Click anywhere in this tooltip for additional help

# -*- coding: utf-8 -*-
"""

"""

import pandas as pd
import quandl
import datetime
import numpy as np
import matplotlib.pyplot as plt   # Import matplotlib

start = datetime.datetime(2008,1,1)
end = datetime.date.today()


#IMPORT OILMARKET stockdata on sheet1 from file "stocksdata".
stock1 = pd.read_csv("Subsea7.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock2 = pd.read_csv("PGS2.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1",erro
stock3 = pd.read_csv("mseis.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock4 = pd.read_csv("mcg.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")

stock5 = pd.read_csv("TGS.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock6 = pd.read_csv("POLARCUS.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock7 = pd.read_csv("SPECTRUM.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")

#reading markets
market1 = pd.read_csv("OSEBX.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
```


```python
market1 = pd.read_csv("OSEBX.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
```


```python
market2 = pd.read_csv("OBOSX.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
spyderdat = pd.read_csv("OILPRICE.csv", parse_dates =True, index_col='DATE', dayfirst =True)
spyderdat = spyderdat.fillna(method='ffill')

#Visualizing several stocks together
#"""
#PGS, MCG, MSEIS

# Below  create a DataFrame consisting of the adjusted closing price of these stocks, first by making a list of th
stocks = pd.DataFrame({"S7": stock1["AdjustedPrice"],
                       "PGS": stock2["AdjustedPrice"],
                       "MSEIS": stock3["AdjustedPrice"],
                       "MCG": stock4["AdjustedPrice"],
                       "TGS": stock5["AdjustedPrice"],
#                       "POLARCUS": stock6["AdjustedPrice"],
                       "SPECTRUM": stock7["AdjustedPrice"]
                       })


stocks = stocks.loc[start:end]
stocks.plot(grid = True)

markets = pd.DataFrame({"OBOSX": market2["Open"],
                       "OSEBX": market1["Open"]
                       })


markets = markets.loc[start:end]
markets.plot(grid = True)
markets = markets.join(spyderdat.loc[:, "DCOILBRENTEU"]).rename(columns={"DCOILBRENTEU": "Oil"})


"""Rearranging axis to get the values to be similar"""
```

```python
ax2.plot(stocks['Oil'], color=color, linewidth = 3, linestyle = ':')
ax2.tick_params(axis='y', labelcolor=color)
fig.tight_layout()
ax1.grid(True)
ax1.legend()
plt.show()


'''Comparing PGS vs SPECTRUM TGS and oil-price'''

fig, ax1 = plt.subplots()
color= 'k'
ax1.set_xlabel('date')
ax1.set_ylabel('Stock price [NOK]')
ax1.plot(stocks['PGS'])
ax1.plot(stocks['TGS'])
ax1.plot(stocks['SPECTRUM'])
ax1.plot(stocks['MSEIS'])

ax1.tick_params(axis='y',labelcolor=color)
ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
#color = 'tab:red'
ax2.set_ylabel('OSEBX', color='k')  # we already handled the x-label with ax1
ax2.plot(markets['OSEBX'], color='k', linewidth = 3, linestyle = '-')
ax2.tick_params(axis='y', labelcolor='k')
fig.tight_layout()  # otherwise the right y-label is slightly clipped
ax1.grid(True)
ax1.legend()
plt.show()



#Comparing OSEMARKED vs oil price
#The OBOSX Index is a free float adjusted total return index (dividend adjusted) composed of the most liquid share
"""Rearranging axis to get the values to be similar"""

"""Calculating the returns of the stocks"""

stock_return = stocks.apply(lambda x: x / x[0])
stock_return.head() - 1
stock_return.plot(grid = True).axhline(y = 1, color = "black", lw = 2)

""" Comparing this to the oilprice market. I want this to be compared to OSEBX (oslo stock exchange)
"""
spyder = spyderdat.loc[start:end]
#spyder.plot(secondary_y = ["DCOILBRENTEU"], grid=True, ax=ax)
#spyder.plot(secondary_y = ["DCOILBRENTEU"], grid=True)
#source https://alfred.stlouisfed.org/series/downloaddata?seid=DCOILBRENTEU

stocks = stocks.join(spyder.loc[:, "DCOILBRENTEU"]).rename(columns={"DCOILBRENTEU": "Oil"})
stocks.plot(grid = True)


'''Comparing stock price vs oil price'''
fig, ax1 = plt.subplots()
color= 'tab:blue'
ax1.set_xlabel('date')
ax1.set_ylabel('Stock price [NOK]', color=color)
ax1.plot(stocks['PGS'])
ax1.plot(stocks['TGS'])
ax1.plot(stocks['SPECTRUM'])
ax1.plot(stocks['MSEIS'])

ax1.tick_params(axis='y',labelcolor=color)
ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
color = 'tab:red'
ax2.set_ylabel('Crude oil price [USD]', color=color)  # we already handled the x-label with ax1
ax2.plot(stocks['Oil'], color=color, linewidth = 3, linestyle = ':')
```

```
#The OBOSX Index is a free float adjusted total return index (dividend adjusted) composed of the most liquid share
                                        No documentation available
fig, ax1 = plt.subplots()               Click anywhere in this tooltip for additional help
color= 'k'
ax1.set_xlabel('date')
ax1.set_ylabel('Market price [NOK]', color=color)
ax1.plot(markets['OSEBX'])
#ax1.plot(markets['OBOSX'])


ax1.tick_params(axis='y',labelcolor=color)
ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
ax2.set_ylabel('Crude oil price [USD]', color='k')  # we already handled the x-label with ax1
ax2.plot(stocks['Oil'], color='k', linewidth = 3, linestyle = '-')
ax2.tick_params(axis='y', labelcolor='k')
fig.tight_layout()  # otherwise the right y-label is slightly clipped
ax1.grid(True)
ax1.legend()
plt.show()


#Comparing PGS vs oil price
#The OBOSX Index is a free float adjusted total return index (dividend adjusted) composed of the most liquid share

fig, ax1 = plt.subplots()
color= 'k'
ax1.set_xlabel('date')
ax1.set_ylabel('Share price [NOK]', color=color)
ax1.plot(stocks['PGS'])
#ax1.plot(markets['OBOSX'])


ax1.tick_params(axis='y',labelcolor=color)
ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
ax2.set_ylabel('Crude oil price [USD] No documentation available       l with ax1
ax2.plot(stocks['Oil'], color='k', li
ax2.tick_params(axis='y', labelcolor=  Click anywhere in this tooltip for additional help
fig.tight_layout()  # otherwise the right y-label is slightly clipped
ax1.grid(True)
ax1.legend()
plt.show()


#Calculating market correlation
macorr=markets['OBOSX'].corr(markets['Oil'])
macorr
# Let's use NumPy's log function, though math's log function would work just as well

stock_change = stocks.apply(lambda x: np.log(x) - np.log(x.shift(1)))
stock_change.head()

stock_change.plot(grid=True).axhline(y = 0, color = "black", lw = 2)

"""Calculating some typical risk metrics

Daily percentage change calculation"""
stock_change_apr = stock_change * 252 * 100    # There are 252 trading days in a year; the 100 converts to percent

stock_change_apr.tail()

#"Risk free rate

"""Calculating norges banks styringsrente and NOWA and using this as a measure of the risk free rate RFF"""
#SOURCE https://www.norges-bank.no/tema/Statistikk/Rentestatistikk/

NOWA = pd.read_csv("NOWA.csv", parse_dates =True, index_col='date', dayfirst =True)
nowa1= NOWA.plot(grid = True, title = 'Styringsrente')
```

```
nowa1.set_xlabel("Date")
nowa1.set_ylabel("%")
NOWA.head()
rrf = NOWA.iloc[0, 1]    # Get the most recent styringsrente
rrf
#plt.plot(NOWA, label='First Line')
#plt.plot(tbill, label='Second Line')

#PLOTTING OIL PRICE VS INTEREST RATE (STYRINGSRENTE)
NOWA = NOWA.join(spyderdat.loc[:, "DCOILBRENTEU"]).rename(columns={"DCOILBRENTEU": "Oil"})
NOWA = NOWA.fillna(method='ffill')
fig, ax1 = plt.subplots()
color= 'tab:red'
ax1.set_xlabel('date')
ax1.set_ylabel('interest rate %', color=color)
ax1.plot(NOWA['STYRINGSRENTE'], color=color)
ax1.tick_params(axis='y',labelcolor=color)
ax2 = ax1.twinx()  # instantiate a second axes that shares the same x-axis
color = 'tab:blue'
ax2.set_ylabel('Crude oil price', color=color)  # we already handled the x-label with ax1
ax2.plot(NOWA['Oil'], color=color)
ax2.tick_params(axis='y', labelcolor=color)
```

```
ax2.tick_params(axis='y', labelcolor=color)
fig.tight_layout()  # otherwise the right y-label is slightly clipped
ax1.grid(True)
plt.show()

#CALCULATING CORRELATION BETWEEN STOCK PRICES AND OIL PRICES
smcorr = stock_change_apr.drop("Oil", 1).corrwith(stock_change_apr.Oil)    # Since RRF is constant it doesn't chan
                                                                          # correlation so we can ignore it in our
                                                                                # calculation
smcorr

# Then we compute alpha and beta"""

sy = stock_change_apr.drop("Oil", 1).std()
sx = stock_change_apr.Oil.std()
sy
ybar = stock_change_apr.drop("Oil", 1).mean() - rrf
xbar = stock_change_apr.Oil.mean() - rrf
ybar
beta = smcorr * sy / sx
alpha = ybar - beta * xbar
beta
alpha
sharpe = (ybar - rrf)/sy

sharpe
(xbar - rrf)/sx


#moving averages fro PGS

PGSAVG=stocks
OILAVG=stocks
```

```
PGSAVG["20d PGS"] = np.round(stocks["No documentation available              n(), 2)
PGSAVG["50d PGS"] = np.round(stocks["                                        n(), 2)
PGSAVG["200d PGS"] = np.round(stocks[Click anywhere in this tooltip for additional help ean(), 2)
OILAVG["20d Oil"] = np.round(stocks["Oil"].rolling(window = 20, center = False).mean(), 2)
OILAVG["50d Oil"] = np.round(stocks["Oil"].rolling(window = 50, center = False).mean(), 2)
OILAVG["200d Oil"] = np.round(stocks["Oil"].rolling(window = 200, center = False).mean(), 2)
#


averagesPGS = pd.DataFrame({"PGS":stocks["PGS"],
                      "20days avg": stocks["20d PGS"],
                      "50days avg": stocks["50d PGS"],
                      "200days avg": stocks["200d PGS"]})
averagesPGS.head()
averagesPGS.plot(grid = True)

averagesOIL = pd.DataFrame({"Oil price":stocks["Oil"],
                      "20days avg": stocks["20d Oil"],
                      "50days avg": stocks["50d Oil"],
                      "200days avg": stocks["200d Oil"]})
averagesOIL.head()
averagesOIL.plot(grid = True)


#PLOTTING 200 day averages of PGS and Oil price

fig, ax= plt.subplots()
ax.plot(averagesOIL["200days avg"],'-b', label='200d avg OIL')
ax.plot(averagesPGS["200days avg"],'--r', label='200d avg PGS')
ax.grid(True)
leg=ax.legend()
plt.show()

fig, ax= plt.subplots()
ax.plot(averagesOIL["50days avg"],'-b', label='50d avg OIL')
ax.plot(averagesPGS["50days avg"],'--r', label='50d avg PGS')
ax.grid(True)
leg=ax.legend()
plt.show()

fig, ax= plt.subplots()
ax.plot(averagesOIL["20days avg"],'-b', label='20d avg OIL')
ax.plot(averagesPGS["20days avg"],'--r', label='20d avg PGS')
ax.grid(True)
leg=ax.legend()
plt.show()
```

[2] Python script 2

```python
"""
#@author: TORE JACOBSEN based on input from https://www.datacamp.com/ & https://www.learndatasci.com/tutorials/pre
"""
import pandas as pd
import datetime
import matplotlib.pyplot as plt   # Import matplotlib
import pylab
import numpy as np
from pandas.plotting import scatter_matrix
from IPython.display import HTML, display
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.sandbox.regression.predstd import wls_prediction_std

start = datetime.datetime(2010,1,1)
end = datetime.date.today()


#IMPORT OILMARKET stockdata on sheet1 from file "stocksdata".
stock1 = pd.read_csv("Subsea7.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock2 = pd.read_csv("PGS2.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1",erro
stock3 = pd.read_csv("mseis.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock4 = pd.read_csv("mcg.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")

stock5 = pd.read_csv("TGS.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock6 = pd.read_csv("POLARCUS.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock7 = pd.read_csv("SPECTRUM.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")
stock8 = pd.read_csv("equinor.csv", index_col='Date', parse_dates =True, dayfirst =True, encoding = "ISO-8859-1")

#reading oilprice
spyderdat = pd.read_csv("OILPRICE.csv", parse_dates =True, index_col='DATE', dayfirst =True)
spyderdat = spyderdat.fillna(method='ffill')

stocks = pd.DataFrame({"S7": stock1["AdjustedPrice"],
                       "PGS": stock2["AdjustedPrice"],
#                       "MSEIS": stock3["AdjustedPrice"],
#                       "MCG": stock4["AdjustedPrice"],
                       "TGS": stock5["AdjustedPrice"],
#                       "POLARCUS": stock6["AdjustedPrice"],
#                       "SPECTRUM": stock7["AdjustedPrice"]
                       "Equinor": stock8["AdjustedPrice"]

                       })

stocks = stocks.loc[start:end]
stocks = stocks.join(spyderdat.loc[:, "DCOILBRENTEU"]).rename(columns={"DCOILBRENTEU": "Oil"})

#stocks["dS7"] = np.round(stocks["S7"].rolling(window = 200, center = False).mean(), 2)
#stocks["dPGS"] = np.round(stocks["PGS"].rolling(window = 200, center = False).mean(), 2)
#stocks["dTGS"] = np.round(stocks["TGS"].rolling(window = 200, center = False).mean(), 2)
#stocks["dEquinor"] = np.round(stocks["Equinor"].rolling(window = 200, center = False).mean(), 2)
#stocks["dOil"] = np.round(stocks["Oil"].rolling(window = 200, center = False).mean(), 2)
#stocks = stocks.fillna(method='bfill')

daily_close = stocks

# Daily returns
daily_pct_change = daily_close.pct_change()
#daily_pct_change = np.log(daily_close)-np.log(daily_close.shift(1))
# Replace NA values with 0
daily_pct_change.fillna(0, inplace=True)

# Inspect daily returns
print(daily_pct_change)

# Plot the distribution of `daily_pct_c`
daily_pct_change.hist(bins=50)
```

```
daily_pct_change.hist(bins=50)

# Show the plot
plt.show()
daily_pct_change.plot(grid = True)
plt.show()

# Pull up summary statistics
print(daily_pct_change.describe())

#Make a scatter matrix excluding the oilprice
scatter_matrix(daily_pct_change, diagonal='kde', alpha=0.1,figsize=(12,12))

#Adding oil price to the array
daily_close = stocks
# Re calculating Daily returns
daily_pct_change = daily_close.pct_change()

#Make a new scatter matrix including the oil price
scatter_matrix(daily_pct_change, diagonal='kde', alpha=0.5,figsize=(20,20))

#
# Define the minumum of periods to consider
min_periods = 75

# Calculate the volatility
vol = daily_pct_change.rolling(min_periods).std() * np.sqrt(min_periods)

# Plot the volatility
vol.plot(figsize=(10, 8))

# Show the plot
plt.show()

#Calculating the logaritmic returns and perecentage change of PGS stock and oil price
#log_retPGS = pd.DataFrame(stocks['PGS'], columns=['PGS'])
#log_retPGS['pct_changePGS']=log_retPGS.PGS.pct_change()
#log_retPGS['log_retPGS']=np.log(log_retPGS.PGS)-np.log(log_retPGS.PGS.shift(1))
#
#log_retOil = pd.DataFrame(stocks['Oil'], columns=['Oil'])
#log_retOil['pct_changeOil']=log_retOil.Oil.pct_change()
#log_retOil['log_retOil']=np.log(log_retOil.Oil)-np.log(log_retOil.Oil.shift(1))
#


#Perform statistical test to see if stock price (logarimtic return) is dependet on PGS price

oil_model = ols("PGS ~ Oil", data=daily_pct_change).fit()
#oil_model = ols("PGS ~ Oil", data=stocks).fit()

# summarize our model
oil_model_summary = oil_model.summary()
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(oil_model, "Oil", fig=fig)
# predictor variable (x) and dependent variable (y)
x = stocks[['PGS']]
y = stocks[['Oil']]
# Retrieve our confidence interval values
_, confidence_interval_lower, confidence_interval_upper = wls_prediction_std(oil_model)

print(oil_model.summary())



#Perform statistical test to see if stock price (logarimtic return) is dependet on PGS price on 200day average. Do
```

```
#oil_model = ols("dPGS~ dOil", data=daily_pct_change).fit()
##oil_model = ols("PGS ~ Oil", data=stocks).fit()
#
## summarize our model
#oil_model_summary = oil_model.summary()
#fig = plt.figure(figsize=(15,8))
#fig = sm.graphics.plot_regress_exog(oil_model, "dOil", fig=fig)
## predictor variable (x) and dependent variable (y)
#x = stocks[['dPGS']]
#y = stocks[['dOil']]
## Retrieve our confidence interval values
#_, confidence_interval_lower, confidence_interval_upper = wls_prediction_std(oil_model)
#
#print(oil_model.summary())

#Perform statistical test to see if stock price (logarimtic return) is dependet on Subsea7 price

oil_model = ols("S7 ~ Oil", data=daily_pct_change).fit()
#oil_model = ols("PGS ~ Oil", data=stocks).fit()
# summarize our model
oil_model_summary = oil_model.summary()
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(oil_model, "Oil", fig=fig)
# predictor variable (x) and dependent variable (y)
x = stocks[['S7']]
y = stocks[['Oil']]
# Retrieve our confidence interval values
_, confidence_interval_lower, confidence_interval_upper = wls_prediction_std(oil_model)
print(oil_model.summary())

#fig, ax = plt.subplots(figsize=(10,7))
## plot the dots
#ax.plot(x, y, 'o', label="data")



#Perform statistical test to see if stock price (logarimtic return) is dependet on TGS price

oil_model = ols("TGS ~ Oil", data=daily_pct_change).fit()
#oil_model = ols("PGS ~ Oil", data=stocks).fit()
# summarize our model
oil_model_summary = oil_model.summary()
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(oil_model, "Oil", fig=fig)
# predictor variable (x) and dependent variable (y)
x = stocks[['TGS']]
y = stocks[['Oil']]
# Retrieve our confidence interval values
_, confidence_interval_lower, confidence_interval_upper = wls_prediction_std(oil_model)
print(oil_model.summary())

#fig, ax = plt.subplots(figsize=(10,7))
## plot the dots
#ax.plot(x, y, 'o', label="data")








#Perform statistical test to see if stock price (logarimtic return) is dependet on Equinor price

oil_model = ols("Equinor ~ Oil", data=daily_pct_change).fit()
#oil_model = ols("PGS ~ Oil", data=stocks).fit()
# summarize our model
```

```
oil_model_summary = oil_model.summary()
fig = plt.figure(figsize=(15,8))
fig = sm.graphics.plot_regress_exog(oil_model, "Oil", fig=fig)
# predictor variable (x) and dependent variable (y)
x = stocks[['Equinor']]
y = stocks[['Oil']]
# Retrieve our confidence interval values
_, confidence_interval_lower, confidence_interval_upper = wls_prediction_std(oil_model)
print(oil_model.summary())

#fig, ax = plt.subplots(figsize=(10,7))
## plot the dots
#ax.plot(x, y, 'o', label="data")
```

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