Thesis Title

by
Jakob Hübertz

Professor SuperProf, Advisor

A thesis submitted in partial fulfillment
of the requirements for the
Degree of Bachelor of Arts with Honors
in Physics

WILLIAMS COLLEGE
Williamstown, Massachusetts
June 15, 2021

Abstract

This thesis is written to investigate the quantile dependence between the oil price and the market value of oil producers. Results are presented to show that the dependence is significant in the lower and upper quantiles, and the lower quantiles are shown to have a particularly large impact. Brent oil is shown to possess stronger connectedness to oil companies compared to WTI oil. Furthermore the time-varying connectedness is investigated, and it is shown to increase during periods of market turmoil.

Acknowledgments

I want to extend my acknowledgement to my supervisor Muhammad Yahya for contributing to spark my interest in the area of risk management, which made me choose this area of finance as the topic of my thesis. I am also grateful for the valuable input along the way. Lastly I want to thank my friends for the interesting and challenging financial discussions over the last years.

...

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Management of risk is one of the most important parts of capital management, and knowledge about how assets covariate is an essential part of the risk assessment. It is even more essential in the volatile oil markets where the next crisis always seems to be approaching. This was proven last year when the COVID pandemic caused the oil price to turn negative for the first time in history. It happened at the end of a volatile decade for the crude oil commodity, which in addition to a pandemic has played a part in a revolutionary wave, that swept through the Middle East causing oil prices to skyrocket, the collapse of an oil dependent economy in Venezuela causing a civil war and a shale oil revolution making United States a net exporter of oil for the first time since the oil embargo in 1973 (Hamilton, 2020). The latter might prove to alter the power dynamics in the continuous fight over access to energy resources. As the importance of oil has been proven to be the underlying reason for many of the geo-political conflicts of the last century (Yergin, 1990).

However, through all these crises the oil companies have persisted, some of them even since the beginning of the twentieth century. Although they have been aided by a continuously rising world activity, wealth increase and industrialization which has contributed to the increasing demand, they have shown a robustness not shared by many other industries. The industry is today experiencing one of the greatest threats to their business model so far. The sentiment surrounding the consumption of hydrocarbons is changing. The fight for reduced emissions has intensified over the last decade, and this culminated in the Paris agreement being signed by 196 countries that states the goal of limiting the temperature increase to 2 degrees above pre-industrialized levels. Responding to this new age of climate consciousness, several oil producers are in the middle of a rebranding process, and are trying to portrait themselves as companies focusing on renewables. The state-owned Norwegian oil company Statoil was renamed Equinor, and Total changed their name to TotalEnergies. Both these rebranding's are examples of efforts to portray themselves as broader energy companies in contrast to old fashioned oil producers, but the fact that they are still mainly crude oil producers remains no secret.

Being dependent on a single commodity makes it an interesting area of study, and we will shed further light on how this dependence plays out in the financial markets. Commodities itself have been subject to large capital inflows during the last decades, and today it plays a natural part in many portfolios and is considered to be an asset class of itself, in line with equities and fixed income securities.

When assessing risk, all aspects of the properties of the assets in question should be known, such that one could expect how the assets perform in relation to each other. Several studies have been conducted to investigate the connectedness between oil prices and market values of oil producers, however in this thesis we utilize the cross-quantilogram to reveal the quantile behaviour of this correlation. This will help us to increase the knowledge, and to help mitigate the risk during extreme market conditions.

We will use the cross-quantilogram (CQ) methodology which was proposed by Han et al. (2016). This method is used to investigate the correlations over different quantiles and provide information about how the oil price and market values depend on each other during all market conditions. To continue the investigation into the connectedness between the oil companies and the oil price, we will utilize the DCC-GARCH model. It will give an overview of the connectedness during the different time periods.

This thesis consists of five sections. It covers a brief background, aim and method that will be used in this thesis. The second section is the theoretical background which focuses on the theory. This section gives an overview to the reader and provides better understanding about the topic. The third section covers the methodology used in the study. This section covers the brief information about the models and theories behind them. The next section covers the empirical analysis and discussion about the results that are drawn from the models. In the last section we will conclude all the sections and sum up the thesis.

Chapter 2

Theoretical Background

2.1 The Crude Oil Market

The oil market has experienced increasing financialization in the last decades. In the earlier days oil was only traded through over-the-counter (OTC) transactions. The introduction of the crude oil future on the New York Mercantile Exchange in 1983 started the financialization of the crude oil market (Razavi, 1989). Since the introduction of futures, the crude oil market has grown to become one of the most developed commodity markets we have today. Crude oil is both the largest commodity in terms of production as well as volume trading on financial exchanges (Dunn and Holloway, 2012).

As only 1% of the futures contracts are being settled and fulfilled, this shows that the oil market consists of a financial instrument rather than actual trading of physical crude oil (Dunn and Holloway, 2012). The futures market allows producers and consumers to manage risk through hedging their transactions. It has also opened up a new market for strictly financial participants speculating on the price movements or performing arbitrage.

OTC transactions are still the most prevalent mode of transaction, when it comes to actual physical trading of crude oil. Forwards, options, and swaps are the most commonly used financial instruments. The reason behind this is the differences in delivery and quality of different oil blends make it difficult to trade through standard contracts like those traded in the futures market.

These differences in quality make it difficult to establish a benchmark price for the commodity. In today's market, the Brent and West Texas Intermediate (WTI) are the two most prevalent benchmarks used to price crude oil. The brent oil is referring to the oil blend made up of crude oil produced in the North Sea and is now "used to assess up to 70% of the oil produced worldwide" (Platts, 2010). WTI is representing the price of oil that passes the requirements of lightness and sweetness delivered to the refineries at Cushing, Oklahoma. The spot price refers to the price of which oil is traded at the open market, for immediate delivery at a specific delivery location.

Although the price indicators are highly correlated, the price spread might fluctuate due to several factors such as market regulations, changes in supply and demand, or logistical factors (Tian and Lai, 2019). This difference was especially evident during the COVID pandemic, when the price of the WTI turned negative, and the spread between Brent and WTI reached \$54.3 on the 20th of April 2020 (Fed, 2021).

2.2 Theory of Storage

The negative pricing of WTI in April 2020 suggests that there were problems accessing storage facilities in the delivery area in Cushing, Oklahoma. The theory of storage suggests that the price volatility decreases when storage is available. This is caused by the way storage decreases the supply to the market during periods of lower oil prices, this reduces the downward pressure on prices. The opposite is true if the oil price is high, as this will provide an incentive to the reduce inventories, leading to an increased supply to the market.

If we assume rational expectations, that the current spot price possesses all relevant information available, and thus the future price cannot be predicted.

Meaning that the error term: μ_{t+1}

$$\mu_{t+1} = E(P_{t+1}|\Omega_t) - E(P_t)$$

Will have mean zero, which is conditional on the current information available, and represented by Ω_t

Then storage would be profitable as long as:

$$\frac{1}{1+r}E(P_{t+1}) > P_t + m(I_t),$$

Where r is the required rate of return, $m(I_t)$ is the marginal cost of storage, P_t is the price of commodity at time t, and $E(P_{t+1})$ is the expected future price.

This will continue to make an effect until marginal benefit balances marginal costs, and the price reaches an equilibrium point. This effect is the basis of arbitrage between the current price and the future price of the commodity.

This is true as long as:

$$0 \leq I_t \leq C$$

Where I_t is storage today and C is the total capacity of storage.

During periods where storage is available and there is no stock-out, autocorrelation tends to be higher and volatility lower. However, there are limits to arbitrage which could lead to extreme price movements. We have seen that extreme price movements often coincide with stockouts and shortage of storage, as the availability of storage is removed and the inelasticity of supply and demand increases. Stock-outs make the price prone to large price hikes to the upside, as no excessive supply is available if the current demand should rise. On the other hand, storage at full capacity may result in large price deviations to the downside, as no more supply could be stored and removed from market.

This seems to have been the case when the price of WTI went negative during the initial phase of the COVID pandemic. In theory, there is nothing that prevents the price from turning negative if the demand for the product was inelastic. According to Büyüksahin et al. (2013) it has been shown that the conditions regarding the storage of the WTI in Cushing, Oklahoma could affect prices non-linearly.

A strong contango with a spread of over $50 between the May and June future indicates that there were limits to arbitrage as it would make storage highly profitable under normal circumstances. When the spread price between the futures contracts surpasses the price of storage and alternative price of money, then the commodity could be stored while performing a hedge by shorting the long-term future. Therefore, there must either have been no storage available making the demand completely inelastic or the storage cost must have surpassed the spread. There could also have been logistical constraints which made storage impossible. The latter seems to have been the case due to the delivery mechanism of the WTI oil, which according to Fattouh (2020) caused delivery problems of the contracts, making this unusually large contango possible.

2.3 Financilzation of the Crude Oil Market

Commodity markets have experienced an influx of money since the beginning of the 2000s. With trading volumes reaching 20 to 30 times of physically traded crude oil. There have been conflicting views on how these financial traders influence price discovery. As the commodity derivatives make up an increasingly larger part of the investment portfolio, a higher correlation could be expected with the financial markets (Silvennoinen and Thorp, 2010).

The inflows of capital from non-producers or consumers of oil started in 2003 and continued to increase throughout the decade (Fattouh et al., 2010). The commodity derivatives assets under management increased from $10 billion at the end of the 2000s to $450 billion in April 2011 (UNCTAD, 2012). There could be many reasons for an entry into the commodity markets for an investor, such as the diversification benefits, inflation hedge, or dollar hedge (Fattouh, 2013).

2.3.1 Hedging pressure

One could expect that the producers of crude oil would be more sensitive to price changes of the commodity than the consumers. For producers, the changes in commodity price would impact their cash flows to a greater extent. For the consumers, however, the commodity in question is often just a smaller part of their input factors. John Maynard Keynes therefore assumed that the producers would be more inclined to enter hedging positions in the futures market. This would lead to a hedging pressure which add a risk premium for anyone taking on the long side of the trade (Keynes, 1923).

Keynes (1923) proposed a theory of normal backwardation in the term structure of the futures market. The theory was based on a notion of risk premiums which had to be available for the financial parties taking the opposite position of the hedging transaction carried out by the producers. The motive of the financial traders taking the other side of the trade is of course to make a profit. However, he neglected the possibility of the financial traders to make any better predictions of the price development than the producers or consumers, he stated that the role of these traders could be better understood as risk-bearers than as 'prophets of the future' (Keynes, 1923).

The only solution to attract financial participants would be a risk premium to offset the risk taken by these market participants. For the producers in capital intensive sectors such as most commodity sectors, paying the risk premium was still beneficial as it allowed them to offset the price risk of the commodity. This allowed them a better management of the huge advance investments that were needed. This led to what Keynes called the 'normal backwardation' of the futures market. Where the term 'normal' referred to normal market conditions, where supply and demand are in balance.

If there was excessive supply, we could instead expect the term structure to be in contango, where the future price of the commodity surpassed the spot price. The contango would not necessarily imply that there was no risk premium, as the forward price could still be below that of the expected spot price at maturity in addition to the price of storage (Fantacci et al., 2010). This would also be the case if the consumer hedging pressure outperform the hedging pressure by consumers (Hambur and Stenner, 2017).

One could expect that the financialization of the crude oil market would increase competition and thus decrease the risk premiums. This will create a favorable environment for physical commodity manufacturers or consumers to reduce risk. This theory is backed by Hambur and Stenner (2017) which investigated the risk premium of different maturities of crude oil over different time frames. They concluded that the risk premiums have significantly decreased after the shift in financialization in 2004.

2.3.2 Market dependency

There is a link between the general stock market, which is represented by the S&P 500 and the price of crude oil. This dependency has been evident over a long time. However, as the financialization increased during the 2000s the dependency between the oil price and the general market has been seen to increase (Shafaai and Masih, 2013).

There has also been shown evidence by Ing-Haw et al.(2017) and Adams and Kartsakli (2017) of investors decreasing their market exposure to commodities as the general market risk, measured by the Volatility Index (VIX index) increases. The withdrawal of assets from the commodity markets makes a downward pressure on prices, thereby increasing the dependency between regular financial markets and the commodity market (Shafaai and Masih, 2013).

Chapter 3

Literature Review

This section covers the main theories of how the price of oil is determined and also how this affects the market values of oil companies.

3.1 Crude Oil Price Fluctuations

The major fluctuations in the price of oil has caused a lot of research into what affects the price volatility. There are proposed several reasons for the price fluctuations. The influence of supply and demand is the most common approach (Bacon, 1991), but there has been done extensive research into other factors that also might affect the price of crude oil. In this paper we will investigate the most established theory of supply and demand, and also the effect investment cycles might have on the price of oil. We will also investigate how the price of crude oil has shown to impact the oil producers.

3.1.1 Demand

According to Bacon (1999) the macroeconomic effect of shifts in the demand has the greatest impact on the price determination of crude oil. In the beginning of the 2000s the oil price increased from $25 to over $140 and this coincided with the rapid industrialization of some of the major Asian economies (Kilian, 2010). The consumption increased from 77.7 million barrels per day in 2001 to 83.7 million barrels per day in 2005 (Scholtzen and Wang, 2008). It has been shown that the increase in the GDP of a country leads to increasing demand for oil (Datta and Vigfusson, 2017). On the other hand distressed macroeconomic periods such as the Asian Crisis in 1998, The Great Financial Crisis in 2008, and the COVID crisis in 2020 also caused sudden demand shocks causing large drops in oil prices.

As crude oil is a necessary good, the short-run demand elasticity is close to zero (Abu Eleyan et al., 2021)(Lee and Cho, 2021). There are few supplements, and the substitution effect only takes place during a longer time frame. According to Fattouh (2008), the substitution effect leads to the long-term price elasticity being higher than the short-term oil elasticity.

There have been done several investigations into the price elasticities, and they have shown some variance. However, one could conclude that the overall price elasticity is low. Dahl (1993) found long-run demand elasticity between -0.13 and -0.26. The short-term elasticity was significantly lower, approaching zero. Gately and Huntington (2002) estimated the income elasticities of OECD countries to be -0.64, while it was estimated at -0.18 in developing countries.

According to Hughes et al. (2006), demand elasticity har declined since the 1970s. They estimated the elasticity to be in the range of -0.21 to -0.34 between 1975 and 1980, which increased to -0.034 and -0.077 in the period from 2001 to 2006. This results in lower sensitivity to prices of crude oil.

The income elasticities also experience differences between the countries in the sample but exhibit substantially greater influence over the demand of oil. Gately and Huntington (2002) find income elasticities for OECD countries at 0.56. While Dahl (1993) estimates the income elasticity of developing countries between 0.79 to 1.4.

Developing countries have shown significantly higher income elasticities. A larger income sensitivity for developing countries could be expected as energy consumption accounts for a larger part of the income, and thus one would be more sensitive to price changes. According to this finding, one could expect an overall decrease in income elasticity as more developing countries continue to increase their incomes (Gately and Huntington, 2002). This would decrease the overall sensitivity towards higher oil prices.

3.1.2 Precautionary demand

Barsky and Kilian (2004) investigated how the assumptions of future supply could contribute to determining the price of oil. The research investigated how geopolitical events might affect the precautionary demand suggests that the exogenous factors affecting supply could be overstated. While not denying that wars and other geo-political events in the Middle East have impacted the price of oil, he suggests that the effect is not as clear as previously considered. Price changes that are earlier believed to be caused by exogenous factors are often endogenous in nature. Barsky and Kilian (2002) claim the price increases in the 1970s were partly to blame by expansionary monetary policy, which increased the demand. They also relate the increasing crude oil price to an increase in the precautionary demand, rather than a change in supply as is commonly believed.

3.1.3 Supply

Several proponents have mentioned the danger of the depletion of oil reserves. In his famous speech about the importance of energy in 1957, Admiral Hyman Rickover, known as the "Father of the Nuclear Navy", stated that he believed the end of oil would arrive some time in the 2000s (Yergin, 1990). However, the prediction has so far been proven wrong as the reserves have continued to rise. The oil production in 1973 was 59 million barrels of oil per day, that increased to 77 million barrels per day in 2003. Despite this rapid increase in production the reserves over the same period increased by over 500 billion barrels. Thus, the reserves to production ratio has increased (Fattouh, 2007).

The major increase in the supply of oil is due to the increase in current fields, not the discovery of new oil fields. The technological advancements are making it possible to locate larger areas of the field and extract larger quantities.

Baumeister and Peersman (2013) investigated the elasticity of supply and discovered that it decreased significantly over time. This could be due to the decrease in the spare capacity of the oil producers. The time it takes from reserves are found until production could be initiated is considerable and this delay of oil supply causes a low short-run supply elasticity. The increase in the volatility of crude oil could partly be explained by the decreasing elasticity of supply after 1986. The producers no longer possess the same ability to increase supply as a response to sudden demand increases (Baumeister and Peersman, 2011).

3.1.4 Investment cycles

The lagged response in the supply of oil can be due to over-investment or under-investment during the different market cycles. By investigating the oil price drop in response to the Asian crisis in 1997, Bacon (1999) shows how the investment cycles could affect the price dynamics. The increased investments during the period of increasing oil prices at the beginning of the 1990s led to an oversupply that intensified the oil price crash during the Asian crisis. This supports the research by Barsky and Kilian (2004) which suggests that the lagged effect of investments causes volatility to increase. In 1974, the high oil prices increased the magnitude of the price decrease in the 1980s.

The various factors and complexity of the price discovery makes it difficult to isolate the factors that affect the crude oil price (Zhang, 2008). The different factors could also change over time as we have experienced with the decreasing price elasticity of supply, causing changes in the behavior of oil price.

3.2 Oil Producers

The price of crude oil is the most decisive factor in determining the cash flow of oil producers. Due to the inelastic properties of oil demand, higher oil prices can be expected to increase the market value of oil companies.

By investigating four oil producers from 1974 to 2015, Diaz et al. (2016) found that the price of the WTI has a short-run positive impact on stock prices. By accounting for the structural change in the oil price volatility observed by Baumeister and Peersman (2013) in 1986 they observe an increasing relationship post-1986. Scholtzen and Wang (2008) used the multi-factor arbitrage pricing theory and the Fama-French five-factor model to evaluate the sensitivity of oil price on the stock market returns of the oil companies listed in the NYSE oil index. Their findings support the view that the oil price has a significant positive impact on the stock returns of the companies in question.

Degiannakis et al. (2017) who did a study of the impact of the oil price on different sectors in the stock market discovered that a change in oil prices had a negative impact on oil consumers, but a positive impact on the market value of oil producers. This was also the fact with Canadian oil producers as discovered by Sadorsky (2001). He also highlighted the importance of risk management through financial instruments. Hedging price risk would allow for better flexibility during distressed market periods, due to securing better management of cash flows. This will allow for better flexibility during times of depressed oil prices, and thus a better long-term allocation of capital.

Analyzing the returns of oil producers from 1990 to 2003, Osmundsen et al. (2006) concluded that the main drivers behind the price returns of the oil producers were the oil price return, as well as the oil and gas production volume. In addition, reserve replacement was shown to have an effect.

Lanza et al. (2003) discovered that the spread between future and spot prices of crude oil impacted the market value of oil producers. Maybe as an expectation that the contango or backwardation of the term structure implies the expected direction of the spot price movements. This has been a widespread belief in parallel with the increasing financialization of the market. As proposed by Masters (2008) in his testimony to Congress he saw the increased activity in the futures market as something that would increase the price to the oil consumers. However, as noted by Peck (1985) the spot price should already contain the future price expectations because of the availability of storage. Therefore, the theory of storage ensures that the futures price does not predict the future prices any more than the current spot price itself. Alquist et al. (2011) tested the predictive power of the oil futures and discovered that the model based on futures prices did not predict the price development any better than a "no-change"-model, based on the current spot price.

The oil price effect on oil producing companies has also been said to have asymmetric properties where price moves to the upside have shown to affect the price more than moves to the downside. Ready (2011) states that the risk, in this case, measured by the VIX, also has a significant impact on the market value of these firms. A larger impact than on the oil price itself.

By looking at this with a quantile approach, we will be able to isolate some of the correlations and gather a further understanding of how the oil price might affect oil producers.

Chapter 4

Methodology

4.1 Stationarity

A requirement to be able to derive meaningful statistical properties from the models is stationary time series (Han et al., 2016). For a time series to be stationary, it would imply that the statistical properties such as the mean or variance are not changing over time and the distribution of the process remains constant.

Time series often possess an increasing or decreasing mean, or a difference in variance or autocorrelation over time. Such a time-series would be considered non-stationary and could be made stationary by simple operations such as differencing to remove time-varying means.

We will use the Augmented Dickey-Fuller approach to test for stationarity of the time series as it allows for processes of higher order. It tests how much of the information of the direction of the process depends on the previous parts of the process. The test is implemented by performing a regression on the change of the time series as follows:

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^{k} \theta \Delta y_{t-1} + \varepsilon_t$$

We will use the AIC to decide the optimal lags. We obtain the Dickey-Fuller test static and test it against the null hypothesis that the time-series possesses a unit root and is non-stationary.

If the test static is less than the critical value, the null hypothesis is rejected.

- $H_0 : \delta = 0$ the time series possesses a unit root and is non-stationary.
- $H_1 : \delta \neq 0$ the time series does not possess a unit root and is stationary.

4.2 Cross-Quantilogram

To evaluate the quantile dependence, we will use the cross-quantilogram (CQ) introduced by Han et al. (2016) to examine the correlations between the return of the oil producers and the WTI and Brent price returns. This method was developed as a bivariate extension of the quantilogram developed by Linton and Whang (2007). The quantilogram is an adaptation of the correlogram that introduced the notion of quantile hits. Contrary to the correlogram the quantilogram does not depend on moments (Han et al., 2016). It is, therefore, suitable to investigate time-series that are prone to large tail deviations. It allows us to investigate how two time-series correlates on a quantile to quantile basis without depending on distributions of finite moments. We will use the cross-quantilogram to evaluate the dependency between the oil producers and the price of Brent and WTI over the different quantiles $q = (0.05, 0.1, \ldots, 0.95)$.

The cross-quantilogram measures the dependency between the two timeseries $\{Y_{1,t}\}_{t=1 \ldots T}$ and $\{Y_{2,t}\}_{t=1 \ldots T}$, conditional on the quantiles τ_1 and τ_2. We will choose 1, 5 and 22 as our lags k, corresponding to daily, weekly, monthly lags. The cross-correlation of these quantile hits are then evaluated using the following formula.

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau_1}\left(y_{1t} - q_{q,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi^2_{\tau_1}\left(y_{1t} - q_{q,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi^2_{\tau_2}\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}}$$

$q_{q,t}(\tau_1)$ and $q_{2,t-k}(\tau_2)$ are calculated based on the quantile function of the conditional cumulative distribution functions of the time series in question $Fx|y$. The quantiles are derived by $q_{i,t}(\tau_i) = inf\left\{v : F_{(y_i|x_i)}(v|x_{it}) \geq \tau_i\right\}$ where $\tau_i \in (0,1)$. We will use the quantiles $q = (0.05, 0.1, \ldots 0.95)$ in this calculation as mentioned above.

$\psi_\tau(u) = I[u < 0] - \tau$, where $I[u < 0]$ is the indicator function resulting in 1 when the quantile function exceeds the corresponding value in the time series, or 0 otherwise.

The stationary bootstrap method is used to evaluate confidence intervals over the different quantiles. The values falling outside of this interval are considered significant. The test states that if $p = 0$, the bootstrap value is within the confidence interval and the dependency between y_t and y_{t_2-1} is non-significant over the respective quantile. However, if $p \neq 0$, then there exists such a correlation. For larger values this would imply that if y_{1t} is above the corresponding quatile τ_1, then the probability of $y_{2,t-k}$ being above the τ_2 quantile increases. The opposite is true for negative values, that if $y_{1,t}$ is above the respective τ_1 quantile, the probability of $y_{2,t-k}$ being below the respective τ_2 quantile is considered significant.

We will evaluate the sample tests in the following way:

$$\hat{\rho}_{\tau}(k)\frac{\sum_{t=k+1}^{T}\psi_{\tau_1}\left(y_{1t}-\hat{q}_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2,t-k}\hat{q}_{2,t-k}(\tau_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\psi_{\tau_1}^2\left(y_{1t}-\hat{q}_{1,t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi_{\tau_2}^2\left(y_{2t}-\hat{q}_{2,t}(\tau_2)\right)}}$$

We will use the Box-Ljung test to test for serial dependency over different lags. The Box-Ljung test is a portmanteau test so that:

$H_0 : p = 0$ is defined as no serial dependency. In other words, the time series are independently distributed.

while

$H_1 : p \neq 0$ indicates that the two time-series exhibit serial correlation.

The test will be performed with a significance level of 0.05, and we will choose 1000 bootstrap iterations.

4.3 DCC-GARCH

We will utilize the DCC-GARCH model proposed by Engle (2002) to evaluate the time-varying connectedness between the oil prices and the stock price behavior. The DCC-GARCH model is one of the multivariate extensions of the univariate GARCH model. Instead of being restricted to testing how the previous volatility affects its own future volatility, the multivariate version allows us to expand the input to test if the volatility of another time-series increases the prediction estimate.

The DCC-GARCH is evaluated as follows:

$$H_t = D_t R_t D_t$$

Where H_t represents the conditional covariance matric. D_t is the matrix of time-varying standard deviations used in the univariate GARCH model and R_t is the symmetric conditional correlation matrix of the standardized errors.

D_t could be expressed as $D_t = diag\left\{h_{i,t}\right\}$.

$$h_{it} = \omega_i + \sum_{q=1}^{Q_i}\alpha_{iq}\epsilon_{i,t-q}^2 + \sum_{p=1}^{p_i}\beta_{ip}h_{i,t-p}^2 \tag{4.1}$$

The standardized error could be calculated as:

$$\varepsilon_t = D_t^{-1} r_t$$

The standardized error could be calculated as:

$$\varepsilon_t = D_t^{-1} r_t$$

The error terms are normally distributed with mean zero and variance R_t. Where R_t is the time-varying conditional correlation matrix of the standardized error terms ε_t, and is evaluated as follows:

$$R_t = \begin{bmatrix} 1 & q_{12,t} & q_{13,t} & \cdots & q_{1n,t} \\ q_{21,t} & 1 & q_{23,t} & \cdots & q_{2n,t} \\ q_{31,t} & q_{32,t} & 1 & \cdots & q_{3n,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ q_{n1,t} & q_{n2,t} & q_{n3,t} & \cdots & 1 \end{bmatrix}$$

R_t has to satisfy the requirements of positivity, to ensure the definite positiveness of the correlation matrix H_t.

Due to R_t being the correlation matrix all values also must be equal to or less than 1. To meet these requirements, it is decomposed as follows:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where

$$Q_t = \left(1 - \sum_{i=1}^{P} \alpha_i - \sum_{j=1}^{Q} \beta_j\right) \bar{Q} + \sum_{i=1}^{P} \alpha_i \varepsilon_{t-1} \varepsilon_{t-1}^T + \sum_{j=1}^{Q} \beta_j Q_{t-j}$$

We note that alpha and beta both has to be greater than zero, but their sum should be less than 1, and $\bar{Q}$ is the conditional covariance matrix of the standardized errors $cov(\varepsilon_t \varepsilon_t^T)$, from earlier calculations.

Q_t^* is the squared diagonal matrix of Q_t

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{q_{33}} \end{bmatrix}$$

4.4 Methodological Discussion

The models chosen in this thesis has been chosen by keeping risk management in mind. We want to test the empirical dependency at the boundaries of the distributions. By utilizing the cross-quantilogram, we get an overview of the dependency over the different quantiles of the return distribution. There are several models which are suitable to measure tail dependency, such as copulas, which is often used to display correlations at the lower end of the distribution. However, contrary to the copula models, the cross-quantilogram is not dependent on marginal distributions. The miscalculation of marginal distributions might cause a discrepancy between theoretical and empirical results (Watts, 2016).

The drawback of the cross-quantilogram is that it does not provide information about how the dependency varies with time. By introducing the DCC-GARCH model we are able to investigate this further.

Chapter 5

Empirical Analysis and Discussion

In this section we will review the results of the statistical tests. First, the statistical properties of the timeseries and the stationarity. Then we will look at the dependency in the different quantiles over the different time lags selected. The results of the cross-quantilograms are visualized in the heatmaps and then we will discuss the differences company wise as well as the differences between the dependency towards the two different oil indices, WTI and Brent. Finally, we will look at how the correlations evolve over time.

5.1 Data selection

The price data is collected from Refinitiv Eikon, over the timeframe from 2010-01-01 to 2021-01-05. The following companies selected are Equinor, China Petroleum, and Chemical, Royal Dutch Shell, BP, Exxon Mobil, Total, Chevron, Lukoil, Rosneft, and Gazprom. The companies were selected based on their production output and Saudi Aramco was switched with Equinor due to lack of data as Saudi Aramco was a private company up until 2016. The companies will be evaluated against the WTI and Brent oil derived from St. Louis Fed (Fed, 2021).

The stock prices are converted from their respective local currencies to US Dollars which helps to remove the currency effect. We deploy the USD as this is the most common currency used in the financial markets, and the currency that crude oil is traded, as well as the Brent and WTI instruments. We will use the first differenced logarithmic returns calculated $\ln(P_t)$ as $\ln(P_{t-1})$, to remove trend.

We have chosen to evaluate the dependency over the last decade. As we have seen the oil price has been through shifts in behavior over the last decades, and thus we will try to capture the latest and most recent price behavior by highlighting the latest years. The data points are daily observations and therefore should include enough data points to derive meaningful results. The companies are listed on six different exchanges.

5.2 Statistical properties

We can see from the table that all the oil producers exhibit large kurtosis, which implies non normality. They also have a negative skew that shows that the deviations to the downside is larger than to the upside. The same is true for the oil indices Brent and WTI, which also possesses kurtosis and negative skew. We can see that WTI is containing by even more extreme values than the rest of the time series. Partly due to the constraints at Cushing, Oklahoma.

The Jarque-Bera coefficient also states that none of the timeseries passes the normality test. We can see that all the timeseries passes the ACF-test, meaning that they are stationary.

Table 5.1: Summary statistics

	Mean	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**ADFc (Lag).value**	**ARCH-LM(5)**
Equinor	0.000	0.023	-0.60	13.89	12357.13***	-49.31(0)***	120.49***
China Petroleum and Chemical	0.000	0.017	-0.21	9.36	4190.10***	-46.95(0)***	134.27***
Royal.Dutch.Shell	0.000	0.019	-0.09	19.59	28340.37***	-46.35(0)***	289.19***
BP	0.000	0.021	0.06	17.47	21563.64***	-45.25(0)***	268.24***
Exxon.Mobil	0.000	0.016	-0.12	11.35	7191.00***	-51.12(0)***	556.01***
Total	0.000	0.020	-0.38	14.55	13803.18***	-32.27(1)***	512.14***
Chevron	0.000	0.018	-0.74	30.67	79050.59***	-33.27(1)***	706.49***
Lukoil	0.000	0.022	-0.69	15.01	15042.22***	-50.25(0)***	165.46***
Rosneft	0.000	0.024	-0.48	10.57	6005.18***	-46.16(0)***	295.99***
Gazprom	0.000	0.023	-0.12	7.96	2542.71***	-46.65(0)***	92.07***
BRENT	0.000	0.030	-2.74	111.83	1222568.66***	-50.34(0)***	347.24***
WTI	0.000	0.044	-11.37	466.74	22195270.92***	-72.16(0)***	256.11***

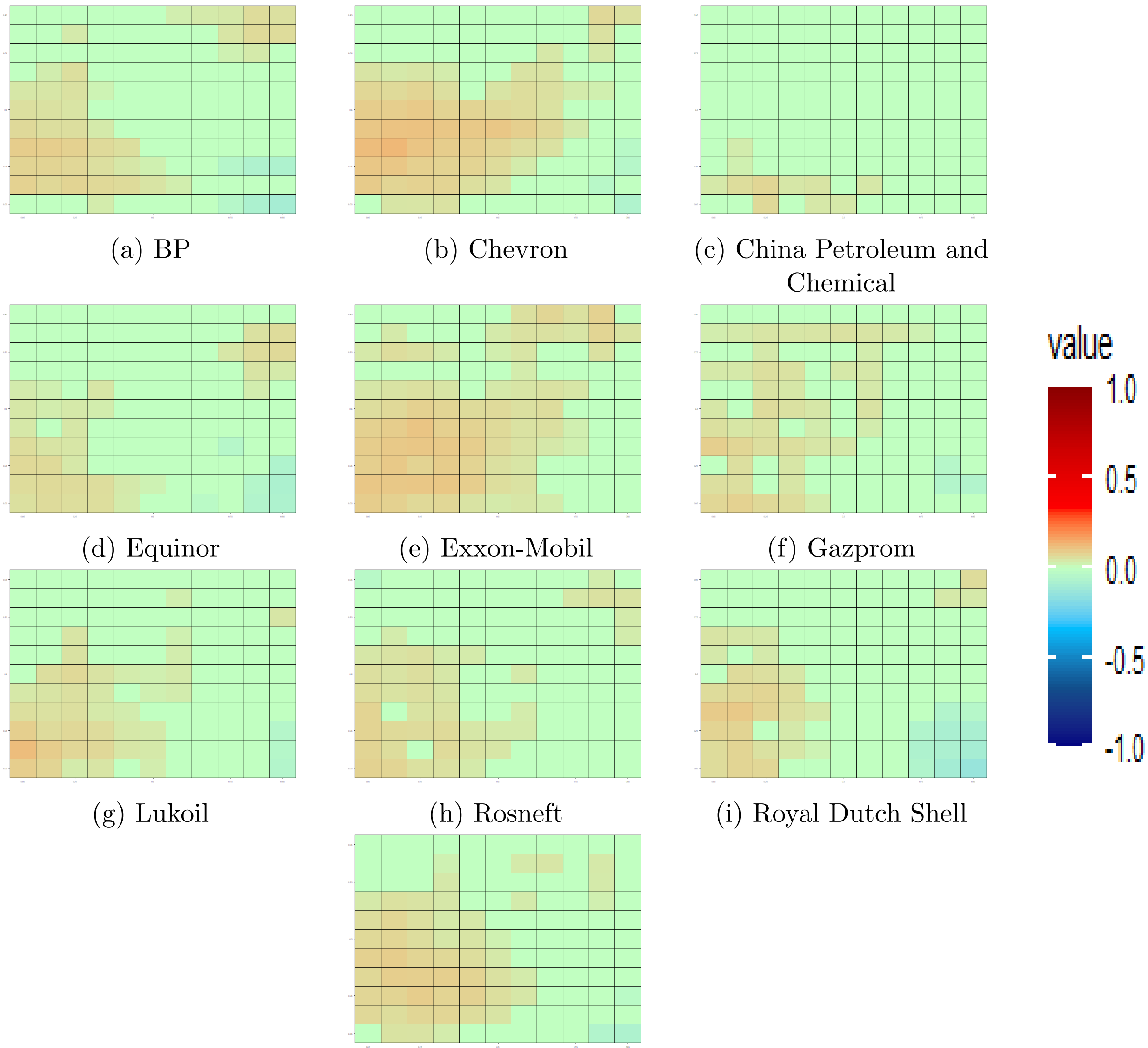
5.3 Cross-quantilogram

5.3.1 Brent and WTI

The WTI and Brent indices could be expected to be strongly correlated due to the similarity of the product and thus we could expect similarity in the dependency between the oil companies and the two indices. However, we can see from the heatmaps that the companies are slightly more correlated with Brent oil during extreme market conditions.

As WTI is the most traded instrument in the futures market it interesting to note that according to these results it acts as a less effective hedge than the Brent oil during large drawdowns, before taking account of the difference in strictly financial trading properties, such as liquidity, spreads and so on.

The WTI has also shown to possess larger price variance and to be exposed to logistical constraints at the delivery point in Cushing, Oklahoma. Such constraints that led to the negative pricing of the WTI futures in April 2020. This event could be seen as a strictly financial or logistical problem, not caused by structural changes to the overall crude oil market. The Brent oil however is being traded free-on-board (FOB) is less prone to such external influence.



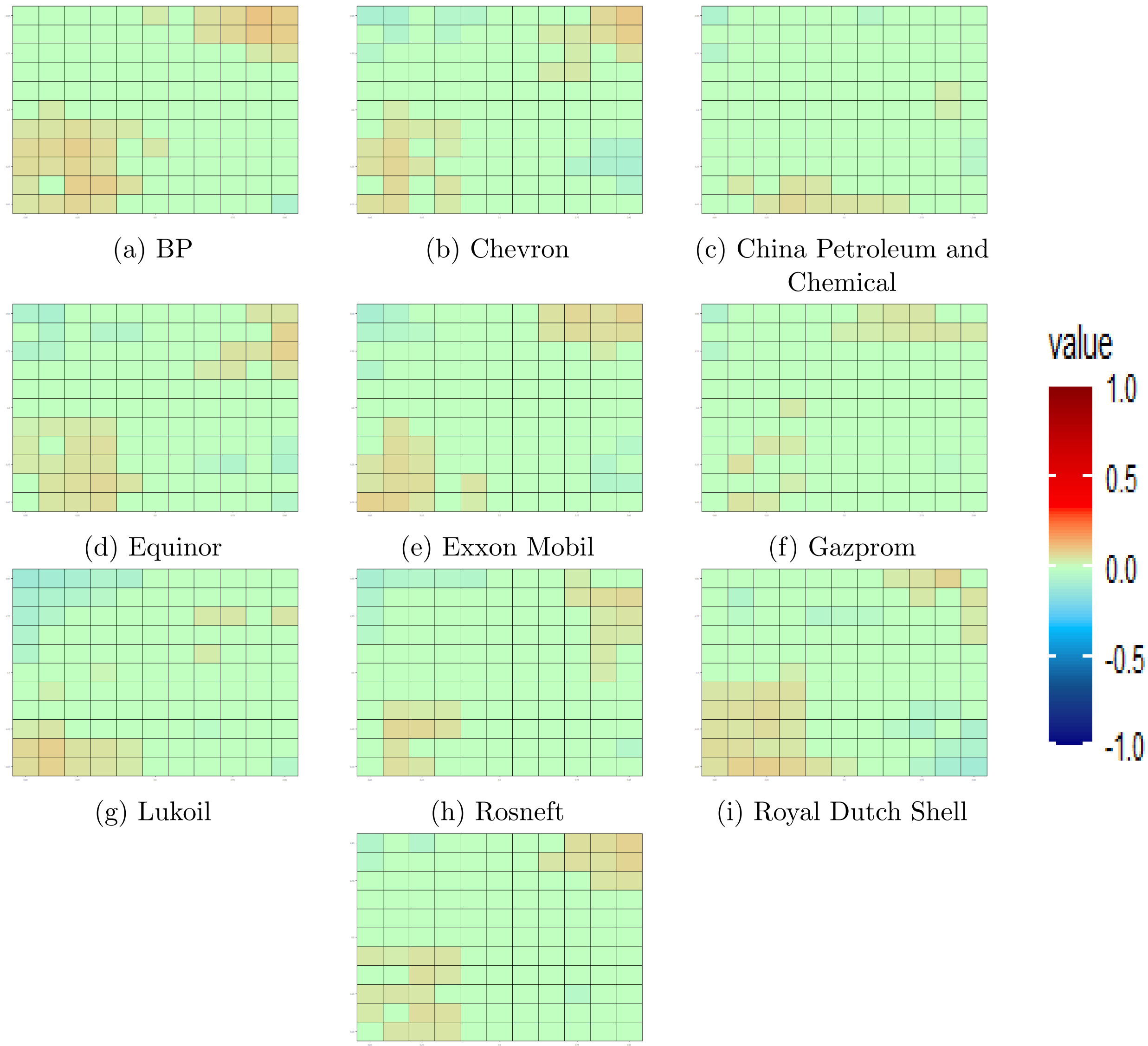
(a) BP (b) Chevron (c) China Petroleum and Chemical

(d) Equinor (e) Exxon-Mobil (f) Gazprom

(g) Lukoil (h) Rosneft (i) Royal Dutch Shell

(j) Total

Figure 5.1: Cross-quantilogram evaluating the dependence between the oil producers and Brent oil.



(a) BP

(b) Chevron

(c) China Petroleum and Chemical

(d) Equinor

(e) Exxon Mobil

(f) Gazprom

(g) Lukoil

(h) Rosneft

(i) Royal Dutch Shell

(j) Total

Figure 5.2: Daily WTI

5.3.2 Firm Dependence

Regarding the different firms, we can see a large difference in the dependency towards the oil indices. From ExxonMobil which possesses significant dependency both in the lowest quantiles as well as through the median quantiles. We also see that for some of the companies the dependency is certainly less significant, such as China Chemical which possesses less correlation to both the indices. Being the only producer located in Asia it could be expected to be less correlated to both WTI and the Brent reference index.

There could also be differences in the firm structure that makes the oil price affect the companies differently. The companies focusing larger part of their business towards upstream activities could be expected to be influenced less. Upstream activities only depend on crude oil as an input factor, by selling refined products to the end consumers. Cheaper input factors could increase their margins. Downstream activities however, accounts for the largest part of the companies in this analysis and those activities would suffer greater cash flow depreciation with reduced oil prices.

We could also expect that different risk management strategies could be part of the reasons for the difference in oil dependency between the companies. Oil producers are known to hedge their future production, even though we could expect no direct financial gain of such activities, if we assume rational assumptions, it could lead to better management flexibility Sadorsky (2001). This could make them able to make investments with higher flexibility compared to their competitors. The leverage could also be a possible cause for these differences, as investors could be expected to gravitate towards companies with stable balance sheets in such circumstances while fleeing the more leveraged producers.

We can see from all the firms that there seems to be a higher oil price dependency during the lowest quantiles. When the oil price experiences returns in their lowest quantiles, oil companies tend to do the same. That financial assets correlate during large market drawdowns is nothing new and we can see that it affects the companies chosen in this thesis as well. There are several reasons for this effect. We could expect that this is mainly due to the expected decrease in cash flows to the producers, as it increases the uncertainty of the development of future cash flows.

There might also be non-fundamental reasons for the correlation. Leveraged traders might experience margin calls that would cause spillover effects to other markets when they have to liquidate their positions in other markets than the one initially affected. It would also be natural to expect traders to reduce positions when risk and volatility increases. We have also seen that the increasing financialization could have affected the co-integration of the oil price.

Even though the distributions were shown to be negatively skewed. We do also see some dependency in the upper quantiles, as large price hikes in the oil price would increase the positive outlook for oil producers. However, significantly less than the lower quantiles.

During normal market conditions, when realized returns are found in the middle quantiles, the Box-Ljung test does turn out to be significant and thus dependency in these quantiles could not be proved.

5.4 Time-Varying Dependency

From the time-varying connectedness plots we can see that the dependence varies over time. Distressed macroeconomic periods are shown to increase the dependency. While connectedness tends to decrease during normal market conditions, or upward trending oil prices.

We also see that the connectedness between the oil companies and the Brent prices tend to vary more than towards the WTI prices.

Chapter 6

Conclusion

In this work we have seen that the oil price returns affects the oil producing firms on a quantile to quantile basis. We have seen that the dependency in the lower quantiles is significantly higher than in the middle quantiles, but that this does not necessarily prove to be the case for all companies. Some companies, such as Exxon and Equinor, prove to be more reactive to changes in the oil price, while the China Chemical, possesses very little connectivity. Correlations in the higher quantiles is also shown to be significant, it is mainly the upper and lower quantiles that stands out as significant. We have also seen how the lags affects this connectedness, and the longer lags are shown to be less significant.

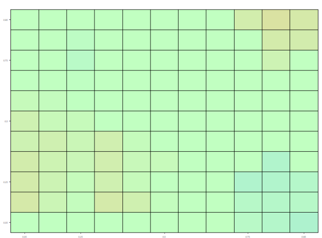
By looking at the difference between the WTI and Brent plots we notice that the Brent plots is correlating stronger against the oil companies both in the cross-quantilograms and when looking at the time-varying connectedness in the DCC-GARCH model.

We have also investigated how the dependency varies over time, and that periods of increasing volatility also increases the dependency between the two timeseries. We also find large differences in how the overall correlation measured by the conditional correlation matrix varies by company, and the companies exhibiting low correlations are the same as in the quantile to quantile basis.

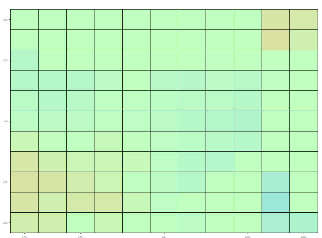
The results indicate that the WTI and Brent indices could be effective in hedging exposure against the largest price falls in the oil producing stocks. According to the results the Brent price would be more effective than the WTI as it experiences a higher dependency.

Appendix A

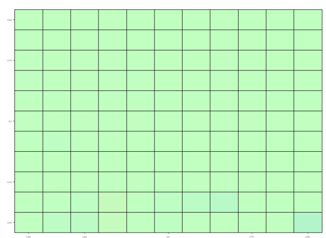
Weekly



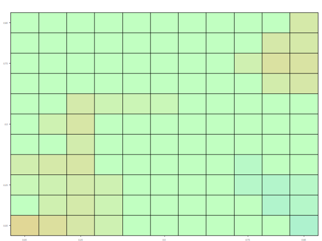
(a) BP



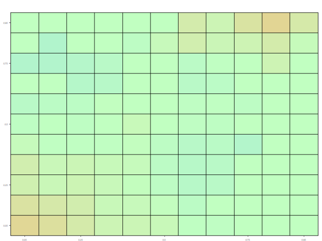
(b) Chevron



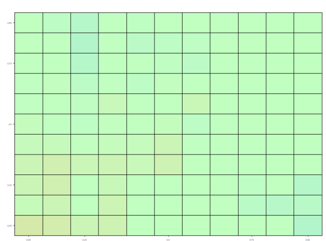
(c) China Petroleum and Chemical



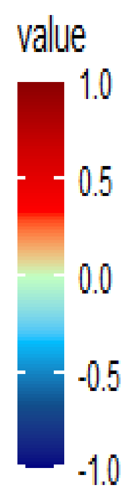
(d) Equinor

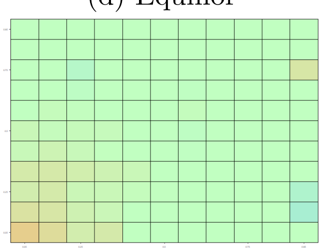


(e) Exxon Mobil

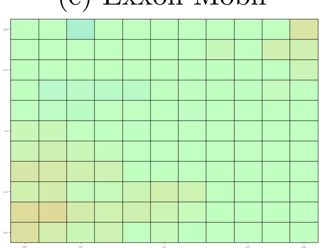


(f) Gazprom

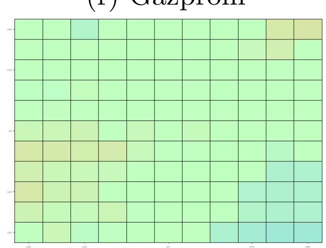




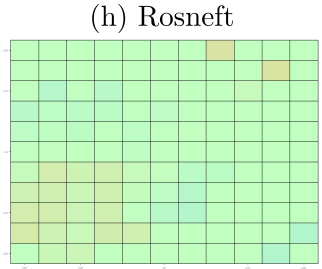
(g) Lukoil



(h) Rosneft

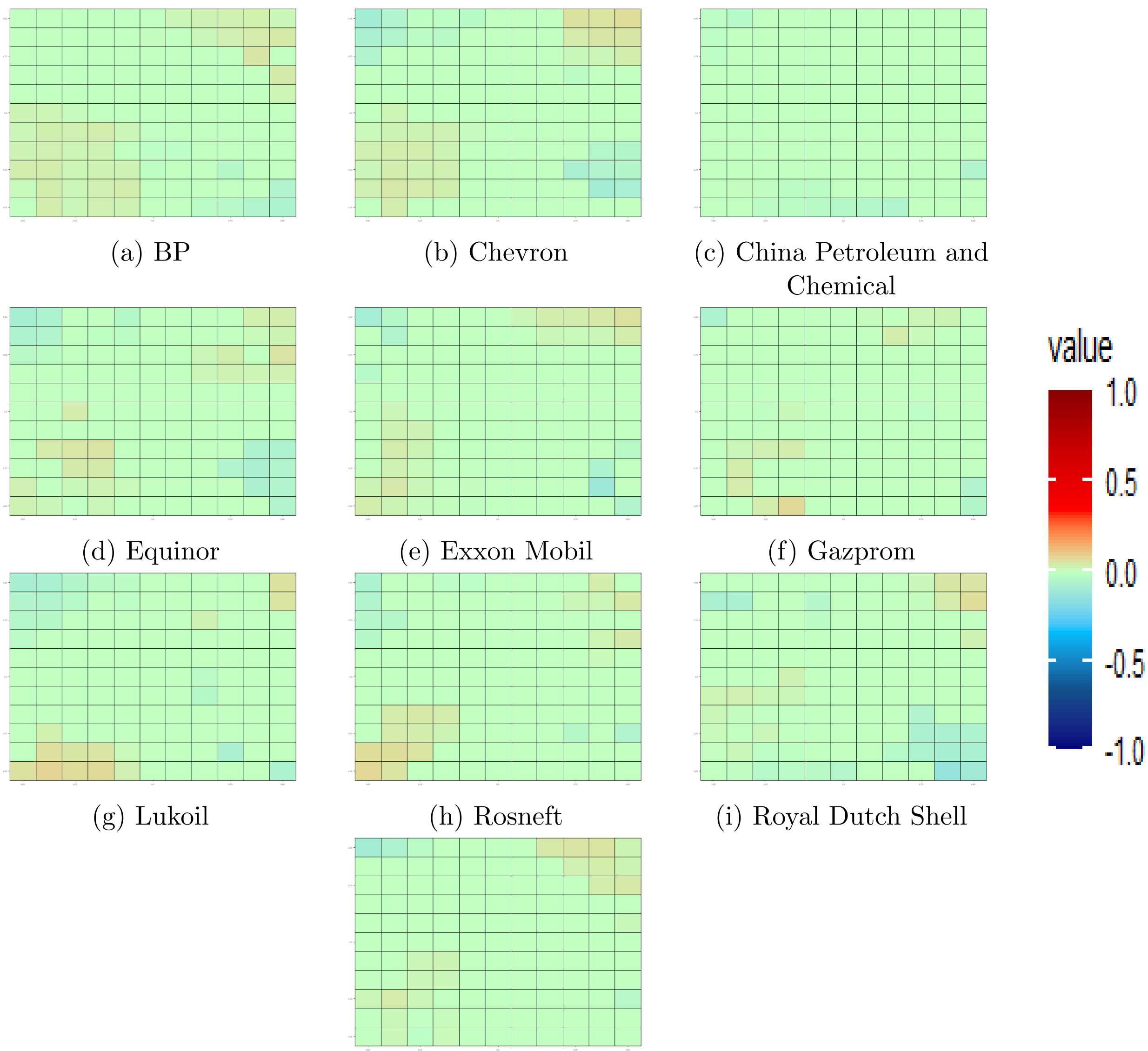


(i) Royal Dutch Shell



(j) Total

Figure A.1: Weekly Brent



(a) BP

(b) Chevron

(c) China Petroleum and Chemical

(d) Equinor

(e) Exxon Mobil

(f) Gazprom

(g) Lukoil

(h) Rosneft

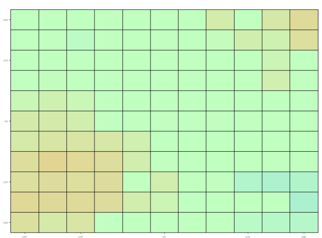
(i) Royal Dutch Shell

(j) Total

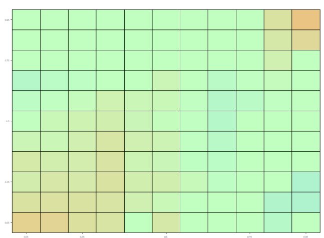
Figure A.2: Weekly WTI

Appendix B

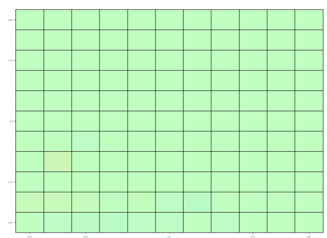
Monthly



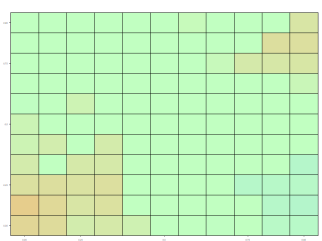
(a) BP



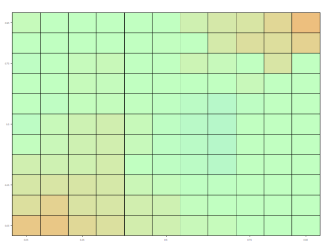
(b) Chevron



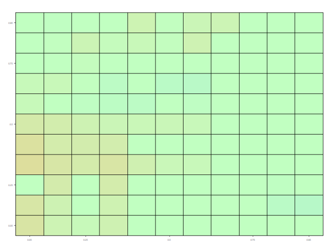
(c) China Petroleum and Chemical



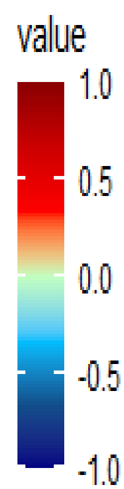
(d) Equinor

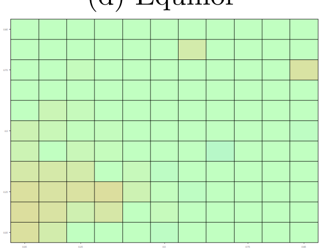


(e) Exxon-Mobil

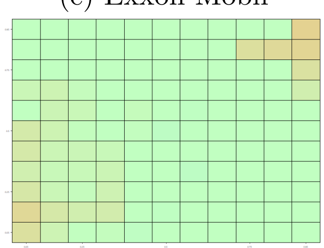


(f) Gazprom

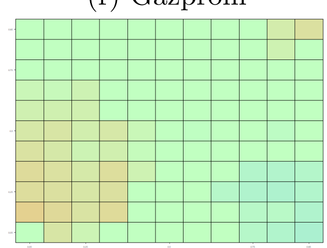




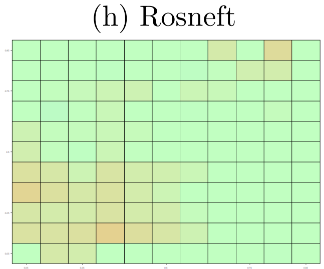
(g) Lukoil



(h) Rosneft

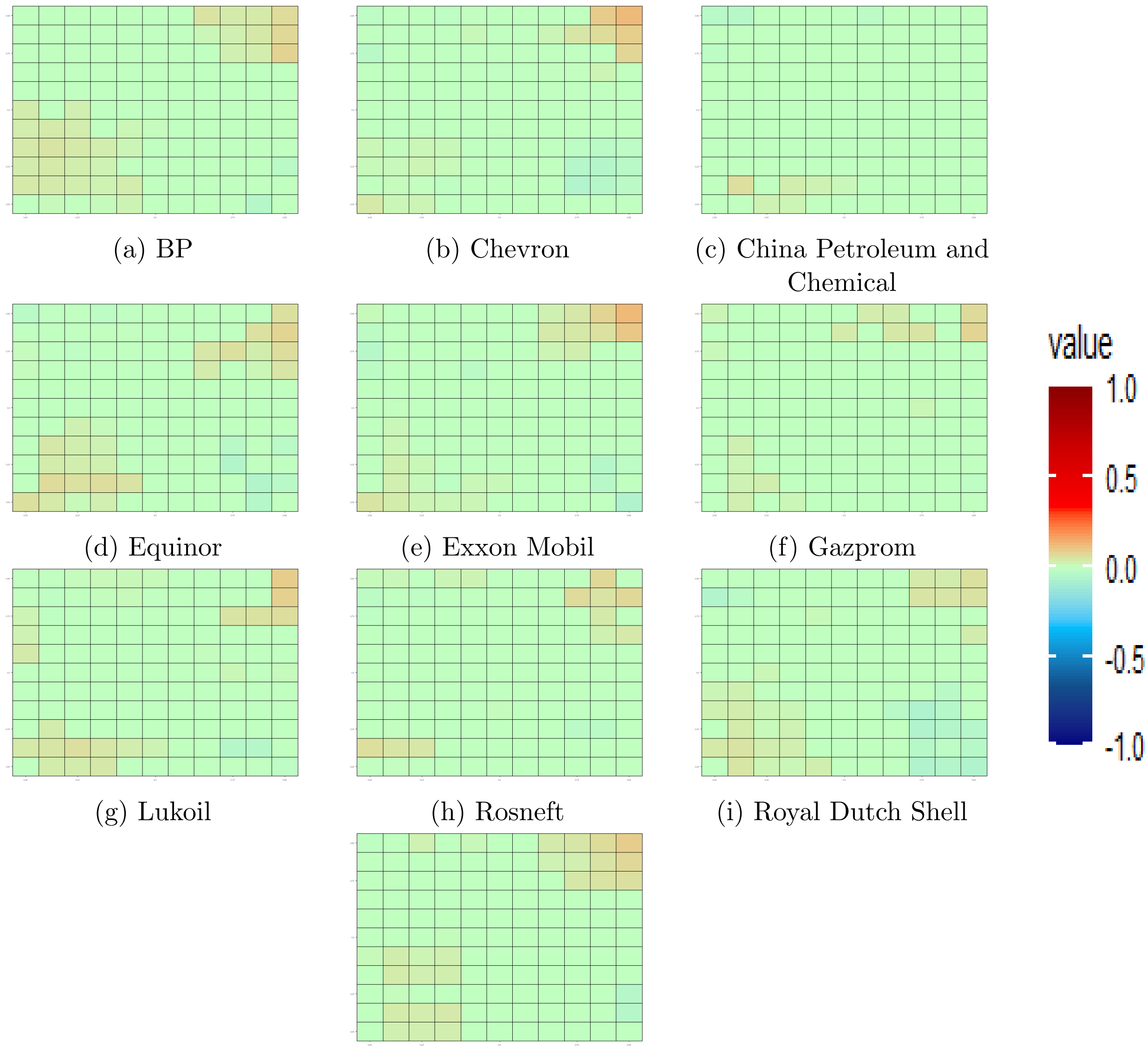


(i) Royal Dutch Shell



(j) Total

Figure B.1: Monthly Brent



(a) BP (b) Chevron (c) China Petroleum and Chemical

(d) Equinor (e) Exxon Mobil (f) Gazprom

(g) Lukoil (h) Rosneft (i) Royal Dutch Shell

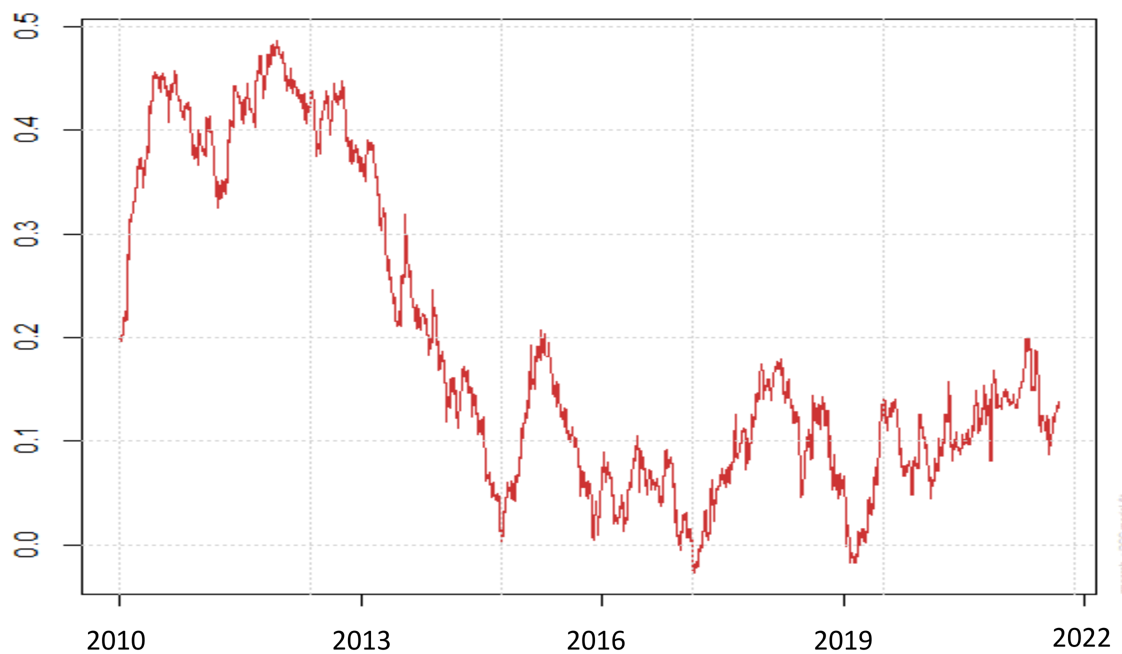
(j) Total

Figure B.2: Monthly WTI

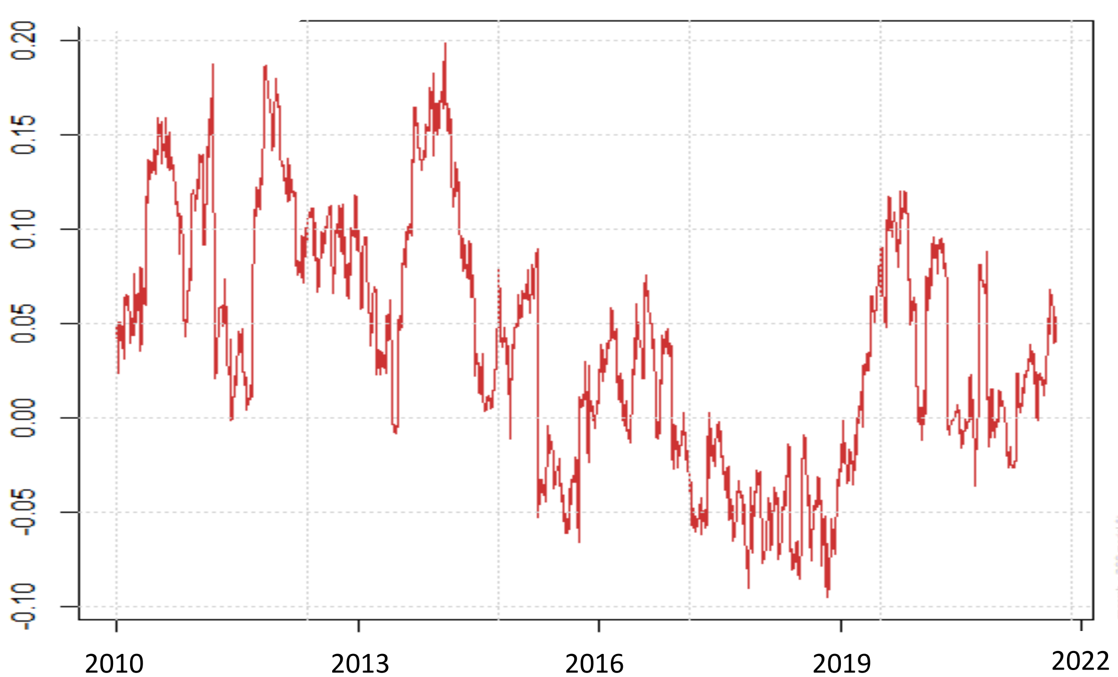
Appendix C

DCC

Equinor



China Petroleum and Chemical



Royal Dutch Shell

ExxonMobil

S

BP

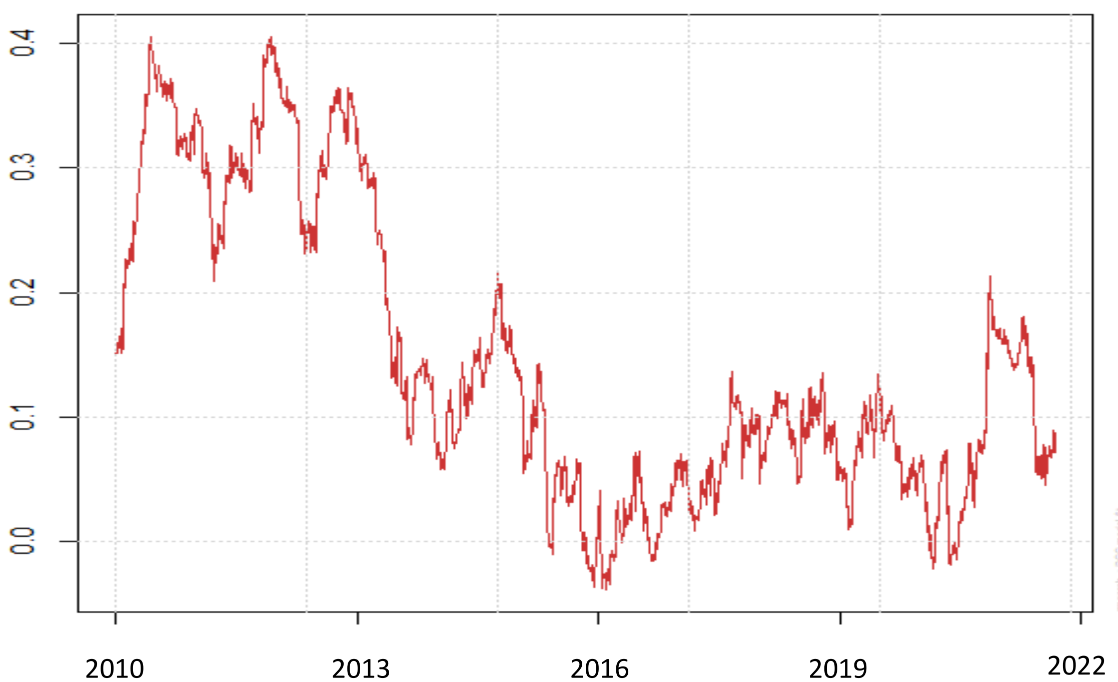

0.4
0.3
0.2
0.1
0.0
-0.1
2010
2013
2016
2019
2022

Total


0.3
0.2
0.1
0.0
-0.1
2010
2013
2016
2019
2022

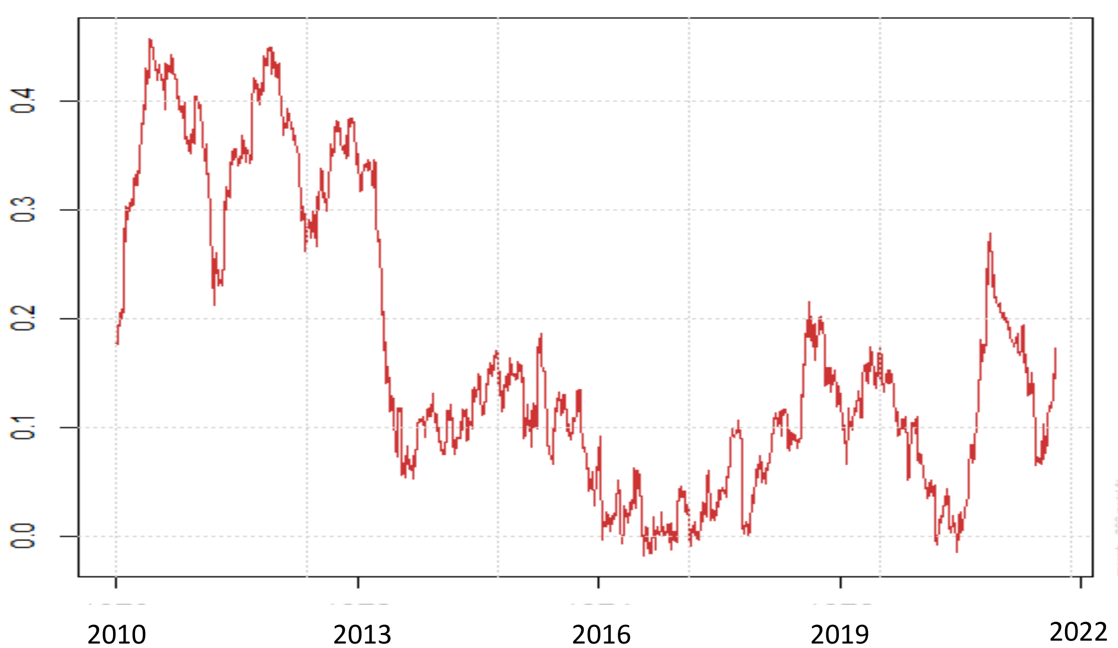
Chevron

Lukoil



Rosneft

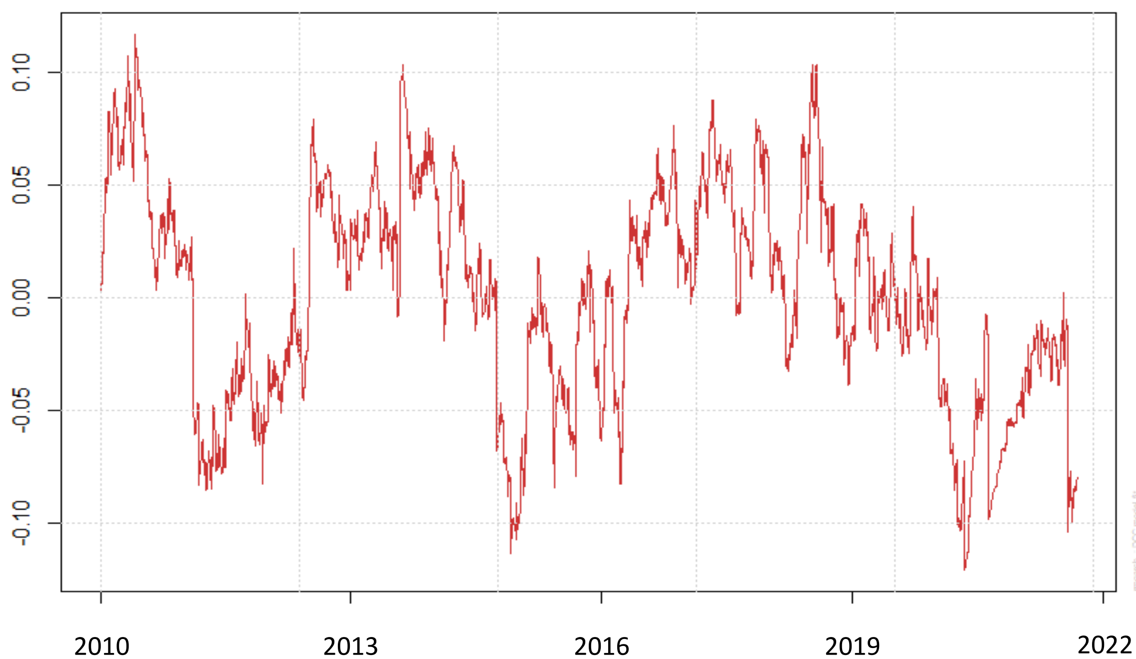
Gazprom



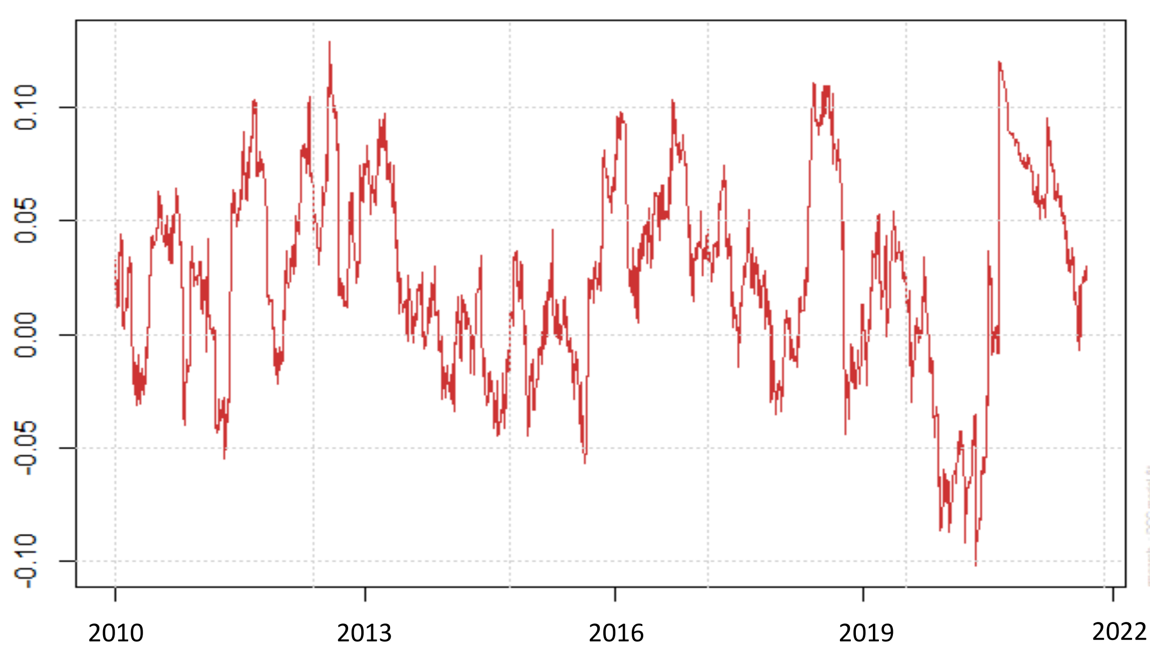
Appendix D

WTI

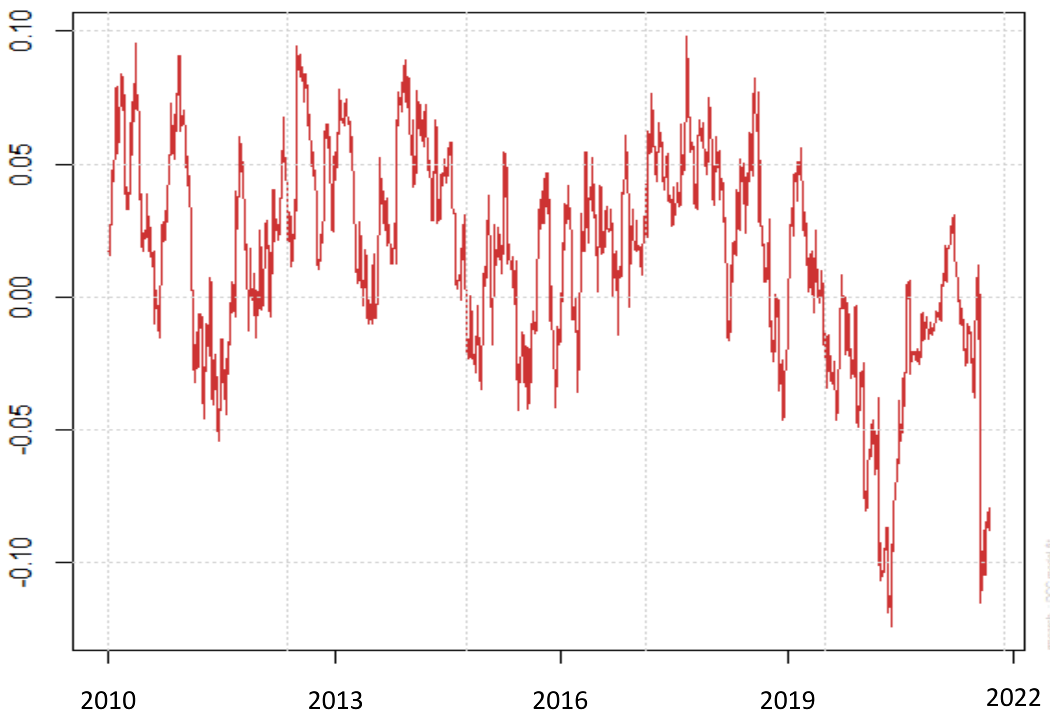
Equinor



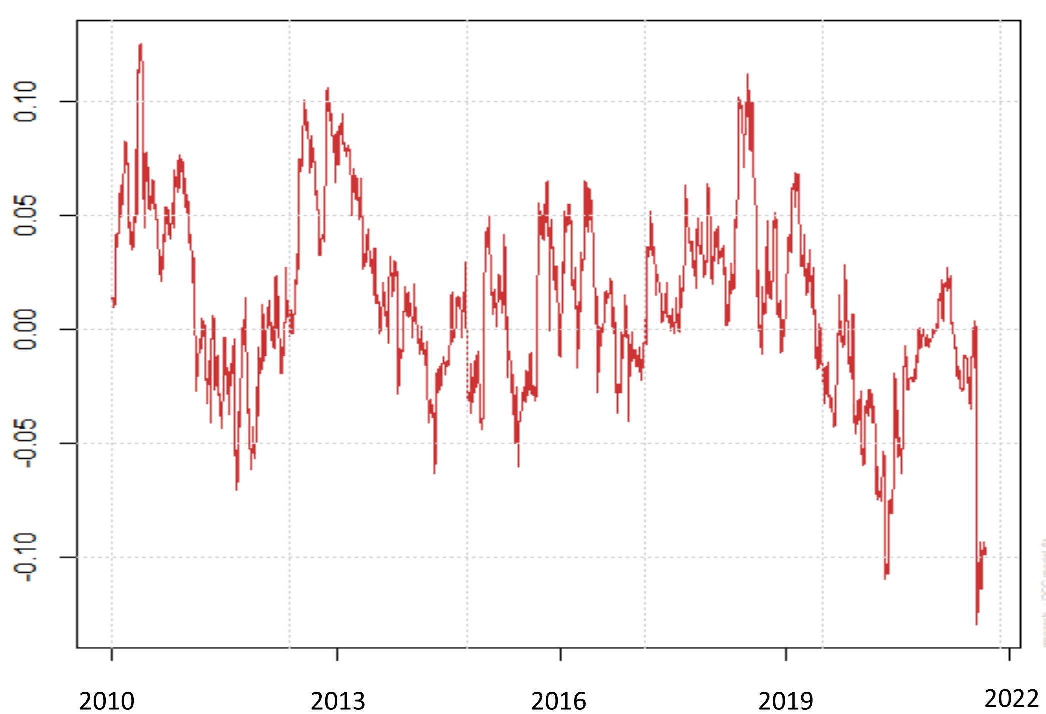
China Petroleum and Chemical



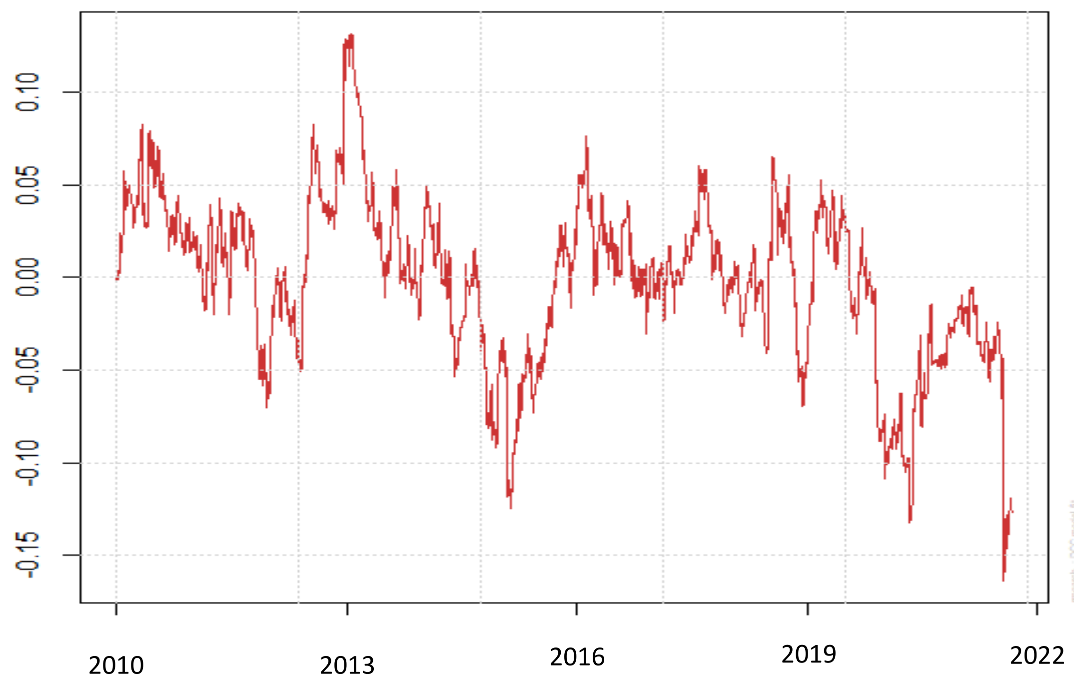
Royal Dutch Shell



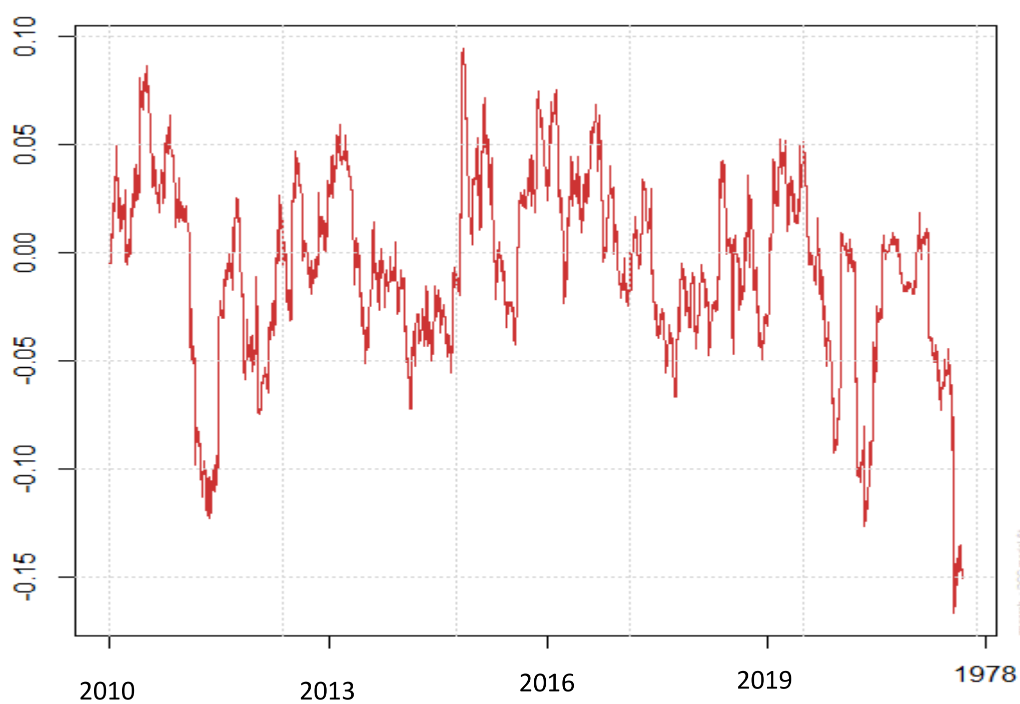
BP



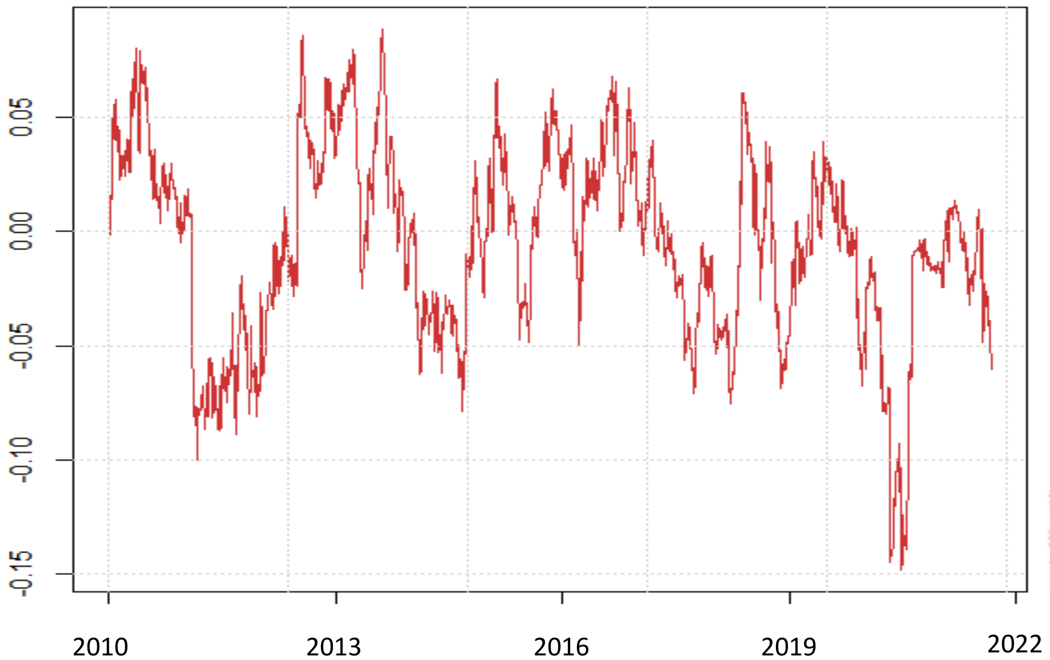
Chevron



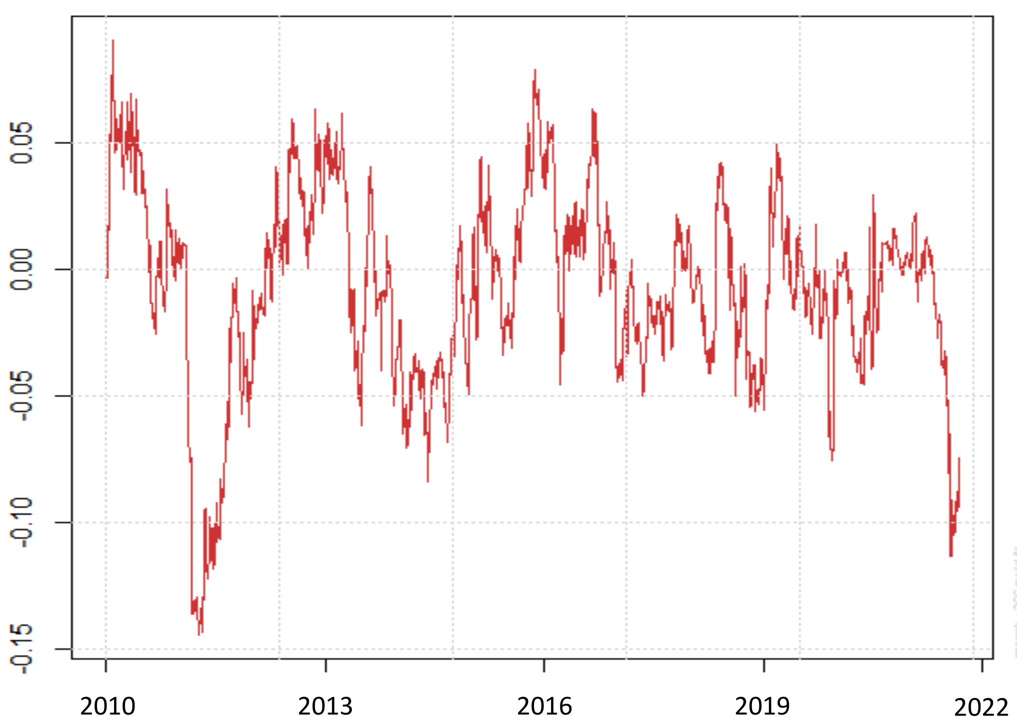
Lukoil



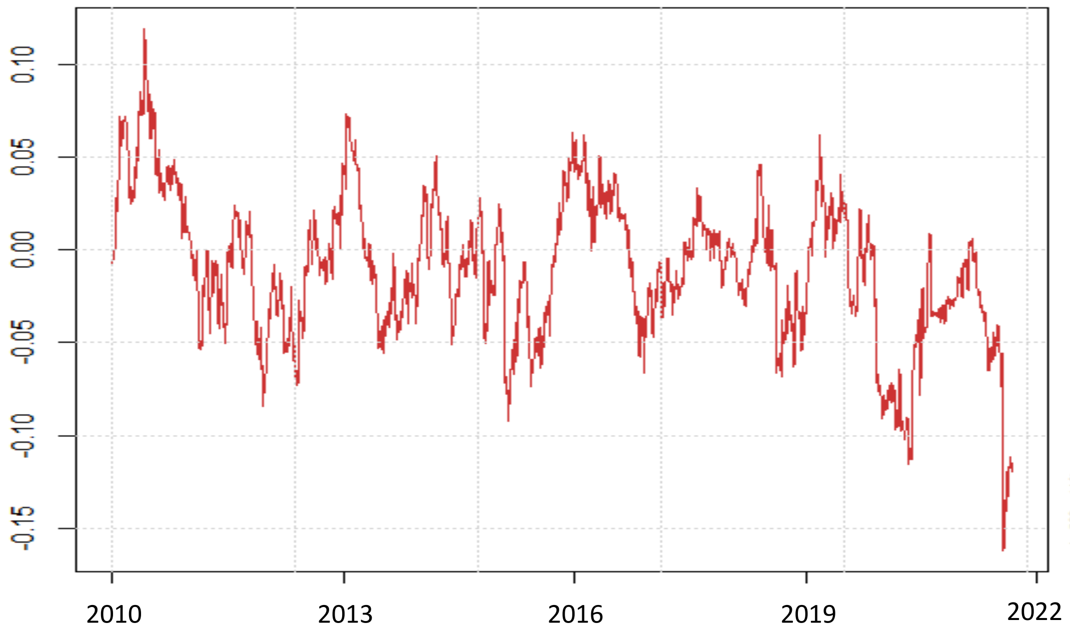
Rosneft



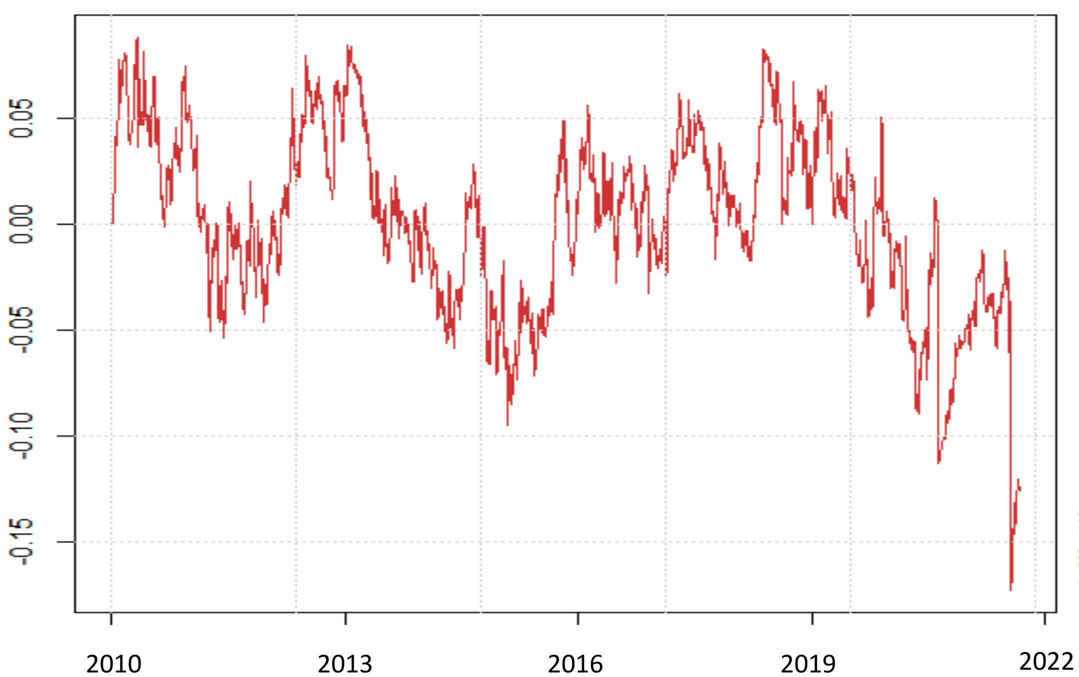
Gazprom



ExxonMobil



Total



Bibliography

Mohammed Abu Eleyan, Abdurrahman Nazif Çatık, and Mehmet Balcilar. Are long-run income and price elasticities of oil demand time- varying? new evidence from brics countries. 2021.

Zeno Adams and Maria Kartsakli. Have commodities become a financial asset? evidence from ten years of financialization. 2017.

Ron Alquist, Lutz Kilian, and Robert Vigfusson. Forecasting the price of oil. 2011.

Robert W Bacon. Convective risk flows in commodity futures markets. pages 17–34, 1991.

Robert W Bacon. The oil price crisis of 1998. pages 17–34, 1999.

Robert Barsky and Lutz Kilian. Do we really know that oil caused the great stagflation? a monetary alternative. 2002.

Robert Barsky and Lutz Kilian. Oil and the macroeconomy since the 1970s. 2004.

Christiane Baumeister and Gert Peersman. The role of time-varying price elasticities in accounting for volatility changes in the crude oil market. 2011.

Christiane Baumeister and Gert Peersman. Time-varying effects of oil supply shocks on the us economy. 2013.

Bahattin Büyüksahin, Thomas K. Lee, James T. Moser, and Michael A. Robe. Markets, paper markets and the wti-brent spread. 2013.

Carol Dahl. A survey of oil demand elasticities for developing countries. 1993.

Deepa Datta and Robert J. Vigfusson. Forecasting china's role in world oil demand. 2017.

Stavros Degiannakis, George Filis, and Vipin Arora. Oil prices and stock markets. 2017.

Elena Maria Diaz, Juan Carlos Molero, and Fernando Pérez de Garcia. Oil price volatility and stock returns in the g7 economies. 2016.

Stephanie Dunn and James Holloway. The pricing of crude oil. *RBA Bulletin*, pages 65–74, 2012.

Robert Engle. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. 2002.

Luca Fantacci, Maria Cristina Marcuzzo, and Eleonora Sanfilippo. Speculation in commodities: Keynes' "practical acquaintance" with futures markets. 2010.

Bassam Fattouh. The drivers of oil prices: the usefulness and limitations of non-structural models, supply-demand frameworks, and informal approaches. 2007.

Bassam Fattouh. The dynamics of crude oil price differentials. 2008.

Bassam Fattouh. The financialization of oil markets: Potential impacts and evidence. 2013.

Bassam Fattouh. Is the worst of the oil crisis behind us? 2020.

Bassam Fattouh, Lutz Kilian, and Lavan Mahadeva. The role of speculation in oil markets: What have we learned so far? 2010.

St. Louis Fed. St.louis fed, brent and wti price data. 2021.

Dermot Gately and Hillard Huntington. The asymmetric effects of changes in price and income on energy and oil demand. 2002.

Jonathan Hambur and Nick Stenner. The term structure of commodity risk premiums and the role of hedging. 2017.

Mason Hamilton. Despite the u.s. becoming a net petroleum exporter, most regions are still net importers. 2020.

Hee joon Han, Oliver Linton, Tatsushi Oka, and Yoon-Jae Whang. The cross-quantilogram: Measuring quantile dependence and testing directional predictability between time series. 2016.

Jonathan Hughes, Christopher Knittel, and Daniel Sperling. Evidence of a shift in the short-run price elasticity of gasoline demand. 2006.

Cheng Ing-Haw, Kirilenko Andrei, and Xiong Wei. Convective risk flows in commodity futures markets. 2017.

John Maynard Keynes. A tract on monetary reform. 1923.

Lutz Kilian. Oil price volatility: Origins and effects. 2010.

Alessandro Lanza, Fondazione Eni Enrico Mattei, Matteo Manera, Margherita Grasso, and Massimo Giovannini. Long-run models of oil stock prices. 2003.

Jihoon Lee and Hong Chong Cho. Impact of structural oil price shock factors on the gasoline market and macroeconomy in south korea. 2021.

Oliver Linton and Yoon-Jae Whang. The quantilogram: With an application to evaluating directional predictability. 2007.

Masters. Testimony of michael w. masters before the financial crisis inquiry commission. 2008.

Petter Osmundsen, Frank Asche, Bård Misund, and Klaus Mohn. Valuation of international oil companies. 2006.

Peck. The economic role of traditional commodity futures markets. 1985.

Platts. Platts oil pricing and moc methodology explained. 2010.

Hossein Razavi. The new era of petroleum trading. 1989.

Robert C Ready. Oil prices and the stock market. 2011.

Perry Sadorsky. Risk factors in stock returns of canadian oil and gas companies. 2001.

Scholtzen and Wang. Oil risk in oil stocks. 2008.

Shafizal Shafaai and Mansur Masih. Stock market and crude oil relationship: A wavelet analysis. 2013.

Annastiina Silvennoinen and Susan Thorp. Financialization, crisis and commodity correlation dynamics. 2010.

Tian and Lai. The causes of stage expansion of wti/brent spread. 2019.

UNCTAD. unctad. 2012.

Samuel Watts. The gaussian copula and the financial crisis: A recipe for disaster or cooking the books? 2016.

Daniel Yergin. The prize: The epic quest for oil, money, and power. *Introduction*, 1990.

Yue-Jun Zhang. Spillover effect of us dollar exchange rate on oil prices. 2008.