Universitetet i Stavanger

DET TEKNISK-NATURVITENSKAPELIGE FAKULTET

MASTEROPPGAVE

Studieprogram/spesialisering: Industrial economics Finance	Vår................semesteret, 20.20 Åpen / Konfidensiell
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Fagansvarlig: Veileder(e): Bård Misund	
Tittel på masteroppgaven: Engelsk tittel: The impact of long-short speculators on volatility of energy commodity futures prices.	
Studiepoeng: 30	
Emneord: GARCH model Long-short speculator Volatility Commodity futures markets Energy futures	Sidetall: ..39................ + vedlegg/annet: ..4........ Stavanger, ..15.06.2020.. dato/år

Abstract

This paper studies the effect of long-short speculators in four energy commodity futures, all traded on the New York Mercantile Exchange (NYMEX) over the period January 2010 to February 2020. Using the Total Open Interest of Long-Short Speculators (S^{Total}) and the Market Share of Long-Short Speculators (S^{Share}) as measures for speculative activity, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is employed to study the impact of long-short speculation on return dynamics. The conclusion of this paper is that long-short speculators do not destabilize the commodity prices. Instead, the evidence points to no effect of long-short speculation on commodity futures prices in the markets and period under scrutiny.

Preface

This thesis concludes my master's degree in Industrial Economics at the University of Stavanger. I would like to thank my supervisor Bård Misund.

Working on this thesis has allowed me to apply acquired knowledge from several courses during my study. It has also allowed me to learn valuable information and tools about the topic and methods in question.

Therese Dahl-Stamnes

15.06.2020

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1. Introduction

Since the beginning of the 2000s there has been a considerable increase of investments in the commodity futures market. As it has become increasingly popular and the number of market participants also skyrocketed with the rapid financialization of commodity markets. This increase in market participants, namely the financial investors, happened at the same time as the markets was experiencing rapid increases and sharp reversals, e.g. the financial crisis in 2007/08 and 2011, and the oil crisis in 2014 (Bohl & Sulewski, 2019). This forms the basis of the motivation to find out more about how speculation affects the commodity futures markets returns and volatility. This has prompted a fair bit of public debate and academic literature on the subject.

As commodity futures have become increasingly popular assets for investors and fund managers and the number of market participants and different types of traders have grown (Andreasson, Bekiros, Nguyen & Uddin, 2016). Therefore, it has become more and more important to understand how these affect the markets in question. Not only to get a better understanding of market behavior, but also get an overview of whether there is a need for regulatory measures. As mentioned by Algieri & Leccadito (2019), financial regulators should be careful in imposing overall regulatory measures to induce market stability, as it might have vastly different effects in different markets.

This thesis will look at four energy commodity futures from the period of January 2010 to February 2020. The commodities in question are Natural Gas, Crude Oil, Heating Oil and Gasoline, all traded on the New York Mercantile Exchange (NYMEX). Using weekly data from the US Commodity Futures Trading Commission's (CFTC) Commitment of Traders (COT) report. More specifically the "non-commercial traders" category to calculate a measure for long-short speculation in the commodity futures markets. It will also look at three different macroeconomic factors that might have an influence on the return dynamics, these will be S&P 500 Index (S&P500), the 3-month Treasury Bill (T-bill) and the Traded Weighted US Dollar Index: Broad, Goods and Services (Exrate). The data for the commodities and macroeconomic factors are collected from Yahoo Finance and Federal Reserve Economic Data (FRED).

The US Commodity Future Trading Commission divides the market participants into two major categories: Commercial and Non-Commercial traders. The commercial trader is a market participant that buys commodity futures to hedge against undesirable price movements of the core commodity of their business. Whereas the non-commercial trader is interested in realizing profit on the commodity futures contract and not the physical asset itself. The non-commercial trader category is often used in empirical literature as a measure of classical or so-called long-short speculators (Alquist & Gervais, 2013; Manera, Nicolini & Vignati, 2016; Bohl & Sulewski, 2019; Bohl & Stefan, 2019). There is also a third category, non-reportable traders. These participants could be commercial or non-commercial. It is therefore important question what percentage of this category should be included in the calculation of long-short speculators.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is implemented to test the effects of the macroeconomic factors and speculation measure on the commodity futures markets. This model was introduced by Bollerslev (1986), and it is a generalization of the ARCH model introduced by Engle (1982). This model is one of the most widely used models for this type of investigation, see among others: Manera et al. (2013, 2016), Andreasson et al. (2016), Bohl & Sulweski (2019) and Bohl & Stefan (2019). Taking an approach using the GARCH model to determine whether the presence of long-short speculators have any, and if so, is it a stabilizing or destabilizing effect on the volatility of the commodity markets under scrutiny.

With the data from CFTC the speculation measures can be calculated. Initial testing will be carried out using Total Open Interest of Long-Short Speculators (S^{Total}), followed by the Market Share of Long-Short Speculators (S^{Share}) (Bohl & Sulewski, 2019). The ratio between speculators and hedger in the non-reportable traders category will also be used in the robustness analysis. The AR-GARCH model will be implemented, as a robustness analysis, to test for linear dependency between the mean and variance equations adequately. Then to check if the estimations using the initial speculation measures are robust, the Working's T Index (Manera et al., 2013; Bohl & Stefan 2019), Long-Only, Short-Only and Net-Long (Manera et al, 2013, 2016; Bohl & Stefan, 2019) positions will be used as a measure for speculative activity in the GARCH model.

The results from the GARCH model estimation indicate that the S&P 500 has a positive and significant effect on returns, the 3-month Treasury Bill is never significant, and the Traded Weighted US Dollar Index: Broad, Goods and Services is negative and significant in three out of four commodities (Natural Gas is not significant). There is no significant effect, neither stabilizing nor destabilizing, of speculative activity on the volatility in the four energy commodity futures markets in the period January 2010 to February 2020.

The thesis will be structured into six sections. The following section (2) will be a review of academic literature on the topic of the commodity futures markets, long-short speculation and volatility, an introduction to the GARCH model and time series data, followed by a description of the speculation measures used in said GARCH model. Section 3 will contain data description. Next, Section 4 will explain the methodology and econometric model used in this thesis. Section 5 will contain results and robustness analysis. Lastly, Section 6 will discuss and conclude the thesis.

2. Literature Review

This section will present relevant literature about the commodity futures market, followed by important literature on whether speculative activity is stabilizing or destabilizing on the volatility in the markets. Following that, literature on the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model will be discussed. Followed by notes on time series data. Lastly, the speculation measures used in this thesis, where the following will be discussed, the Total Open Interest of Long-Short Speculators (S^{Total}) and the Market Share of Long-Short Speculators (S^{Share}) as proposed by Aulerich, Irwin & Garcia (2014), Bohl & Stefan (2019) and Bohl & Sulewski (2019). The Working's T index (Working, 1960, 1967; Manera et al., 2013), followed by the Long-Only, Short-Only and Net-Long positions of speculators (Manera et al., 2013, 2016; Bohl & Stefan, 2019).

2.1. Commodity Futures Market

A commodity futures is an agreement to buy or sell a prearranged amount of a commodity at a specific price on a specific date in the future. Typical assets can be natural gas, crude oil, wheat, corn, silver, gold, etc. A futures contract is often used as a tool to hedge or safeguard an investment against risk in the price movement of the underlying asset. This is because the future spot price is unknown and with a futures contract the hedger can lock the terms of trade for upcoming transactions.

A futures contract holder has an obligation to act. Meaning that the holder must act on the position before the expiration or they must buy/sell the underlying asset at the decided price. Noted by Johnson (1976), that for nearly all futures markets the participants are more interested in the desire to trade on price movements than the actual delivery of the underlying asset.

As mentioned above, the use of commodity futures for hedging purposes is one of the main uses for commodity futures contracts, the other one is speculation. Here the speculator makes bets on the price movement of the underlying asset. The speculator can either take a long (buy) position or a short (sell) position in the commodity. Johnson (1976) also notes that speculators server a major role in the futures market, as they take on the risk that hedgers desire to transfer away. Where the hedger is paying a premium to avoid the price risk, the speculator is interested in the futures market for the collection of a premium. It is therefore important to understand how these different types of participants effect the markets.

2.2. Is Speculation in the Futures Market Stabilizing or Destabilizing

There is a vast literature pool on how speculators affect the commodity futures markets. Smith (2008) points out, "Speculation is not price manipulation, but is sometimes used to exploit efforts to manipulate prices, by other means. In such cases, it is the manipulation of prices that is objectionable, not speculation, per se" (p. 26). The presence of speculators is a fundamental to market stability and effective operation (Manera et al., 2013). There is however, in the literature, a heated debate on whether the presence of speculators act in a stabilizing or destabilizing manner.

On one side, the traditional theory put forward by Friedman (1953), in which the conclusion is that speculative activity stabilizes prices because they are buying when the price is low and selling when the price is high. Powers (1970) shows that presence of speculative activity in futures trading reduces the random part of price difference. In the more recent years, Alquist & Gervais (2013) examined that the increase in oil price where explained by demand shocks coming from emerging countries and not specifically by speculators. Manera et al. (2013) also found that long term speculation does not destabilize price, which follows the findings of Brunetti & Büyükşahin (2009) who finds speculative trading to reduce the volatility levels.

On the other hand, Hart & Kreps (1986) argues that speculative activity may destabilize prices. Stein (1987) also argues in favor of a destabilizing effect from speculative activity in a market. He argues that the speculators are a less or uniformed type of trader and thus lowers the informativeness of the price to existing traders, which might have a destabilizing effect on price and in turn increase the volatility.

The increased financialization of the commodity futures market over the past decades have caused many and heated debates in academic literature as well as in public debate. These debates are based on the unprecedented price variations alongside pronounced price spikes and sharp reversals in 2007/2008 with the financial crisis as well as in 2011, and in 2014 with the oil crisis. This along with the fact that commodity futures became increasingly utilized by financial investors because of their diversification benefits, strengths when it comes to inflation hedging (Miffre & Brooks, 2013) and their equity-like returns (Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006), this causing a large increase in trading volumes and open interest (Irwin & Sanders, 2012). Paulson, Liu & Odening (2013) mentions that these synchronized trends of commodity prices, trading volume and open interest held by speculators (financial investors) have caused debates on whether or not speculation is a key driver of these exceptional commodity price movements and perhaps the reason for the implementation of new regulatory measures.

While the presence of speculators increases market liquidity and thus reducing price volatility. There are also those that argue that increasing the trading volume, particularly by speculators, positively influence (destabilizes) volatility. Speculators have often been alleged to influence commodity price levels and drive their increases (Masters, 2008). The Masters (2008) hypothesis contends that long-only positions by commodity index funds drove up commodity prices throughout the 2000s. There has been many debates on the legitimacy of the Masters hypothesis, with several studies, for example; by Sanders, Irwin & Merrin (2010), Irwin & Sanders (2013), Büyükşahin & Harris (2011), Hamilton & Wu (2015), and Brunetti, Büyükşahin & Harris (2016), and the general consensus is a rejection of the hypothesis's central claim.

Although there has been extensive empirical literature on speculation in commodity market the public debate has mainly been focused on the commodity index traders (CITs). Traders which appeared as prominent market participants at the same time as commodity markets became more and more volatile. In the empirical literature pertaining CITs the so called Masters hypothesis is rejected (e.g. Stoll & Whaley, 2010; Irwin & Sanders, 2011, 2012; Hamilton & Wu, 2015; Brunetti & Reiffen, 2014). There has however, been little attention given to the role of classical speculators, the so-called long-short speculators. This is particularly noteworthy, as classical speculators and commodity index traders have widely varying investment strategies. Thus, the market impact would be substantially different between these types of traders.

The literature on the role of long-short speculators is less impressive. Nevertheless, there are some that have investigated the impact these speculators have on the commodity futures market return dynamics and volatility. Brunetti & Büyükşahin (2009) found evidence for a stabilizing effect of speculative trading when looking at crude oil, natural gas, corn, interest rate (Eurodollar) and mini-Dow. Miffre & Brooks (2013) looked at 27 different commodities, spread across as follows: random length lumber, five metals, five energy futures, four livestock futures and 12 agricultural futures. Their results found no support for the hypothesis that speculators destabilize the commodity priced by the increase in volatility or co-movements with conventional assets. Manera et al. (2013), when investigating four energy commodities and seven non-energy commodities, they found that the short-term speculation (scalping) has a positive impact on volatility, while the long-term speculation does not destabilize prices. Bohl & Sulewski (2019) also found that the presence of classical speculators does not act destabilizing on commodity prices, rather that they either had no effect or a calming effect on volatility when looking at five agricultural commodities. Bohl & Stefan (2019) looked at thinly trades commodity futures, in particular those that exhibited a large presence of long-short speculators. Their results showed that speculation measured by the speculation ratio (volume divided by open interest) does not significantly affect returns, whereas the variance equation indicates that speculation does influence volatility. Which indicated that speculation does not randomly drive returns away from their fundamentals. The results from the literature have a general consensus that the presence of speculative trading, in the form of long-short speculators, does not have a destabilizing effect on the volatility in the commodity futures market.

2.3. Generalized Autoregressive Conditional Heteroskedasticity Model

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was first introduced by Bollerslev (1986) and Taylor (1987). The GARCH model is an extension of the Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982). Engles ARCH model was pioneering in the way that it recognized the flaws of traditional econometric models, models which assumed a constant one-period forecast variance. He generalized this assumption and created a new class of stochastic models called ARCH processes. These processes are mean zero and serially uncorrelated with changeable variances conditional on the previous, but constant unconditional variances. This means that the past gives information about the future forecast's variance.

One of the main abilities of the ARCH model is that it recognized that there is a difference between the unconditional and conditional variance, which allows for the latter to change over time as a function of past errors (Bollerslev, 1987). Bollerslev (1987) saw that there was of practical interest to extend the ARCH model. This because of the long lags in the conditional variance introduced in empirical applications. This led to the extension of the ARCH model, in which the model allowed for both longer memory and a more flexible lag structure.

The GARCH model is frequently used in financial econometrics. It is used to predict volatility of returns. The model is used to analyze time-series data where the variance is believed to be autocorrelated (Chappelow, 2019). In the ARCH(q) model the conditional variance is specified as the linear function of past values of sample variance, whereas the GARCH(p, q) model introduces the lagged conditional variance as well (Bollerslev, 1987). Thus, the model has a more adaptive learning process.

The model as introduced by Bollerslev (1987) is given by the following, the GARCH(p, q) process:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=0}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=0}^{p} \beta_i h_{t-i} = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t \tag{2}$$

where

$p \geq 0, \qquad q > 0$

$\alpha_0 > 0, \qquad \alpha_i \geq 0, \quad i = 1, \dots, q$

$\beta_i \geq 0, \qquad i = 1, \dots, p$

If *p = 0* the GARCH(p, q) is reduced to the ARCH(q) process, and if *p = q = 0* it is reduced to white noise only (ε_t). Further, the GARCH(p, q) regression is found by letting ε_t be the innovations in the linear regression,

$\varepsilon_t = y_t - x_t' b,$

Where y_t is the dependent variable, x_t is a vector of explanatory (independent) variables, and *b* is a vector of unknown parameters.

In the following analysis the GARCH(1, 1) model will be implemented. This is generally considered a good model for the estimations at hand, see among others, Miffre & Brooks (2013), Bohl & Stefan (2019) and Bohl & Sulewski (2019).

2.4. Time Series Data

Time is a major factor in the data for this thesis, as prices change through time. A time series could be defined as numerous observations of a variable through time. The assumption that the observed data is independent of its own history is a strong assumption in economics. It is therefore an important dimension to time series data that past events can influence the future outcome. Most time series data are correlated to its historical data to some degree. Woolridge (2013) acknowledges that a chronological arrangement of observed data may offer important information.

Data frequency is another important factor that needs to be paid attention to. Woolridge (2013) notes that the most common data frequencies are daily, weekly, monthly, quarterly, and annually. It is important to choose an appropriate data frequency. Generally, if the variables have low volatility it would be suitable to use frequencies that cover larger time periods. Vice versa for a high volatility variable, the appropriate frequency would be higher. As mentioned, the publicly available data in CFTC's COT report is at a weekly basis, and this is therefore the adopted frequency in this thesis.

Time series data can be stationary or non-stationary. A criterion for stationarity is constant mean and variance over a time-period. Additionally, the covariance is not reliant on observed time, but on the length of time (Hill, Lim & Griffiths, 2012, pp. 476-477). Hill et al. (2012) describes these equations as an argument:

$$E(y_t) = \mu \tag{3}$$

$$Var(y_t) = \sigma^2 \tag{4}$$

$$Cov(y_t, y_{t+h}) = Cov(y_t, y_{t-h}) = \gamma_h \tag{5}$$

Stationarity is present if the mean of y_t (equation 3) and the variance of y_t (equation 4) is constant. From equation 5 we get that, for $h \geq 1$, the equation only depends on h (which is here referred to as the length of time). The correlation between the two terms is then only dependent on h. This is what Woolridge (2012) defines as a covariance stationary process.

Checking for stationarity is an important step when dealing with time series data, as failing to do so may result in false conclusions. To test for stationarity in the time series data the Augmented Dickey-Fuller (ADF) test can be implemented, this will be further discussed in section 4.3.

2.5. The Speculation Measures

The speculation measures used for the initial estimation of the GARCH model are Total Open Interest of Long-Short Speculators (S^{Total}), followed by Market Share of Long-Short Speculators (S^{Share}). Then in the robustness analysis the Working's T Index, Long-Only and Short-Only and Net-Long speculators will be considered.

To measure the activities of long-short speculators the Total Open Interest of Long-Short Speculators (S^{Total}) is implemented as a proxy. This is motivated by Aulerich et al. (2014) and Bohl & Sulewski (2019). This index consists of non-commercial long, non-commercial short and a share of the non-reporting traders given in the data from the US Commitment of Futures Trading Commission (CFTC). The last part of including a share of non-reporting traders into the speculation measure is motivated by Sanders et al. (2010) and Kim (2015). The Market Share of Long-Short Speculators (S^{Share}), motivated by Manera et al. (2016) and Bohl & Sulewski (2019), is implemented as a robustness check.

The Working's T (1960) index is one of the most widely used measures of speculation in literature. It can be used as a proxy for long-short speculation. Given the position data provided by the CFTC's COT report, this index measures the excess of speculation relative to hedging based on the position data. The logic behind this index is that any trade by a hedger must be matched by one in the opposite direction of a speculator (Bohl & Stefan, 2019). The Working's T Index will be implemented as a robustness checking tool.

Lastly, motivated by Manera et al. (2013, 2016) and Bohl & Stefan (2019), these are other measures used for robustness analysis is based on Long-Only, Short-Only and Net-Long positions of the non-commercial traders.

3. Data Collection and Description

This section will present the where the data is collected from and some introductory calculations.

3.1. Energy Commodities and Macroeconomic Factors

Data is collected on the futures prices of four energy commodities. The commodities are Natural Gas, Crude Oil, Heating Oil and Gasoline. All traded on the New York Mercantile Exchange (NYMEX). Daily data are obtained from Yahoo Finance and Federal Reserve Economic Data (FRED) for all the commodities. The macroeconomic factors are S&P500 Index (S&P500), 3-month Treasury Bill (T-bill) and the Traded Weighted US Dollar Index: Broad, Goods and Services (Exrate). These factors are chosen as they are often used as macroeconomic factors in the present literature, among other Brooks, Prokopczuk & Wu (2015), Manera et al. (2013, 2016), Kim (2015) and Bohl & Sulewski (2018). As the data from the CFTC's COT report is on a weekly basis, the commodities and macroeconomic factors data are then calculated into weekly returns of futures prices, using the logarithmic price difference.

The S&P 500 Index is included to capture the influence of overall economic development and is expected to have a positive value. The 3-month Treasury Bill (T-Bill) rate accounts for impacts of monetary policies and serves as the risk-free rate (Bohl & Sulewski, 2018), this is expected to be negative. The Traded Weighted US Dollar Index: Broad, Goods and Services (Exrate) is expected to be negative. As the commodities in question are traded in US dollars, therefore the appreciation of the US Dollar will lead to devaluation of commodity prices.

3.2. Commitment of Traders

The US Commodity Futures Trading Commission (CFTC) provides data in form of a Commitment of Traders (COT) report. This report has the advantage that is differentiates between different types of traders. These classifications are non-commercial[1], commercial[2], commodity index and non-reporting[3] traders. As discussed earlier, Alquist & Gervais (2013), Manera et al. (2016), Bohl & Sulewski (2019) and Bohl & Stefan (2019), the empirical literature refers to non-commercial traders as speculators and commercial traders as hedgers. Bohl & Sulewski (2019) further notices that since the COT report differentiates between the non-commercial category and index traders, that the non-commercial category can be referred to as classical or long-short speculators.

Table 1 gives a short overview over the markets in question. Including the number of observations, the open interest, along with the number of traders in each commodity futures market, as reported by the CFTC's COT report. From Table 1, we can note that Crude Oil has the highest number for open interest and number of traders. Heating Oil has the smallest number of traders. However, Gasoline appears to have the smallest open interest of the four energy commodities.

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[1]This category consists of market participants that are interested in making profits from buying and selling futures contracts (Manera et al., 2013)

[2] The CFTC defines this category by: "All of a trader's reported futures positions in a commodity are classified as commercial if the trader uses futures contracts in that particular commodity for hedging as defined in CFTC Regulation 1.3, 17 CFR 1.3(z). […]". (see https://www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm). Also as mentioned by Manera et al. (2013), Bohl & Sulewski (2019) and Bohl & Stefan (2019), commercial agents are agents that are active in the sport market.

[3] The CFTC defines this category as: "The long and short open interest shown as "Nonreportable Positions" is derived by subtracting total long and short "Reportable Positions" from the total open interest. Accordingly, for "Nonreportable Positions", the number of traders involved and the commercial/non-commercial classification of each trader are unknown." (see https://www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm)

Table 1: Number of Observations, Open Interest & Number of Traders

Futures contract	Contract size	No. Obs.	Open Interest	No. Traders
Natural Gas	10 000 mmBTU	530	1154079	306.3
Crude Oil	1 000 Barrels	530	1794190	360.8
Heating Oil	42 000 US Gallons	530	356725	181.7
Gasoline	42 000 US Gallons	530	344169	231.5

Note: Number of Observations, Open Interest, and Number of Traders are all own calculations of averages of the markets in question. Data from Commitment of Traders (COT) report provided by the UC Commodity of Futures Trading Commission (CFTC). All series range from January 2010 to February 2020.

Since the data obtained from US Commodity Future Trading Commissions (CFTC) are on a weekly basis and is the only publicly available data of this sort, this is the data frequency adopted[4]. This data frequency does however impose some problems as changes in positions and price can happen in short time periods. This can cause problems when assessing the impact the traders position has on changes in price (Bohl & Sulweski, 2019). Nevertheless, as this is the only publicly available data, this data frequency for measuring speculative activity has been utilized in earlier academic literature.

Figure 1 displays the spot price of Crude Oil over the period in question, January 2010 to February 2020 (for the other commodities see Appendix A1-A3). From Figure 1 we can see that there are several spikes and declines in the spot price for Crude Oil in the period in question. The most notable crash in 2014 with the Oil Crisis. This is also similar for the other commodities.

[4] Daily data exist, but these are not publicly available.

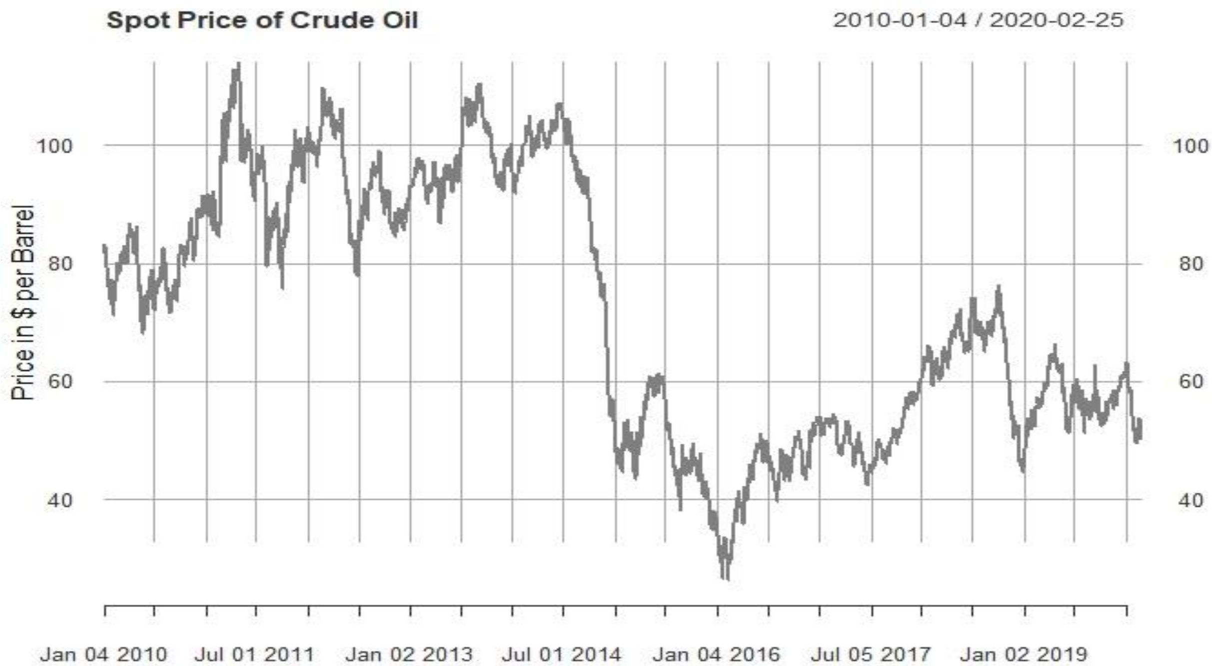

Figure 1: Spot Price of Crude Oil from January 2010 to February 2020. Data collected from Yahoo Finance.

4. Methodology

This section will present the methodology used in the estimation for relationship between speculative activity and volatility in energy commodity futures prices. In the following, the speculation measures implemented in this these will be discussed. There is also a check for correlation and multicollinearity in the data. Followed by the summary statistics for the data and unit-root testing. Followed, lastly, by the econometric model used for the estimation.

4.1. Speculation Measures

Here the speculation measures used in the econometric model are introduced. For the first estimation of the GARCH model the Total Open Interest of Long-Short Speculators (S^{Total}) is implemented as a proxy for speculative activity, followed by Market Share of Long-Short Speculators (S^{Share}). Then in the additional robustness analysis the Working's T Index, Long-Only, Short-Only and Net-Long positions will be considered. Below all the speculation measures will be discussed.

As suggested by Aulerich et al. (2014) as well as Bohl & Sulewski (2019), the position held by long-short speculators can be quantified in two measures based on the open interest of the non-commercial traders. The first is the Total Open Interest of Long-Short Speculators (S^{Total}), and this can be represented by the following equation:

$$S_{i,t}^{Total} = SS_{i,t} + SL_{i,t} \tag{6}$$

Where $S_{i,t}^{Total}$ is the Total Open Interest of Long-Short Speculators of commodity *i* at time *t*, $SS_{i,t}$ is speculation short of commodity *i* at time *t*, $SL_{i,t}$ is speculation long of commodity *i* at time *t*.

Along the lines of Manera et al. (2016) and Bohl & Sulewski (2019) we can use the Market Share of Long-Short Speculators (S^{Share}) as a robustness check, this is represented by the following equation:

$$S_{i,t}^{Share} = \frac{SS_{i,t} + SL_{i,t}}{2 * OI_{i,t}} \tag{7}$$

Where $S_{i,t}^{Share}$ is the Market Share of Long-Short Speculators of commodity *i* at time *t*, $SS_{i,t}$ is speculation short of commodity *i* at time *t*, $SL_{i,t}$ is speculation long of commodity *i* at time *t* and $OI_{i,t}$ is the open interest of commodity *i* at time *t*.

4.1.1. Speculation Measures used in the Robustness Analysis

From the data collected form the CFTC's COT report the calculation of the Working's T index can be obtained. This index is a measure for speculative activity (Manera et al., 2013; Andreasson et al., 2016; Bohl & Stefan, 2019). The underlying reasoning for the index is that any trade by a hedger is opposed by a speculative trade (Bohl & Stefan, 2019). It is calculated to be the proportion of non-commercial positions to total commercial positions, and is represented by the following equation:

$$WT_{i,t} = \begin{cases} 1 + \dfrac{SS_{i,t}}{HL_{i,t} + HS_{i,t}} & if\ HS_{i,t} \geq HL_{i,t} \\ 1 + \dfrac{SL_{i,t}}{HL_{i,t} + HS_{i,t}} & if\ HS_{i,t} < HL_{i,t} \end{cases} \tag{8}$$

Where $WT_{i,t}$ is Working's T index of commodity *i* at time *t*, $SS_{i,t}$ is speculation short of commodity *i* at time *t*, $SL_{i,t}$ is speculation long of commodity *i* at time *t*, $HS_{i,t}$ is hedging short of commodity *i* at time *t* and $HL_{i,t}$ is hedging long of commodity *i* at time *t*.

Motivated by Manera et al. (2013) the Long-Only, Short-Only and Net-long positions are considered as a measure for speculative activity. These are denoted as $S_{i,t}^{l}$, $S_{i,t}^{s}$ and $S_{i,t}^{nl}$, respectively, and defined as:

$$S_{i,t}^{l} = \frac{SL_{i,t}}{OI_{i.t}} \tag{9}$$

$$S_{i,t}^{s} = \frac{SS_{i,t}}{OI_{i.t}} \tag{10}$$

$$S_{i,t}^{nl} = \frac{SL_{i,t} - SS_{i,t}}{OI_{i.t}} \tag{11}$$

Where $S_{i,t}^{l}$ is the Long-Only positions of commodity *i* at time *t*, $S_{i,t}^{s}$ is the Short-Only positions of commodity *i* at time *t*, $S_{i,t}^{nl}$ is the Net-Long positions of commodity *i* at time *t*, $SS_{i,t}$ is speculation short of commodity *i* at time *t*, $SL_{i,t}$ is speculation long of commodity *i* at time *t* and $OI_{i,t}$ is the open interest of commodity *i* at time *t*.

4.1.2. Non-Reporting Traders

As mentioned by Manera et al. (2013) it should be noted that these measures of speculative activity are reliant on the classification of market participants as hedgers and speculators. The COT report does not provide this distinction in the data for "Non-Reportable" agents, these agents are not included in the commercial or non-commercial category. Nevertheless, some of these participants should be included in the calculation of the speculation indexes. The ratio between speculators and hedgers in the non-reporting category will be denoted α.

There have been proposed several ways of handling the non-reportable participants. Manera et at. (2013) following a 70/30 ratio, that is 70% of the non-reportable positions are speculators and 30% are hedgers. Bohl & Stefan (2019) initially suggested 20% speculators and 80% hedgers, which is quite different from the aforementioned. However, they argue that in the market they were looking at (feeder cattle), it would be more likely to be a ratio heavier towards hedging than speculation. They furthered the analysis by changing the ratio to all hedgers, 60% hedgers and 20% hedgers. Sanders et al. (2010), Kim (2015) and Bohl & Sulewski (2019) all suggested that the ratio between hedgers and speculators in the nonreportable positions category follows the same distribution patterns as observed in the reporting categories.

The following analysis will first implement a 70/30 ratio between speculators and hedgers, and in the robustness analysis it will be changed (0/100, 30/70, 50/50 and 100/0). Therefore, we need to incorporate the non-reportable traders into the variables for the speculation measures. For this the following equations are used:

$$SL_{i,t} = NCL_{i,t} + \alpha * NRL_{i,t} \tag{12}$$

$$SS_{i,t} = NCS_{i,t} + \alpha * NRS_{i,t} \tag{13}$$

$$HL_{i,t} = CL_{i,t} + (1 - \alpha) * NRL_{i,t} \tag{14}$$

and

$$HS_{i,t} = CS_{i,t} + (1 - \alpha) * NRS_{i,t} \tag{15}$$

Where $NCL_{i,t}$ is non-commercial long of commodity *i* at time *t*, $NRL_{i,t}$ is non-reportable long of commodity *i* at time *t* $NCS_{i,t}$ is non-commercial short of commodity *i* at time *t*, $NRS_{i,t}$ is non-reportable short of commodity *i* at time *t*, $CL_{i,t}$ is commercial long of commodity *i* at time *t*, $CS_{i,t}$ is commercial short of commodity *i* at time *t* and α is the ratio between speculators and hedgers. Where *α* is a fixed number between 0 and 1 (0 being all hedgers and 1 being all speculators). In the initial testing α is set to 0.7, meaning a ratio of 70% speculators to 30% hedgers among the non-reporting positions.

4.2. Correlation and Multicollinearity

Here we check for correlation between the different variables. The correlation is calculated using the following formula between two random variables X and Y:

$$corr(X,Y) = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E(X)^2}\sqrt{E(Y^2) - E(Y)^2}} \quad (16)$$

Results of the correlation calculations are presented in Table 2. From the table we can see that none of the variables exhibit very strong correlations. All being below +/- 0.4.

Table 2: Correlation Matrix

	NG	S&P500	T-Bill	Exrate		CO	S&P500	T-Bill	Exrate
NG	1				**CO**	1			
S&P500	0.069	1			**S&P500**	0.396	1		
T-Bill	0.049	0.043	1		**T-Bill**	0.062	0.043	1	
Exrate	-0.065	-0.377	0.033	1	**Exrate**	-0.363	-0.379	0.033	1
	HO	**S&P500**	**T-Bill**	**Exrate**		**GL**	**S&P500**	**T-Bill**	**Exrate**
HO	1				**GL**	1			
S&P500	0.358	1			**S&P500**	0.198	1		
T-Bill	0.063	0.043	1		**T-Bill**	0.028	0.043	1	
Exrate	-0.350	-0.377	0.033	1	**Exrate**	-0.188	-0.379	0.033	1

Note: Own calculations based on data from Yahoo Finance and Federal Reserve Economic Data (FRED). Abbreviations: NG, Natural Gas; CO, Crude Oil; HO, Heating Oil; GL, Gasoline; T-Bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.

Following that, we test for multicollinearity in the data sets. This is done to see if two or more of the explanatory variables are highly correlated. For this the Variance Inflation Factor (VIF) is utilized, this coefficient measures how much the variance of a regression is inflated due to multicollinearity in the model. The VIF is calculated in a two-step process, first run an Ordinary Least Square (OLS) regression on the commodity in question dependent on the macroeconomic factors:

$$r_{i,t} = \alpha_0 + \alpha_1 SP500_t + \alpha_2 Tbill_t + \alpha_3 Exrate_t + e \quad (17)$$

Whew α_0 is a constant and *e* is the error term. Obtaining the R^2 from the OLS regression the VIF can be calculated by the following formula:

$$VIF_i = \frac{1}{1 - R_i^2} \tag{18}$$

If the value of the VIF exceeds 10 there will be problems due to collinearity. The results of the VIF test are presented in Table 3 below. From the table it emerges that none of the values are above 1.2, hence there is no reason to be worried about multicollinearity in the data sets.

Table 3: Multicollinearity for the different markets using Variance Inflation Factor

	Natural Gas	Crude Oil	Heating Oil	Gasoline
S&P500	1.170	1.172	1.170	1.172
T-bill	1.005	1.005	1.005	1.005
Exrate	1.169	1.171	1.169	1.171

Note: Own calculations based on data from Yahoo Finance and Federal Reserve Economic Data (FRED). Abbreviations: S&P500, S&P 500 Index; T-Bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.

4.3. Summary Statistic and Unit-Root Testing

To test for stationarity in the data sets the Augmented Dickey Fuller (ADF) test is applied (Dickey & Fuller, 1981). The ADF test expands the Dickey-Fuller test to include higher order regressive processes. It tests if there is a unit root, which can cause statistical interference, present in a time series. The presence of a unit root makes the time series non-stationary. With the null hypothesis of a unit root is present in the time series (H_0: γ = 1), the ADF test is the following model:

$$y_t = c + \beta t + \gamma y_{t-1} + \varphi_1 \Delta Y_{t-1} + \varphi_2 \Delta Y_{t-2} \ldots + \varphi_n \Delta Y_{t-n} + e_t \tag{19}$$

Where *c* is a constant, β is the coefficient of a time trend, *n* is the lag order, y_{t-1} is the first lag of the time series and ΔY_{t-n} is the n[th] difference of the time series at time *t-1*.

The unit root test can now be carried out using the null hypothesis, H_0: γ = 0 and the alternative hypothesis γ < 0. The test statistic is computed with the following:

$$DF_T = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \tag{20}$$

Once the test statistic is computed it can be compared to the appropriate critical values for the Dickey-Fuller Test. These are -2.570, - 2.860 and -3.430 for 10%, 5% and 1%, respectively.

Table 4 provides summary statistics and unit root test for the variables used in the analysis. From the first and third panel in Table 4 and the ADF test it emerges that some of the variables are non-stationary in level (Natural Gas, Gasoline and S&P 500 are stationary). To ensure that the variables are stationary in level, all the variables are integrated into the model as the logarithmic price differences. Here we use the weekly returns multiplied by one hundred, $r_{i,t} = \left[\ln\left(P_{i,t}\right) - \ln\left(P_{i,t-1}\right)\right] * 100$. This is displayed in the second and fourth panel of Table 4. Also note that the transformation performed between panel one (three) and two (four) allows for stationarity in all the variables according to the ADF test.

Table 4: Summary Statistics and Unit-Root Test for the Commodities and Macroeconomic Factors

	Obs	Mean	Stv.Dev.	Min	Max	Unit-Root Test
			FUTURES PRICES (daily)			
Natural Gas	2535	3.280	0.820	1.640	6.150	-3.709***
Crude Oil	2537	72.20	21.90	26.21	113.9	-2.325
Heating Oil	2538	2.250	0.620	0.810	3.320	-2.203
Gasoline	2548	2.280	0.600	0.620	4.180	-3.710***
			RETURNS (weekly)			
Natural Gas	530	-0.060	1.280	-5.720	4.510	-7.486***
Crude Oil	530	-0.020	0.860	-3.130	3.180	-6.693***
Heating Oil	530	-0.020	0.780	-4.140	2.410	-7.463***
Gasoline	530	-0.010	1.710	-8.780	13.60	-9.426***
			MACROECONOMIC VARIABLES (daily)			
S&P500	2553	1982	606.1	1023	3386	-3.428**
T-Bill	2531	0.570	0.780	0.000	2.410	-1.167
Exrate	2521	102.6	10.55	85.49	119.2	-2.222
			RETURN MACROECONOMIC VARIABLES (weekly)			
S&P500	530	0.040	0.430	-3.240	1.430	-7.617***
T-bill	530	0.120	10.64	-53.65	62.42	-9.539***
Exrate	530	0.010	0.150	-0.660	0.570	-7.359***

*Note: own calculation based on data obtained from Yahoo Finance and Federal Reserve Economic Data (FRED). The unit-root statistics are calculated using the Augmented Dickey-Fuller (ADF) test. The critical values for the ADF test are -2.570, -2,860 and -3,430 for the 10%, 5% and 1% level of significance, respectively. They are marked in the table as *, ** and ***, respectively. Abbreviations: S&P500, S&P 500 Index; T-bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.*

Figure 1 displays the time series of return on the commodity Crude Oil. For the other commodities see Appendix B1-B3. For all the commodities in question we can see that they all follow a constant mean, with some more notable spikes and variations.

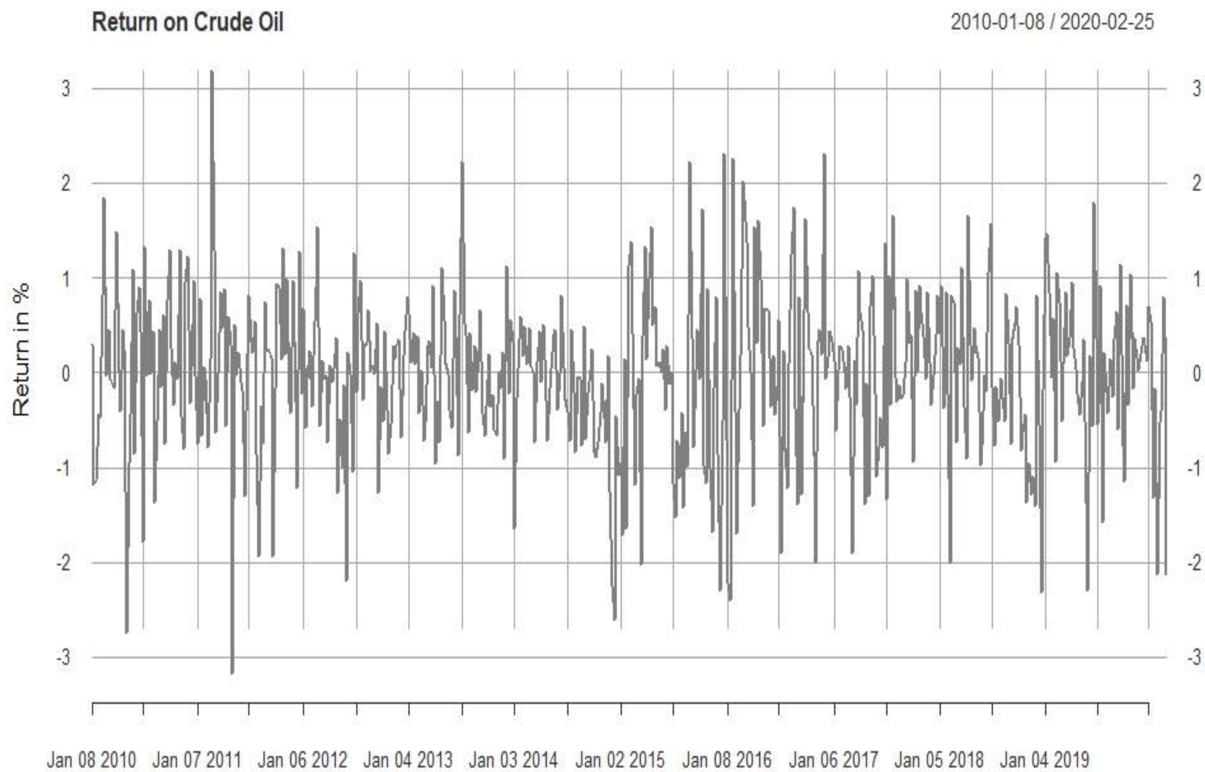

Figure 2: Return on Crude Oil, based on own calculation, from January 2010 to February 2020.

Table 5 gives an overview of the speculation indexes for the four energy commodities, The S^{Total} and S^{Share}. For the S^{Total} index these range from 171 631.5 (Heating Oil) to 768 800.5 (Crude Oil). And for the S^{Share} these range from 0.210 (Crude Oil) to 0.310 (Natural Gas). It appears, from Table 5, that some of the indexes are not stationary in level according to the ADF test. Therefore, we transform these in the logarithmic manner as well. The ADF test for the transformed values is reported in the last column of Table 5.

Table 5: Summary Statistics and Unit-Root Test for Speculation Indexes

	Obs	Mean	Stv.Dev.	Min	Max	Unit-Root Test	
				S^{Total}			
Natural Gas	530	711815.1	124028.2	388561.7	1048184	-2.807*	-7.546***
Crude Oil	530	768802.5	164274.3	496680.1	1145432	-1.722	-8.013***
Heating Oil	530	171631.5	37493.7	103547.4	299510.1	-2.203	-9.546***
Gasoline	530	180276.6	48632.4	88580.2	317984.3	-3.624***	-9.449***

				S^{Share}			
Natural Gas	530	0.310	0.050	0.210	0.440	-1.993	-8.024***
Crude Oil	530	0.210	0.020	0.170	0.280	-1.858	-9.215***
Heating Oil	530	0.240	0.040	0.170	0.350	-2.683*	-8.347***
Gasoline	530	0.260	0.040	0.180	0.370	-3.464***	-8.488**

*Note: own calculation based on data obtained from Commitment of Traders (COT) reports provided by the US Commodity Futures Trading Commission (CFTC). The unit-root statistics are calculated using the Augmented Dickey-Fuller (ADF) test. The critical values for the ADF test are -2.570, -2,860 and -3,430 for the 10%, 5% and 1% level of significance, respectively. They are marked in the table as *, ** and ***, respectively. Abbreviations: S&P500, S&P 500 Index; T-Bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.*

4.4. Econometric Model

After testing for stationarity in the variables (reported in Table 4 and Table 5 – Unit-Root Test) the model can be constructed and estimated. Here we will start with the econometric model where we estimate the return for each commodity *i* at time *t*. With the help of two sets of explanatory variables, macroeconomic and speculative factor. This can be presented by the following equation:

$$r_{i,t} = \alpha_0 + \alpha_1 SP500_t + \alpha_2 Tbill_t + \alpha_3 Exrate_t + \alpha_4 Speculation_{i,t} + \varepsilon_{it} \qquad (21)$$

Where $r_{i,t}$ is the return on commodity *i* at time *t*, $SP500_t$ in the S&P 500 Index at time *t*, $Tbill_t$ is the 3-month Treasury Bill at time *t*, $Exrate_t$ is the Traded Weighted US Dollar Index: Broad, Goods and Services at time *t*, $Speculation_{i,t}$ is the measure of speculative activity of commodity *i* at time *t*.

The first step is to use the model Ordinary Least Squares (OLS) to obtain the residuals, these residuals are then used in the ARCH (Engle, 1982) testing. This test allows the presence of autocorrelation, the ARCH effect, to be discovered. The null hypothesis states that there is no ARCH effect in the data set. In the case of rejecting the null hypothesis, the conclusion would state that there are ARCH effects in the data set. This model is used in the case where the data has variance varying in time and depend on lagged effects.

If there is a presence of ARCH effect, we move on the GARCH model. Table 6 reports the results of the ARCH test. From Table 6 we can see that there is presence of ARCH effects in all commodities. Therefore, we move on to the GARCH model for further investigation.

Table 6: ARCH Test of Residuals

Market	Q-statistic
Natural Gas	41.249***
Crude Oil	16.892***
Heating Oil	20.260***
Gasoline	23.437***

*Note: Own calculations based on data from Yahoo Finance, Federal Reserve Economic Data (FRED). Here the ARCH effect is calculated using Lagrange Multiplier. Significance levels are 10%, 5% and 1%, marked in the table with *, ** and ***, respectively.*

For the GARCH model we are going to follow Miffre & Brooks (2013), Manera et al. (2013), Bohl & Sulewski (2019) and Bohl & Stefan (2019) with the GARCH(p, q) specifications of *p = q = 1*. The GARCH(1, 1) mean model will therefore be:

$$r_{i,t} = \gamma_0 + \gamma_1 SP500_t + \gamma_2 Tbill_t + \gamma_3 Exrate_t + \varepsilon_{i,t} \tag{22}$$

Where $\varepsilon_{i,t} \sim N(0, \sigma_{it}^2)$. The return on the futures prices is defined as $r_{i,t} = \left[\ln(P_{i,t}) - \ln(P_{i,t-1})\right] * 100$, where $P_{i,t}$ denotes the future price of commodity *i* at time *t*. The following variance equation will be:

$$\sigma_{it}^2 = \beta_0 + \beta_1 \varepsilon_{i,t-1}^2 + \beta_2 \sigma_{i,t-1}^2 + \beta_3 Speculation_{i,t} \tag{23}$$

where $\sigma_{i,t}^2$ is the conditional volatility of commodity *i* at time *t*. The ARCH effect is described with the parameter β_1 in the variance equation. The GARCH effect is described with the parameter β_2 in the variance equation. The estimates for ARCH and GARCH are expected to be positive and their sum smaller than one ($\beta_1 > 0,\ \beta_2 > 0 \text{ and } \beta_1 + \beta_2 < 1$) (Bohl & Sulewski, 2019). This is to ensure that there is stationarity in the covariance and that the conditional variance is never negative. If the sign for β_3 is positive, it indicates that speculation has a destabilizing effect on the conditional volatility. If it is negative it would indicate that speculative activity has a stabilizing effect on the conditional volatility.

5. Results

In this section the results of the initial GARCH modelling will be presented and discussed. Following that, some robustness checking using different speculator/hedger ratio (α) for the non-reporting traders. Following that the AR-GARCH model will also be tested as a robustness check. Lastly, the results the GARCH estimation for the other speculation measures, Working's T Index, Long-Only, Short-Only and Net-Long, used as a robustness analysis will be presented.

5.1. Initial Testing with GARCH model

To investigate the impact of speculation in the commodity market the model is first estimated based on Total Open Interest of Long-Short Speculators, S^{Total} (equation 6). Following that the model is estimated using the Market Share of Long-Short Speculators, S^{Share} (equation 7). The results will be discussed below.

5.1.1. Total Open Interest of Long-Short Speculators

The initial estimation of the GARCH model is done utilizing the Total Open Interest of Long-Short Speculators (S^{Total}, equation 6) as a measure for speculative activity. The estimated results of the mean and variance equation is presented in Table 7 and will be discussed below.

The S&P 500 which is incorporated as a proxy for the overall economic development, and it is highly significant and positive for Crude Oil, Heating Oil and Gasoline. For Natural Gas, the S&P 500 is significant and positive. It ranges from 0.210 (Natural Gas) to 0.582 (Crude Oil).

The results also indicate that the 3-month Treasury Bill (T-bill), which is a proxy for the impact of monetary policies, does not have a significant impact on the commodity price movements.

The Traded Weighted US Dollar Index: Broad, Goods and Services (Exrate) is as expected negative and highly significant for three out of four of the energy commodities under scrutiny. The only exception being Natural Gas, for which it is negative, but it is however not significant. It ranges from -0.270 (Natural Gas, not significant) to -1.652 (Gasoline). As mentioned, this macroeconomic factor is negative for all commodities which is to be expected as all commodities are traded in the US Dollar.

Table 7: Estimates of GARCH model based on S^{Total}

	Natural Gas	Crude Oil	Heating Oil	Gasoline
		Mean Equation		
S&P500	0.210*	0.582***	0.476***	0.550***
	(0.127)	(0.081)	(0.077)	(0.171)
T-Bill	0.004	0.005	0.004	0.007
	(0.005)	(0.003)	(0.003)	(0.005)
Exrate	-0.270	-1.386***	-1.254***	-1.653***
	(0.367	(0.242)	(0.220)	(0.440)
Constant	-0.052	-0.021	-0.024	-0.012
	(0.049)	(0.032)	(0.029)	(0.057)
		Variance Equation		
ARCH term	0.212***	0.036*	0.069***	0.134***
	(0.057)	(0.019)	(0.025)	(0.044)
GARCH term	0.643***	0.931***	0.751***	0.834***
	(0.076)	(0.044)	(0.031)	(0.063)
S^{Total}	-0.092	0.019	-0.100***	-0.178
	(1.790)	(0.017)	(0.003)	(1.165)
Constant	0.344	0.000	1.089***	0.279
	(1.803)	(0.004)	(0.003)	(1.176)
ARCH+GARCH term	0.855	0.967	0.810	0.968
AIC	3.268	2.302	2.125	3.637
BIC	3.333	2.366	2.189	3.701

*Note: the GARCH models are estimated using S^{Total} (Equation 6) as a measure for speculative activity. Significance levels are 10%, 5% and 1%, marked in the table with *, ** and ***, respectively. Standard errors are provided in the parentheses. Abbreviations: S&P500, S&P 500 Index; T-Bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.*

The variance equation estimates show that all ARCH and GARCH terms are highly significant (except the ARCH term for Crude Oil, which is only significant at a 10% level of significance). They also follow the constraints imposed, namely $\beta_1 > 0$ (ARCH term), $\beta_2 > 0$ (GARCH term) and $\beta_1 + \beta_2 < 1$. These constraints are to ensure covariance stationarity and a positive conditional variance for all commodities (Bohl & Sulewski, 2019). Generally, the estimate for β_2 are closer to one, ranging from 0.643 (Natural Gas) to 0.931 (Crude Oil). While β_1 are generally close to 0.1 (except for Natural Gas, which is 0.212). This indicates the persistence of volatility shocks.

The speculation measure is generally not significant in this estimation, except for the commodity Heating Oil (-0.100). This implies, except for Heating Oil, the speculative activity in the market has no impact on the volatility of the commodities. For Heating Oil, as the value is negative, which would indicate that the presence of speculators has a stabilizing effect on the volatility.

5.1.2. Market Share of Long-Short Speculators

The model is replicated using Market Share of Long-Short Speculators, S^{Share} (equation 6). This is done since the result could potentially be influenced by choice of speculative measure (Bohl & Sulewski, 2019). The results for the estimated GARCH model using the Market Share of Long-Short Speculators are represented in Table 8.

Table 8: Estimates of GARCH model based on S^{Share}

	Natural Gas	**Crude Oil**	**Heating Oil**	**Gasoline**
		Mean Equation		
S&P500	0.210*	0.582***	0.467***	0.549***
	(0.125)	(0.081)	(0.076)	(0.169)
T-Bill	0.004	0.005	0.005	0.008
	(0.005)	(0.003)	(0.003)	(0.005)
Exrate	-0.258	-1.385***	-1.270***	-1.659***
	(0.368)	(0.242)	(0.223)	(0.440)
Constant	-0.052	-0.021	-0.024	-0.010
	(0.049)	(0.032)	(0.030)	(0.057)
		Variance Equation		
ARCH term	0.209***	0.036*	0.058**	0.133***
	(0.055)	(0.020)	(0.024)	(0.042)
GARCH term	0.642***	0.931***	0.855***	0.835***
	(0.073)	(0.045)	(0.074)	(0.059)
S^{Share}	-0.999	0.019	0.043	0.100
	(1.704)	(0.017)	(0.028)	(0.067)
Constant	1.257	0.000	0.000	0.000
	(1.718)	(0.002)	(0.003)	(0.008)
ARCH+GARCH term	0.851	0.967	0.913	0.968
AIC	3.268	2.302	2.136	3.637
BIC	3.332	2.366	2.201	3.701

*Note: the GARCH models are estimated using S^{Share} (Equation 7) as a measure for speculative activity. Significance levels are 10%, 5% and 1%, marked in the table with *, ** and ***, respectively. Standard errors are provided in the parentheses. Abbreviations: S&P500, S&P 500 Index; T-Bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.*

The estimated results using S^{Share} shows that they are similar in value and significance as the results using S^{Total}. The results show that none of the commodities have a significant value for the speculation measure. Indicating that there is no effect of speculative activity on the volatility of the commodity futures markets in question. As mentioned, when using S^{Total} as the speculation measure, Heating Oil displayed a calming effect of speculation on volatility. However, as seen from the results using S^{Share}, this is no longer the case. The result could therefore have been influenced by the choice of speculative measure.

5.2. Robustness Analysis

For the robustness analysis we will first look at the share of non-reporting traders that should be included in the calculations, this parameter is earlier mentioned as α. For this robustness check the focus is on Crude Oil. Following that the AR-GARCH model will be considered for all commodities. Lastly, we will look at some different measures of speculation, among them Working's T index for all commodities, followed by Long-Only, Short-Only and Net-Long for Crude Oil.

5.2.1. Share of Non-Reporting Traders (α)

The share of non-reporting traders which to include in the calculations of the speculation measures has been discussed above. This section will look closer at one of the commodities, namely Crude Oil, and change the value of α. Here, the α will be set to 0, meaning no speculators, 0.3, meaning 30% speculators, 70% hedgers (opposite of what the initial tests were done with), 0.5, meaning a 50/50 split between speculators and hedgers, and lastly 1, meaning all speculators. At first the estimation is done using S^{Total} as the speculation measure, then it is repeated using S^{Share}.

The results of the variance equation in the GARCH model estimations for Crude Oil using S^{Total} and S^{Share} while changing the ratio between speculators and hedgers in non-reporting traders are reported in Table 9 below (the initial test using 70/30 is also reported here). From Table 9 we can see that there is extremely little difference between the estimations while changing the ratio of speculators to hedgers, keeping all other variables the constant. The results are also in compliance with previous analysis. Indicating that there is no influence on volatility coming from the speculative activity.

Table 9: Robustness checking with different levels of speculation

Ratio (S/H)	0/100	30/70	50/50	70/30	100/0
			Variance Equation based on S^{Total}		
ARCH term	0.036*	0.036*	0.036*	0.036*	0.036*
	(0.019)	(0.020)	(0.019)	(0.019)	(0.019)
GARCH term	0.931***	0.931***	0.931***	0.931***	0.931***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
S^{Total}	0.019	0.019	0.019	0.019	0.019
	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Constant	0.000	0.000	0.000	0.000	0.000
	(0.009)	(0.004)	(0.004)	(0.004)	(0.003)
			Variance Equation based on S^{Share}		
ARCH term	0.036*	0.036*	0.036*	0.036*	0.036*
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
GARCH term	0.931***	0.931***	0.931***	0.931***	0.931***
	(0.044)	(0.045)	(0.045)	(0.045)	(0.045)
S^{Share}	0.019	0.019	0.019	0.019	0.019
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Constant	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

*Note: the GARCH models are estimated for Crude Oil using S^{Total} (Equation 6, panel 1) and S^{Share} (Equation 7, panel 2) as a measure for speculative activity. The ratio between speculators and hedgers are changed throughout the estimates in this table. Significance levels are 10%, 5% and 1%, marked in the table with *, ** and ***, respectively. Standard errors are provided in the parentheses. Abbreviations: Ratio (S/H), ratio between speculators (S) and hedgers (H).*

5.2.2. AR-GARCH

The AR(m)-GARCH(p, q) model using the Total Open Interest of Long-Short Speculators as speculation measure is also implemented as a robustness check. The model is estimated using $m = p = q = 1$. This is done to capture the linear dependence in the mean and variance model adequately. The results are presented in Table 10. From Table 10, we can see that the results are generally in compliance with the initial testing using the GARCH model with S^{Total} as the speculation measure.

Only one of the four commodities (Heating Oil) displays significant for the speculation measure, and it is negative which would indicate a calming (stabilizing) effect of speculation on the volatility. However, as mentioned in the first section, this could be the result of the chosen speculation measure. Repeating the AR-GARCH model for Heating Oil using Market Share of Long-Short Speculators (S^{Share}) as speculation measure reveals that the speculative activity has no effect on the volatility (last column in Table 10, market in *"Grey Cursive")*. This is similar to the initial results of the GARCH model estimations in Table 7 and 8. Where when using S^{Total} the model estimated a calming effect of speculative activity on volatility for Heating Oil, but when changed to S^{Share} the result is no effect.

The AR(1)-term is only slightly significant in one of the four energy commodities (Gasoline).

Table 10: Robustness checking using AR-GARCH model

	Natural Gas	**Crude Oil**	**Heating Oil**	**Gasoline**	***Heating Oil***
			Mean Equation		
S&P500	0.210*	0.572***	0.474***	0.518**	*0.0464****
	(0.127)	(0.081)	(0.077)	(0.162)	*(0.076)*
T-Bill	0.004	0.005	0.004	0.007	*0.004*
	(0.005)	(0.003)	(0.003)	(0.005)	*(0.003)*
Exrate	-0.272	-1.370***	-1.249***	-1.751***	*-1.262****
	(0.377)	(0.241)	(0.212)	(0.439)	*(0.223)*
AR(1)	-0.008	0.057	0.019	-0.082*	*0.023*
	(0.048)	(0.045)	(0.046)	(0.047)	*(0.046)*
Constant	-0.052	-0.021	-0.025	-0.006	*-0.024*
	(0.049)	(0.034)	(0.030)	(0.053)	*(0.030)*

Variance Equation					
ARCH term	0.212***	0.034**	0.067**	0.128***	*0.056***
	(0.057)	(0.017)	(0.025)	(0.037)	*(0.024)*
GARCH term	0.643***	0.937***	0.753***	0.848***	*0.858****
	(0.075)	(0.036)	(0.032)	(0.048)	*(0.075)*
S^{Total}	-0.125	0.017	-0.999***	-0.043	*0.042*
S^{Share}	(1.799)	(0.014)	(0.004)	(1.114)	*(0.028)*
Constant	0.377	0.000	1.089***	0.128	*0.000*
	(1.811)	(0.003)	(0.220)	(1.119)	*0.003*
ARCH+GARCH term	0.855	0.971	0.820	0.974	*0.914*
AIC	3.272	2.303	2.128	3.645	*2.139*
BIC	3.345	2.375	2.200	3.707	*2.212*

*Note: the AR-GARCH models are estimated using S^{Total} (Equation 6) as a measure for speculative activity. The AR-GARCH estimation for Heating Oil is repeated with S^{Share} (Equation 7) in the last column, market in "Grey Cursive". Significance levels are 10%, 5% and 1%, marked in the table with *, ** and ***, respectively. Standard errors are provided in the parentheses. Abbreviations: S&P500, S&P 500 Index; T-Bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.*

5.2.3. Working's T Index

For the other speculation measures the Working's T Index (equation 8, α = 0.70) is utilized in the GARCH model to estimate the effect of speculation in the markets. In this section the ratio between speculators and hedgers are back to the initial 70% speculators to 30% hedgers among the non-reporting traders. This is implemented as a robustness check to verify that changes in the measure of the speculative activity does not affect the results of the model estimations.

Table 11 presents the summary statistics and unit root test (ADF test) for the Working's T Index of the energy commodities in question. From Table 11, the Working's T index ranged from 1.24 (Heating Oil) to 1.33 (Natural Gas). It also appears that Natural Gas and Crude Oil are non-stationary in level, while Heating Oil and Gasoline are stationary in level.

Table 11: Summary Statistics and Unit-Root Test for Working's T Index

	Obs	Mean	Stv.Dev.	Min	Max	Unit-Root Test	
				WORKING'S T INDEX			
Natural Gas	530	1.33	0.10	1.15	1.56	-1.784	-8.911***
Crude Oil	530	1.32	0.06	1.19	1.42	-1.835	-9.178***
Heating Oil	530	1.24	0.06	1.13	1.42	-2.894**	-8.168***
Gasoline	530	1.31	0.06	1.18	1.51	-3.718***	-8.219***

*Note: own calculation based on data obtained Commitment of Traders (COT) reports provided by the US Commodity Futures Trading Commission (CFTC). The unit-root statistics are calculated using the Augmented Dickey-Fuller (ADF) test. The critical values for the ADF test are -2.570, -2,860 and -3,430 for the 10%, 5% and 1% level of significance, respectively. They are marked in the table as *, ** and ***, respectively.*

The results of the GARCH model estimation for all commodities based on Working's T index is presented in Table 12. The results from the estimates using Working's T Index as speculative measures are in compliance with the results for the estimation of S^{Total} and S^{Share}. Also note that the estimate for Heating Oil is not significant here either, indicating that the initial result when using S^{Total} was influenced by the choice of speculative measure.

Table 12: Estimates of GARCH model based on Working's T

	Natural Gas	Crude Oil	Heating Oil	Gasoline
		Mean Equation		
S&P500	0.212*	0.583***	0.470***	0.563***
	(0.125)	(0.081)	(0.076)	(0.187)
T-Bill	0.005	0.005	0.004	0.008
	(0.005)	(0.003)	(0.003)	(0.005)
Exrate	-0.256	-1.384***	-1.265***	-1.652***
	(0.365)	(0.242)	(0.223)	(0.440)
Constant	-0.055	-0.021	-0.024	-0.012
	(0.048)	(0.032)	(0.030)	(0.058)
		Variance Equation		
ARCH term	0.230***	0.033*	0.057**	0.140**
	(0.059)	(0.019)	(0.025)	(0.059)
GARCH term	0.625***	0.932***	0.853	0.820***
	(0.078)	(0.045)	(0.078)	(0.096)
Working's T	-0.377	0.015	0.035	0.091
	(0.327)	(0.013)	(0.024)	(0.084)
Constant	0.760	0.000	0.000	0.000
	(0.473)	(0.001)	(0.002)	(0.002)

ARCH+GARCH term	0.855	0.965	0.910	0.960
AIC	3.266	2.301	2.135	3.635
BIC	3.330	2.365	2.200	3.700

*Note: the GARCH models are estimated using Working's T index (Equation 8) as a measure for speculative activity. Significance levels are 10%, 5% and 1%, marked in the table with *, ** and ***, respectively. Standard errors are provided in the parentheses. Abbreviations: S&P500, S&P 500 Index; T-Bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.*

5.2.4. Long-Only, Short-Only and Net-Long

For this robustness check the GARCH model is implemented for Crude Oil with $\alpha = 0.70$ and the speculation measures of Long-Only, Short-Only and Net-Long (equation 9, 10 and 11, respectively). This way of measuring speculative activity is implemented for similar reasons as the Working's T Index.

In Table 13 the summary statistics and unit-root test are presented. It appears that all three of the speculation measures are stationary in level.

Table 13: Summary Statistics and Unit-Root Test for Long-Only, Short-Only and Net-Long

	Obs	Mean	Stv.Dev.	Min	Max	Unit-Root Test
Long-Only	530	0.32	0.04	0.23	0.39	-2.825*
Short-Only	530	0.14	0.04	0.06	0.26	-3.040**
Net-Long	530	0.17	0.06	0.02	0.30	-4.199***

*Note: own calculation based on data obtained Commitment of Traders (COT) reports provided by the US Commodity Futures Trading Commission (CFTC). The unit-root statistics are calculated using the Augmented Dickey-Fuller (ADF) test. The critical values for the ADF test are -2.570, -2,860 and -3,430 for the 10%, 5% and 1% level of significance, respectively. They are marked in the table as *, ** and ***, respectively.*

The results from the GARCH model estimations for Crude Oil using Long-Only, Short-Only and Net-Long as speculation measures are presented in Table 14. From Table 14 we can see that the results of these estimations are also in compliance with the other previous estimations. Showing no effect of long-short speculators on the volatility of the commodity futures markets in question.

Table 14: Robustness Checking using Long-Only, Short-Only and Net-Long for Crude Oil

	Long-Only	Short-Only	Net-Long
		Mean Equation	
S&P500	0.589***	0.581***	0.582***
	(0.082)	(0.081)	(0.081)
T-Bill	0.005	0.005	0.005
	(0.003)	(0.003)	(0.003)
Exrate	-1.374***	-1.399***	-1.384***
	(0.242)	(0.243)	(0.242)
Constant	-0.020	-0.025	-0.020
	(0.033)	(0.033)	(0.032)
		Variance Equation	
ARCH term	0.029	0.036*	0.036*
	(0.019)	(0.020)	(0.020)
GARCH term	0.932***	0.921***	0.932***
	(0.053)	(0.058)	(0.043)
Speculation Measure	0.074	0.083	0.003
	(0.074)	(0.115)	(0.045)
Constant	0.000	0.015	0.018
	(0.001)	(0.018)	(0.019)
ARCH+GARCH term	0.961	0.957	0.968
AIC	2.299	2.300	2.302
BIC	2.364	2.365	2.366

*Note: the GARCH models for Crude Oil are estimated using Long-Only, Short-Only and Net-Long (Equation 9, 10 and 11, respectively) as a measure for speculative activity. Significance levels are 10%, 5% and 1%, marked in the table with *, ** and ***, respectively. Standard errors are provided in the parentheses. Abbreviations: S&P500, S&P 500 Index; T-Bill, 3-month Treasury Bill; Exrate, Traded Weighted US Dollar Index: Broad, Goods and Services.*

6. Conclusion and discussion

Motivated by spikes and crashes in the four energy commodities over the past decade the impact of long-short speculators on the conditional volatility of the commodity futures price is investigates. To test for this relationship data for futures prices on Natural Gas, Crude Oil, Heating Oil, and Gasoline (all traded on New York Mercantile Exchange) over the period January 2010 to February 2020 at a weekly frequency is utilized. With the focus on Long-Short speculators, which have been given little attention in academic literature, this paper attempts to contribute to the debate on the impact this type of trader has on the volatility in the commodity futures market.

This paper uses data from the Commitment of Traders report provided by the US Commitment of Futures Trader Commission to calculate different measures for speculative activity to test if there is a destabilizing impact of long-short speculation on volatility in energy commodity futures prices.

Using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to estimate the return and volatility while controlling for possible influences from macroeconomic factors (S&P 500 Index, 3-month Treasury Bill and the Traded Weighted US Dollar Index: Broad, Goods and Services). The results from the GARCH model estimation indicate that, among macroeconomic factors S&P 500 Index is generally positive and highly significant. Which is in accordance with previous literature. The 3-month Treasury Bill (T-Bill), however, is positive although expected to be negative. Nevertheless, the 3-month Treasury Bill never significant for any of the commodities in question. The Traded Weighted US Dollar Index: Broad, Goods and Services is negative and highly significant for three of the four commodities. This is also in compliance with previous academic literature.

The results of the GARCH model estimation reveal that long-short speculators have no influence on conditional volatility regardless of the underlying speculation measure for the period in question. Which in turn means that the estimations from the GARCH model indicate that there is neither a stabilizing nor destabilizing effect of speculation on volatility on the commodity futures price.

Robustness analysis using different ratios between hedgers and speculators in the non-reporting traders category or changing the speculation measure yields similar results as the initial GARCH model estimates. Testing with an AR-GARCH model using Total Open Interest of Long-Short Speculators (and Market Share of Long-Short Speculators for Heating Oil) reveals similar results to that of the initial GARCH model estimations, that speculative activity have no influence on the volatility in this period.

The literature has generally found a calming effect of speculation on the volatility, and that speculation does not drive the price away from the fundamentals. Bohl & Sulewski (2019) found, although in agricultural commodities, that the presence of long-short speculators had either no or a calming effect on volatility. This is more along the lines of what is found in this paper.

6.1. Limitations and Further Research

Although the Commitment of Traders report is frequently used in academic literature it has some limitations. One of the major disadvantages is the frequency of the data that is provided by the CFTC reports, as the publicly available data is on a weekly basis. As noted by Bohl & Sulewski (2019) this low data frequency can yield it difficult in the testing procedure, as it may fail to find an impact of position changes on commodity prices. This is due to the fact that price changes and changes in positions can occur in very short time periods. However, as this is the only publicly available data it has been utilized in the academic literature.

Another limitation lies in the classification of the traders. Being based on the major trading strategy of the individual trader it follows that all positions held by this trader are then classified accordingly. This can be problematic as the traders, independent of category, can hold speculative or hedging positions. Ederington and Lee (2002) and Dewally, Ederington & Fernando (2013) notes that this is especially relevant for the commercial category. However, these classifications have been utilized in several academic studies as more adequate data does not exist.

Further research on the topic of long-short speculators impact on the volatility in energy commodities could include looking at different time frequencies. Another interesting direction would be different econometric models, for example Exponential GARCH (eGARCH) or Threshold ARCH (TARCH). It seems that further research on the impact of all types of speculation are harmful or beneficial would be of interest. Especially if the policy makers would provide more disaggregated data at higher frequencies.

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Appendix A

Appendix A1

Figure 3: Spot Price of Natural Gas in the period January 2010 to February 2020. Data collected from Yahoo Finance

Appendix A2

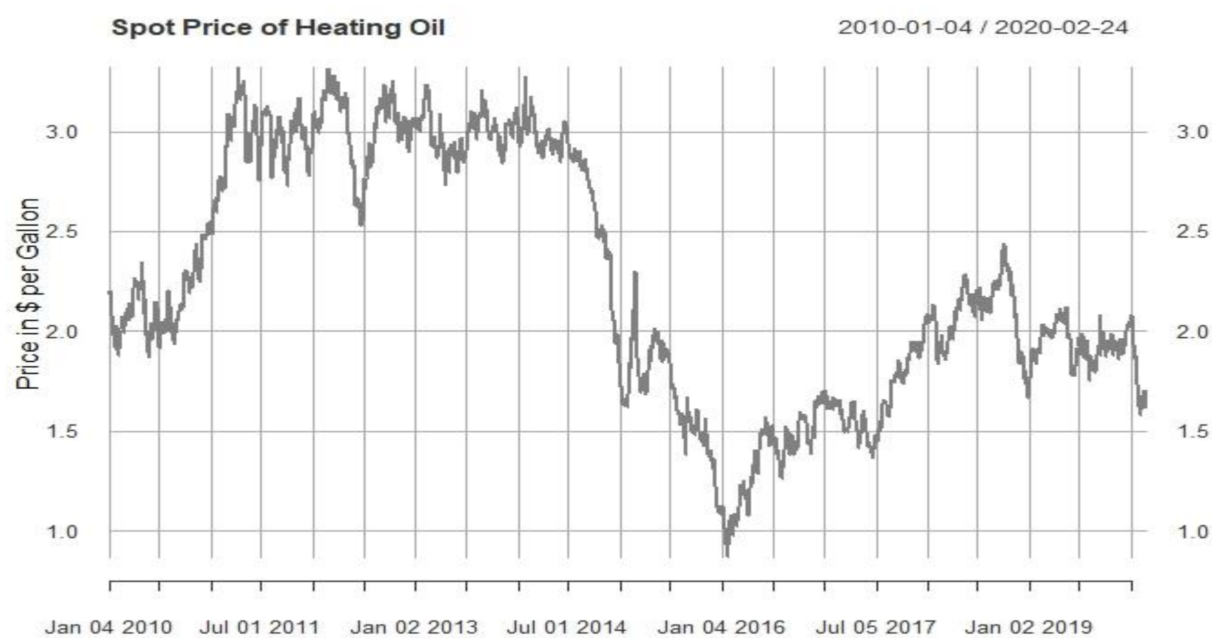

Figure 4: Spot Price of Heating Oil in the period January 2010 to February 2020. Data collected from Yahoo Finance.

Appendix A3

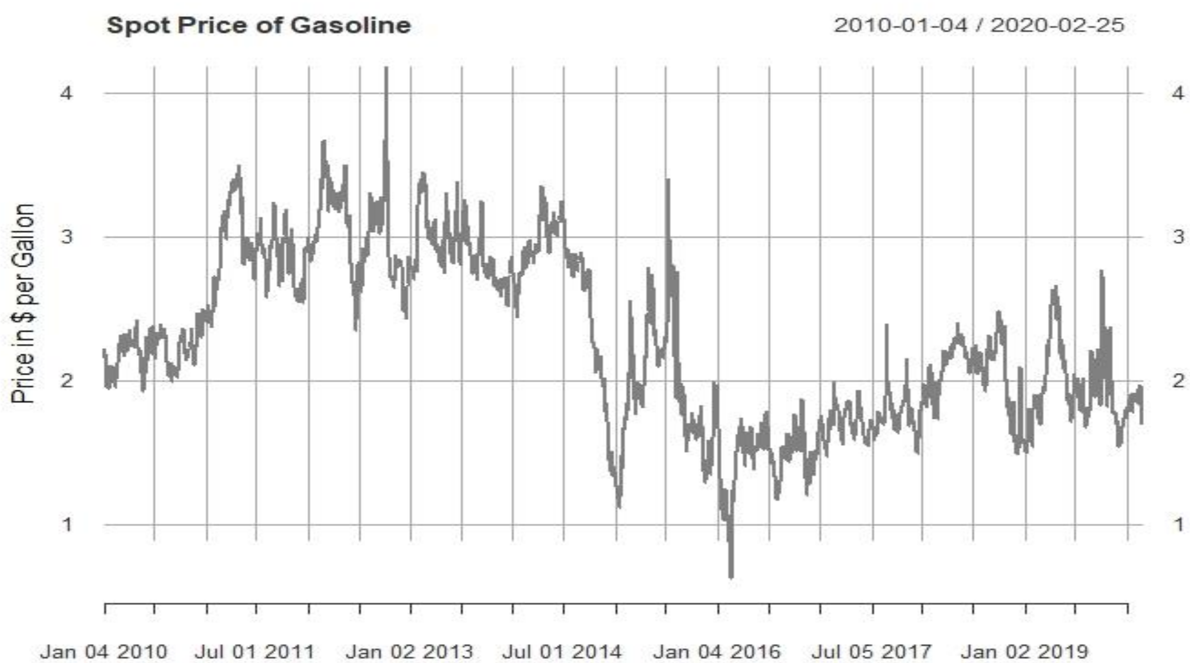

Figure 5: Spot Price of Gasoline in the period January 2010 to February 2020. Data collected from Federal Reserve Economic Data (FRED)

Appendix B

Appendix B1

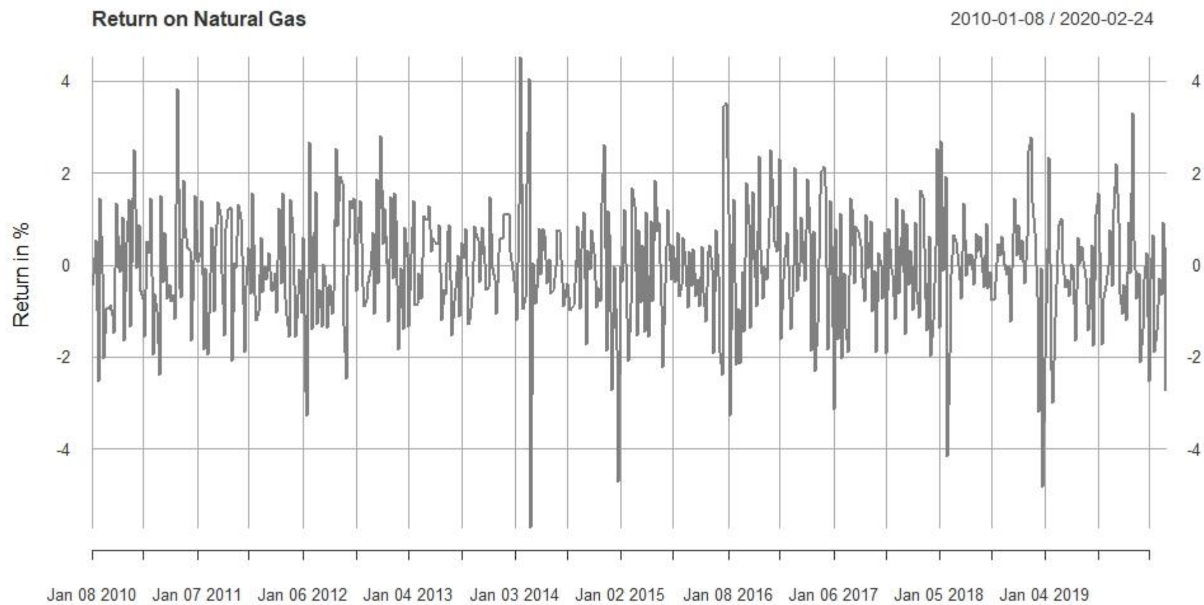

Figure 6: Return on Natural Gas, based on own calculations, from January 2010 to February 2020.

Appendix B2

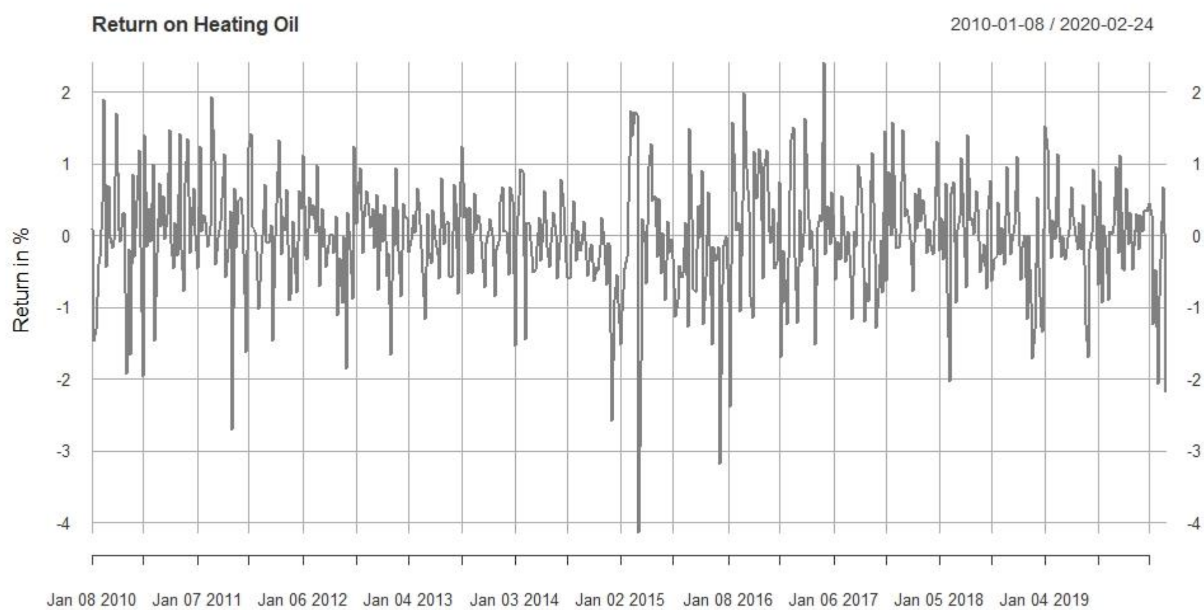

Figure 7: Return on Heating Oil, based on own calculations, from January 2010 to February 2020.

Appendix B3

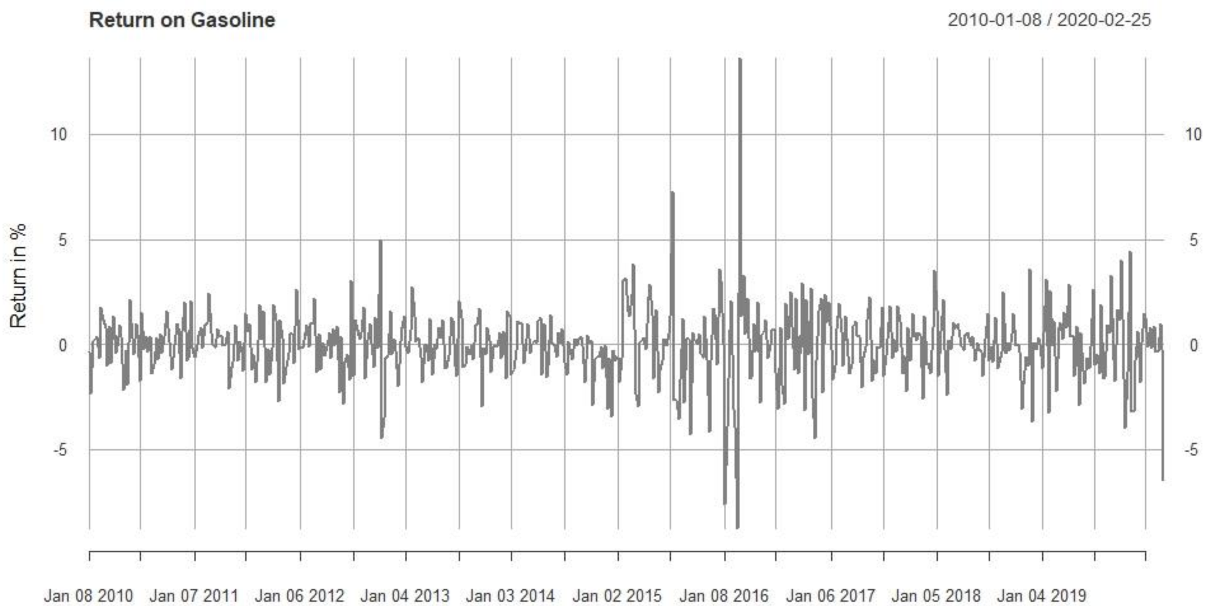

Figure 8: Return on Gasoline, based on own calculations, from January 2010 to February 2020.