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What Drives Risk in the Oil Market? An Empirical Study of Oil Price Risk in the Period 2008-2017

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Abstract

The thesis will consist of two parts. In part 1 I look at how speculative positions effect the price risk in the oil price market. The effect will be measured towards two different risk measures. First I estimate GARCH(1.1) type models to analyze whether the speculative market as a whole has an impact on the price risk in the market, before I split the sample into the sub-categories given by Commodity Futures Trading Commission (CFTC). Second, I look at the risk benchmark, the oil volatility index (OVX), measuring this with the COT-numbers using an ordinary least squares-type regression. I do not find any relationship between speculative positions and oil price risk. Splitting speculators into four categories, and dividing the sample into two periods, I find that an increase in Money Manager positions reduce oil price risk after 2013. The same results were obtained for Brent, in addition to a finding indicating a positive relationship between Brent oil risk and long non-reportable positions. For the OVX-analysis, findings indicate a positive relationship between both long and short speculators. This relationship seems to be with short money managers, and long swap dealers, who both are found to be positive and significant.

Part 2 is an attempt to investigate if an event study on volatility can be done using a simpler analytical framework then what's been seen in other event studies on this. OPEC announcements are used in the analysis. These are split into three distinct announcements, signals of increased production, maintained production, and increased production, for a total of 21. Estimating a 5, 10 and 30 days event window using other research as a benchmark, I find that the results are not satisfactory. It is found that the issues increase, with an increased event window.

Sammendrag

Oppgaven består av to deler. I del 1 ser jeg på hvordan spekulative posisjoner påvirker pris risikoen i oljemarkedene. Denne effekten blir målt ved hjelp av to ulike risikomål. Først blir det estimert GARCH(1.1) type modeller, for å analysere om det spekulative markedet som en helhet har en påvirkning på prisrisikoen. Etter dette blir de fire underkategoriene, som de er gitt av Commodity Futures Trading Commission (CFTC), benyttet i analysen. Deretter blir risiko benchmarken, Oil Volatility Index (OVX), brukt i en ordinary least squares lineær regresjon mot de samme tallene. Jeg finner ingen sammenheng mellom spekulative posisjoner og oljepris risiko. Når utvalget blir splittet inn i sine fire kategorier, som gitt i COTrapportene, og perioden blir delt i to, finner jeg at økt handels aktivitet fra Money Managers reduserer pris risiko fra 2013 for både Brent og WTI. For Brent finner jeg i tillegg en positiv sammenheng med short non-reportables. Både long og short spekulanter blir funnet å være signifikante og positive mot OVX. Denne sammenhengen viser seg å spesielt være mellom OVX, short money managers og long swap dealers.

Del 2 er et forsøk på å undersøke om en event-studie på volatilitet kan gjennomføres ved hjelp av et enklere analytisk rammeverk. OPEC kunngjørelser er brukt i analysene. Disse er delt inn i tre distinkt forskjellige kunngjørelser, signaler om økt produksjon, fortsatt produksjon på samme nivå, og redusert produksjon, med total 21 kunngjørelser. Ved å estimere 5, 10 og 30 dagers event vinduer, og ved hjelp av tidligere analyse som benchmark, finner jeg at resultatene ikke er gode. Det blir også funnet at problemene øker, med et økt event vindu.

Acknowledgments

I would like to thank my guidance counselors, Ole Gjølberg and Marie Steen. Their ability to ask the correct and critical questions have helped push this thesis forward.

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Introduction

The role of speculators on the price risk of oil, seems to be a never-ending discussion. Where one side claims that free trade in the commodity futures markets only helps to bid up the price underlying asset, which ultimately makes it more expensive for the end-user, using this as an argument for more regulations for this market. On the opposite side of the spectrum we find those who argue that speculators in the market are a necessity to reduces price uncertainty for both sellers and consumers of the commodity. This discussion is the basis for this thesis' first part. Using the Commitment of Traders (COT) reports, given every Tuesday by the Commodity Futures Trading Commission (CFTC), I analyse changes in both speculative position, and changes in the four sub-categories given by the CFTC, to see if I can identify an influence from the broad speculator, or from the smaller categories. This is done by employing a General Autoregressive Conditional Heteroscadacity (GARCH)(1,1) model on the effect of both the changes of speculators as a whole, and four identified sub-categories, on both Brent and WTI. Further an analysis on these same trader's effect on the Oil Volatility Index utilizing a OLS-based model. This thesis will only look to identify if changes in speculative positioning has any influence on oil price risk. No thoughts on the degree of regulation will be given.

In the second part, an effort to conduct a volatility event study using a simple framework. To my knowledge, all other event studies done on volatility is based on more complex econometric methods, nor does it seem to be a universal accepted model to t-test the findings, which leaves it to each individual researcher to estimate their own models. This might scare other researchers off from conducting these kinds of analysis. The purpose of this second part of the thesis will be to investigate if I can reach the same conclusions as a benchmarke study on the volatility changes following an OPEC announcement. This will be done by estimating a GARCH(1,1) model based on daily returns spanning 400 observations preceding pre-determined event windows (5, 10, and 30-days), to determine the expected volatility. This will be measured against a running 400 observation variance, as the observed volatility. The t-test will be conducted on CAR t-test framework used to test abnormal returns, altered to fit our volatility measures.

Part 1: Does Commitment of Traders Drive Risk in the Oil market?

When a commodity is introduced on the futures market this will bring with it speculators. These traders are necessary for the market to function optimally. If one trader is utilizing futures to hedge against price movements, they need an opposite trader that is willing to have this risk transferred to them. Today speculative traders dominate the trade in oil futures, because of these traders, daily trade in the market are 7 times as many barrels as the global suppliers are extracting. Because of this, speculators are a controversial subject. While some say that they are a crucial player in allowing others to hedge their positions, others claim that a “pure” speculator[1] does more harm than good. People supporting the latter claim that speculators add little no value as they bid up the price and increase the volatility to obtain financial gains.

This never-ending discussion will serve as the basis for this thesis, which will look further into the claim that speculators “bid-up” the volatility in the crude oil market. This will be done in a couple of different ways. First, , a risk measure will be constructed using a GARCH(1,1)-model approach. Where we once again will measure the impact of net speculative behavior. A GARCH-type model takes into account that the assets variance is not constant, which it rearly is in financial timesseries. Since these types of models are based on the assets own lagged squared returns and variance, it is takes into account volatility clustering.

Second, the *Oil Volatility Index* (OVX) will be employed as a risk measure. Where a simple regression model will be used to see if changes in the net positioning of speculative traders have an impact. The OVX is an asset, where traders can buy and sell on oil price risk. It is therefore a measure of the market expectation of the future oil price risk, and is used by researchers as a risk benchmark. Since this already is a risk measure, analyzing this using a GARCH be overkill. The simpler linear regression methodology will therefore be employed.

[1] Speculators that buy and sell financial papers, without ever taking a physical position in the commodity.

Spurred on by the public debate on speculators impact in the futures market, several studies have been conducted to try to explain speculators impact on price fluctuations. The result of these studies has been varied.

Fattouh, Kilian, and Mahadeva (2013) Did not find any evidence that changes in in financial traders' positions predict any change in prices of oil futures. Using a structural VAR approach, they found strong evidence of speculation in independent periods, but no evidence that this was the case after 2003, but rather that both spot and futures prices were driven by fundamentals.

It is well known that the 2000's brought a large increase in commodity prices, followed by a large fall in late 2008. Many have been quick to point their fingers towards speculators and blame them for this development. Carter, Rausser, and Smith (2011) offers a different view. Comparing the 2007-2008 price increase and fall with the boom and bust of 1973-1974 they found several similarities. First of all, both periods saw a strong increase followed by a strong decline in prices over several commodities. They were both preceded by strong economic growth in developing countries, and a low real interest rate in developed countries, which resulted in a weakened currency. These factors contributed to a tight supply-demand balance and a reduction in inventories, which made the markets vulnerable to shocks. Further they noted a spillover effect to a broader set of commodities then those who were affected directly by fundamental shocks. Due this they find little evidence to support that the 2007-2008 period were significantly different to the situation of 1973-1974. Suggesting that the large price changes were due to a so-called "bubble" rather than driven by speculators. Sanders and Irwin (2010) do not share the sentiment. They argue that a bubble scenario would suggest that returns are positively correlated across markets. To prove their statement, they used both a Fama-Macbeth approach and traditional cross-sectional test on twelve commodity markets. The null-hypothesis of no cross-sectional impact were only rejected for one of these.

Davidson (2008) notes that oil futures prices had increased by 86% in one year, while oil demand in the same period had only increased by approximately 2%, According to this paper this suggest that hedge funds and other speculators might now be engaged in speculation that is adding market demand. On the other hand, there is claimed that high futures prices today may lead some to hoard oil today in hopes of selling for a higher profit in the future. But according to this same article, reported oil inventories where not especially full, and there were few signs of hoarding.

Kilian and Murphy (2014) finds no evidence that speculators influence oil prices. A structural model was estimated to test the hypothesis that excessive speculation (purely financial speculation) drove oil prices up. No evidence was found to support this hypothesis.

Kesicki (2010) conducted a historical analysis where he studied if the accumulation of crude oil reserves had an impact on the pricing of the commodity. The findings indicate that speculative behavior have a small and short-term effect, compared to more fundamental variables.

Bu (2011) found through Granger Causality testes and GARCH-type models that speculators had a positive feedback on the volatility in the market. Through a GARCH(1.1) he discovered that an increase in the net long positions of none commercial and money manager traders drove the oil prices higher, while an reduction in the net positions drove prices down. Further they discovered that an increase in these prices in turn drove in more speculative long positions, driving the prices up further.

Bessembinder and Seguin (1993) found in their research that volatility in the futures markets where negatively related to open interest. It is claimed that open interest is viewed as a proxy for capital dedicated to a market at the beginning of a trading session. A reason for this, they claim, is the belief that variation in open interest reflect changes in market depth. Further they find that trades that result in changes in open interest have a greater impact on volatility then trades that does not result in these changes.

Cox (1976) influenced by the legislation in the US, which prohibited futures trading in the onion market, wanted to investigate if the how an influx of investors into the market influenced price movements. A common argument, then as now, was that speculators helped to drive prices up, making the commodity more expensive for the end consumer. Cox's research suggest that this is not the case. An increase in traders will instead bring with it an increase in available information, and by extent bring more accurate signals for resource allocation when futures trading in a commodity is allowed. This research only holds for commodity where there is no futures market, and no insight into restrictions on existing markets are given.

C. Wang (2002) used the CFTC's CoT reports to study the effects of net speculators on the six biggest currency future markets. His findings suggest that changes in speculative positions, in fact, was able to destabilize the currency market. Further he claims that there is an asymmetric amount of information held by the different traders, where hedgers likely possess certain private information, while smaller traders hold little to none.

Data and Methodology

The data consists of weekly three-month future prices for WTI and Brent, as well as the weekly commitment of traders (COT) reports from April 2008 to the end of 2017, leaving us with 509 points of data. An initial problem arose looking through the gathered data. Three observations were missing from the COT dataset, this issue was solved by simply removing the oil prices where the corresponding COT positions were missing. Oil prices where downloaded using Thomas-Reuter's Datastream, where the futures prices are delivered by ICE, Brent spot by EIA and the WTI spot by Thomas-Reuter themselves. COT numbers were supplied by the CFTC. The COT numbers are published Tuesday each week, and gives us the positions from the Tuesday the week before. Because of this, the Tuesday oil prices will also be used in the analysis.

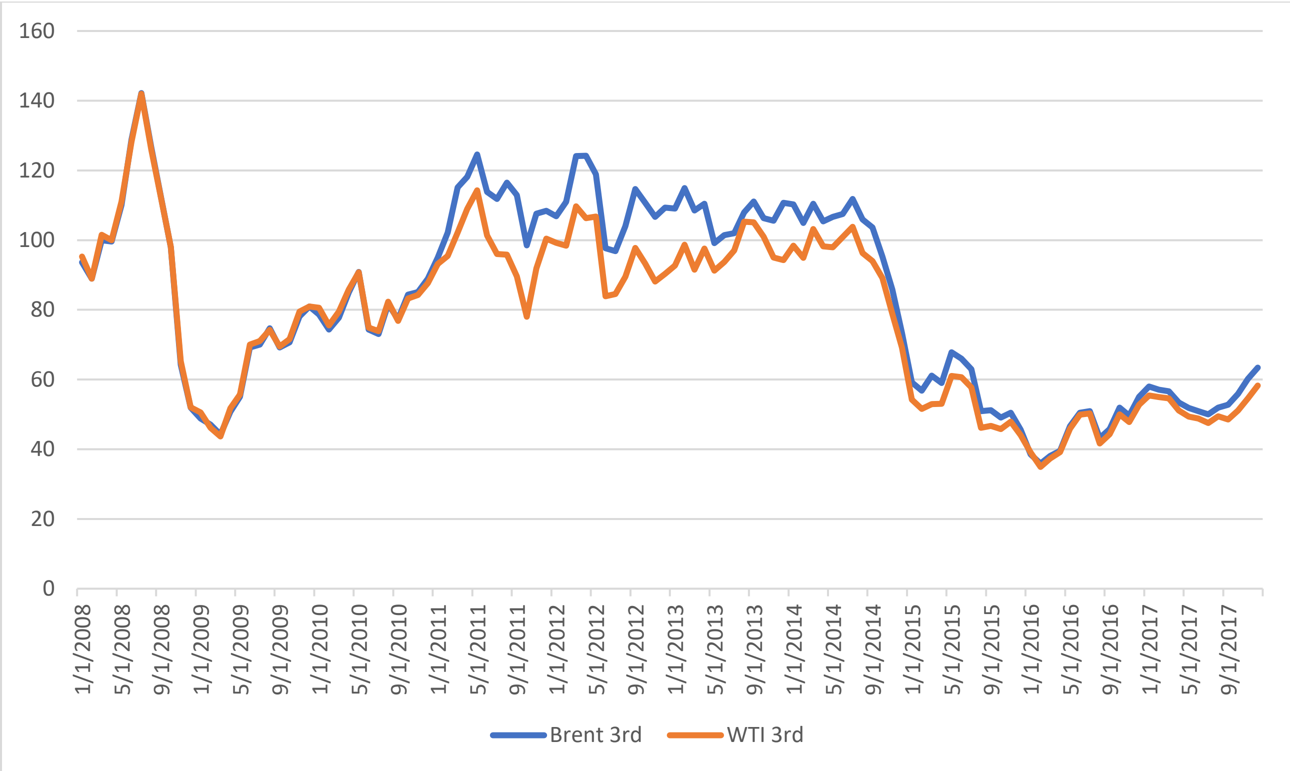

Figure 1: Monthly price movements of Brent and WTI spot prices. January 2008 to December 2017

The price data includes some rather large movements. First, we see a large price drop in 2008 during the global recession. During this year, prices dropped by nearly 70%. After this initial fall we can see the prices gradually increasing towards their pre-financial crisis levels, before we see another large fall in 2014. Several factors led to this decrease. Emerging economies who had seen rapid growth and expansion throughout the start of the 21st century, such as China, began to slow down after 2010. A drop in demand from the markets that helped push the prices up post 2008, pushed these back downward in 2014. Because of negative effect of high oil prices on their economies, USA and Canada increased their efforts to extract oil. Because of this local production, the two countries where able to cut their oil imports, putting further pressure on world prices. Saudi Arabia also acted in a way that would negatively affect these prices. With the sharp price drop they were faced with the decision of keeping their production up, or ceding market shares in an attempt to push back up.. With one of the largest oil reserves on the planet, they believed that they could keep oil prices low for a longer period of time, without hurting their economy. Methods, such as fracking, is an expensive way of extracting oil and therefore not profitable if oil prices remain low. Saudi Arabia hoped that by supporting low oil prices, countries like USA and Canada would have to abandon their costlier production methods due to a lack of profitability.

Since a GARCH-type model will be utilized in the analysis, the variance of the oil will be used as the volatility measure for this part of the analysis. The variance for both oil contracts are reported in the figure below. When visualizing the measure this way, it brings with it a few pro's, since the variance is calculated as the squared standard deviation, it helps to remove noise, as all values are positive.

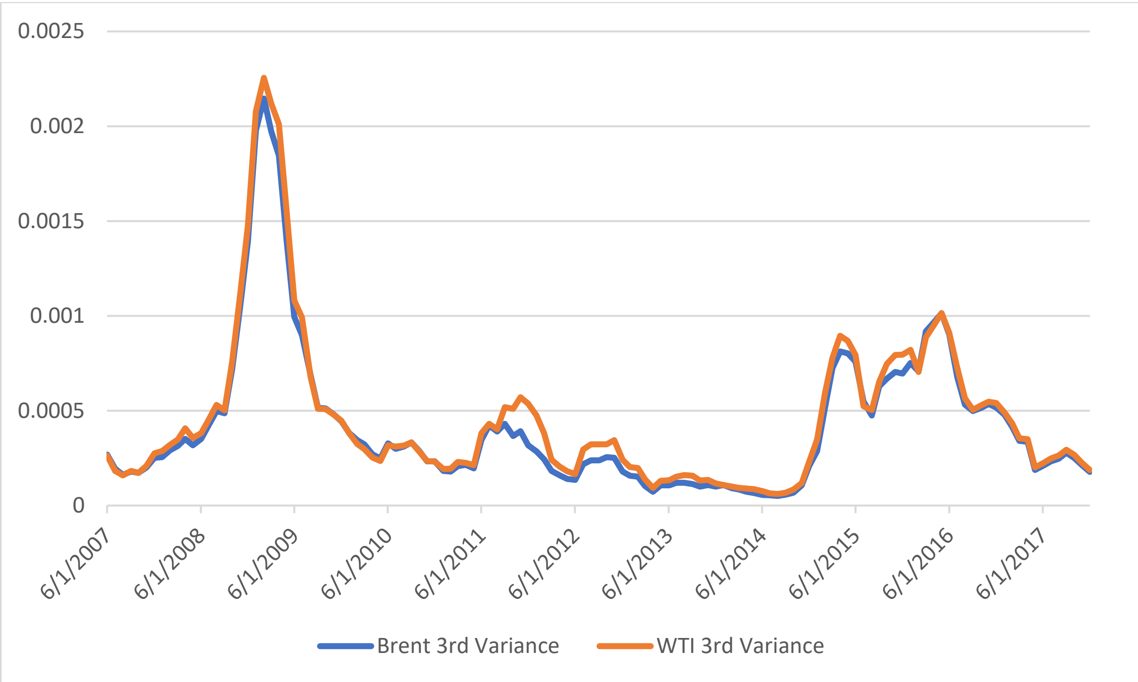

Figure 2: Monthly variance for the oils, reported as a rolling 100-days window. June 2007 to December 2017

Unsurprisingly we can see a large spike in the volatility around the height of the financial crisis in 2009, before it falls back to a lower level. These levels stay relatively stable with a few larger movements scattered around the sample period, before we get an unusual quiet period for both oils from late 2012 to mid-2014. In 2013 many of the factors that had been driving the price volatility during up to this point started to mitigate. During this period Europe had started to recover from its debt crisis and the unemployment rate in the US fell. Although we saw an attempt at overthrowing the Libyan government this year, Saudi Arabia maintained its production to smooth out this effect. Rising oil production in the US also helped the world supply to be more in line with expectation. From late 2014 we can again see quite large movements in the oil prices, these large spikes in volatility are in large part due to supply and demand issues. Late 2014 was met with a lower demand than expected, resulting in supply stocking up and prices plummeting. Even after this was known, producers around the world refused to reduce their production to support this new, lower, demand. Even OPEC, who typically reduces its supply when demand is reduced, increased its supplies to capture market shares. The United States also increased their production of shale oil, despite facing these falling prices. The market was also concerned with new oil from Iran flooding the market. After the West's sanctions were lifted, due to the Iranian nuclear deal Iran said it would immediately boost its output with 500,000 barrels per day as soon as these sanctions were lifted, putting further pressure on the global oil prices.

The entire period has an annual standard deviation of 38,41% for Brent and 33.67% for WTI. The period with the least noise, from early 2011 towards late 2014 has the lowest annualized standard deviation of 21.39 and 23.44% for Brent and WTI respectively. For the large price drop in 2014 towards the end of the sample period we saw a large jump in volatility with a standard deviation of 40 and 35% respectively.

Since both oil's variance follows each other closely, only the WTI will be used for further illustrative purposes.

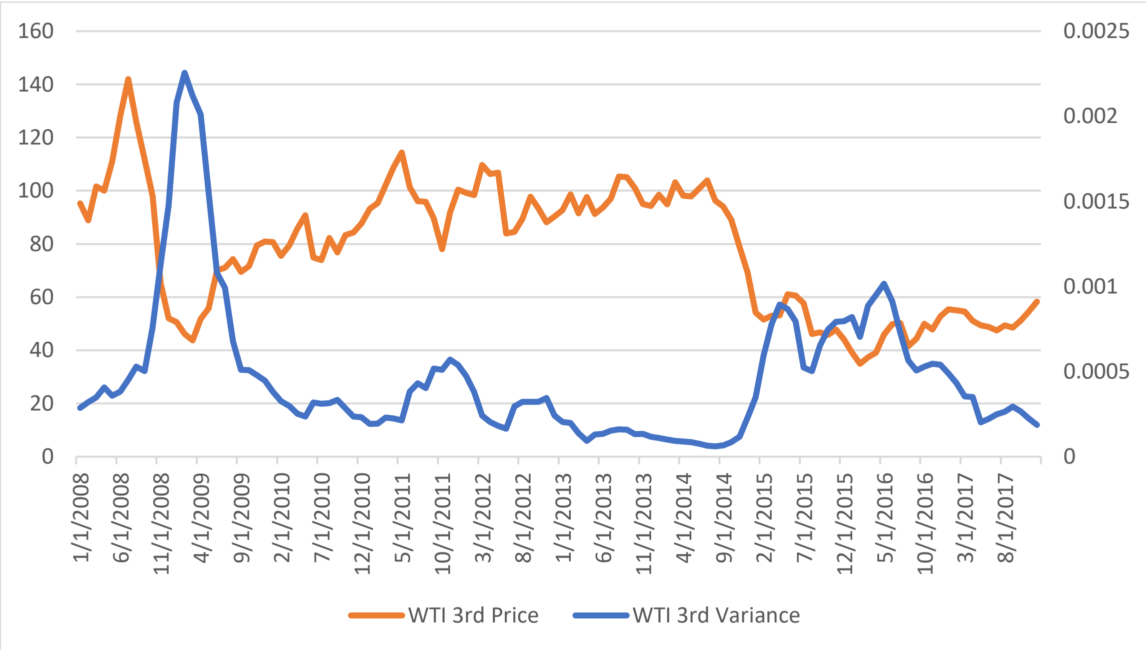

Figure 3: WTI 3-month futures price and variance January 2008 to December 2017. Variance reported on the right axis

Figure 3 shows the WTI variance graphed against the WTI three-month price. The volatility seems to increase in periods with lower prices, especially following a larger price fall, as seen after the oil price fall in 2009, and the oil price fall in 2014. The volatility seems to decrease as prices climbs back up from these falls. Unsurprisingly the volatility seems to be at a low point during periods of small price movements.

A closer look at the sample make it apparent that the data is not gaussian. As we can see from table 1, both excess kurtosis and skewness are present.

Table 1: Kurtosis and Skewness for the Weekly Oil Price Changes. April 2008 to December 2017. No Excess Kurtosis = 3

	Brent	WTI
Kurtosis	2.86	2.23
Skewness	-0.99	-0.89

This leaves us with an initial problem for the choice of models. The traditional OLS models assume that we reside in a world with normally distributed prices which are homoscedastic. For oil prices this is clearly not the case, meaning that these types of models will be less than optimal. The ARCH-type models, or more specific for this thesis the GARCH-model, are a way to circumvent this issue. The General Autoregressive Conditionally Heteroscedastic (GARCH) model, unsurprisingly, builds on the ARCH. In which the variance of the time series is dependent on the previous period's squared price changes. An ARCH-type model is preferred for a couple of reasons; first, the variance is not expected to be constant, which they rarely are in financial timeseries, the model rather helps us describe how the variance of the errors evolve (e.g Ahmad, Muhammad, Nian, and Yaziz (2011)). Secondly, these types of models consider so-called volatility clustering. It is well documented that price risk in financial markets is dependent upon itself, where large changes tend to follow large changes, and vice versa. (e.g Lux and Marchesi (2000) and Cont (2007)) Looking back to figure 2, we can see that this appears to be the case for our oil prices as well. The GARCH model builds further on this, by also allowing the conditional variance of today, to be dependent upon its own lagged values. We can also extend the GARCH model to incorporate exogenous variables we think are relevant in calculating the variance in question. To estimate the GARCH-model, the maximum likelihood technique will be used. This process will be done through the computing program *Eviews*, but a quick rundown of the logistics will be presented here. First a log-likelihood function (LLF) will be specified to maximize under a normality assumption for the disturbances. The computing program will construct and maximize this function and construct their parameters and standard error. A general GARCH model is estimated as follow:

$$\sigma_t^2 = \alpha_o + \sum_{t=j}^{p} \alpha_j \mu_{t-j}^2 + \sum_{t=k}^{q} \beta_k \sigma_{t-k}^2 \quad (1.1)$$

Equitation 1.1 shows that the variance given by a GARCH model is calculated by adding the lagged values of both the lagged squared returns and the lagged variance. These p,q lags can, in principle be lagged towards infinity. There have, however, been several cases where economists have found that one lag on both the ARCH-effect and the GARCH-effect are more than sufficient to capture the heteroscedastic variance and volatility clustering in financial time series. For the analysis of this thesis a GARCH(1,1) will therefore be employed (e.g Y. Wang, Wu, and Wei (2011), Sadorsky (1999) and Efimova and Serletis (2014))

A possible issue with the GARCH might arise if the oil price risk affected more by a negative (positive) shock then by a positive (negative) shock. The GARCH model enforce a symmetric response of volatility to negative and positive shocks.

Even though the conditional variance of a GARCH model is changing, the unconditional variance is constant:

$$var(u_t) = \frac{\alpha_0}{1-(\alpha_1+\beta)} \quad (1.2)$$

Equation 1.2 show the unconditional variance of the GARCH model, if $\alpha_1 + \beta < 1$. If this is not the case, the unconditional variance of u_t can't be defined, this is known as "non-stationarity in variance". For stationary models, conditional variance forecasts converge upon the long-term average value of the variance as the prediction horizon increases.

Oil Price Risk as Measured by The Oil Volatility Index

The Oil Volatility Index (OVX) is a measure for the markets expectation of oil volatility 30-days ahead applying the VIX methodology. It is calculated as an aggregated weighted average of options of oil-ETFs, puts and calls, spanning over several strikes and maturities, using the Black-Scholes formula to find the implied volatility. The OVX is traded on the Chicago Board Options Exchange (CBOE) who disseminate information and release this data daily through their own website, as well through all other major data vendors. The pricing works as with other options on financial assets, where a higher price equals higher implied volatility and vice versa. After its release for trade on CBOE in 2008 the OVX has been used as a benchmark when measuring volatility by researcher all over the world. Aboura and Chevallier (2013) found, using the OVX, that oil prices exhibits an inverse leverage effect, that is that an increase in the volatility subsequent to an increase in crude oil prices. Fretheim (2017) used the OVX in her PhD-thesis to prove that long and short hedgers altered their positions in the market after the expected future volatility, and further argued that this could be speculative behavior on their part.

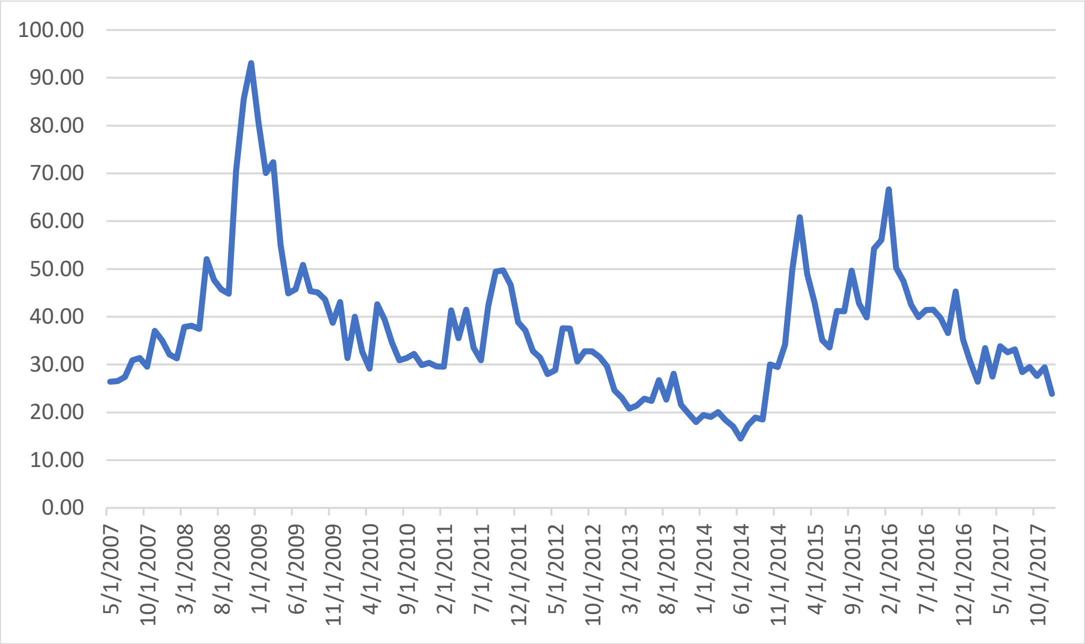

Figure 4: OVX Prices January 2007 to December 2017

Figure 4 shows the monthly price movements for the OVX calculated back to 2007 towards the end of 2017. As with the oil prices we can clearly see a lot of movement in these prices as well. As with the prices for oil, we can see a large spike during the financial crisis of 2009, which seems to quiet down as the oil price reach its minimum value. As the oil price moves towards its new height in 2011 we see small bursts in the OVIX coinciding with large price jumps in the oil prices, before slowing down and reaching its lowest point during the crudes quite period starting in 2013. Before it, once again, raises in 2014, during Saudi-Arabian overproduction and increased activity in North-America.

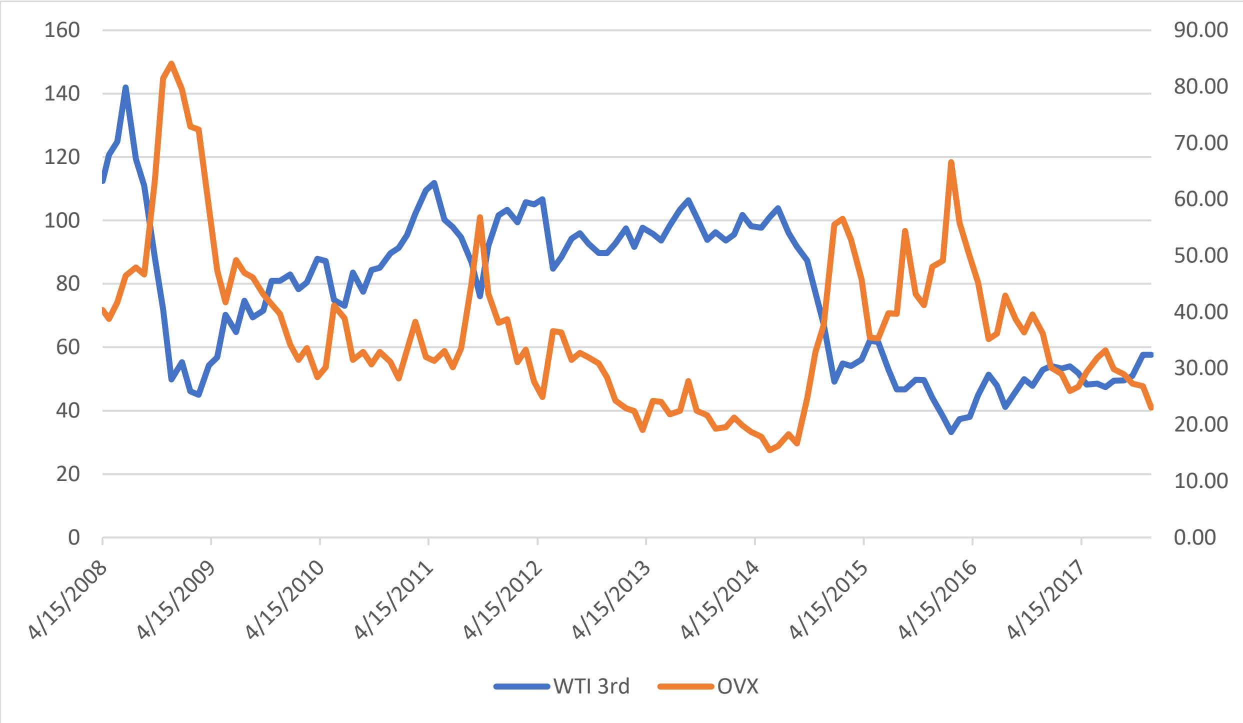

Figure 5: OVX Against the 3-month WTI future April 2008 to December 2017. OVX Prices on Right Hand Axis

Figure 5 shows the OVX against the 3-month WTI future price. The OVX seems to be rising with falling futures prices and falling when it increases. Using a simple correlation analysis, it is found that the relationship is inverse with a correlation of -0.6. This relationship seems to especially strong when there are large negative price movements. Looking at the financial crisis, we can see the oil price falling 68.2% from November 2008 towards March 2009. During the same period the price of the OVX increased with 55.9%. We continue to see the OVX having peaks around periods of falling oil prices. During the period of small price movements starting in 2013, the OVX continue falling until the oil prices start falling again in 2015. The OVX therefore seems to be most influenced by prices falling, and the least influenced by periods of small price movements.

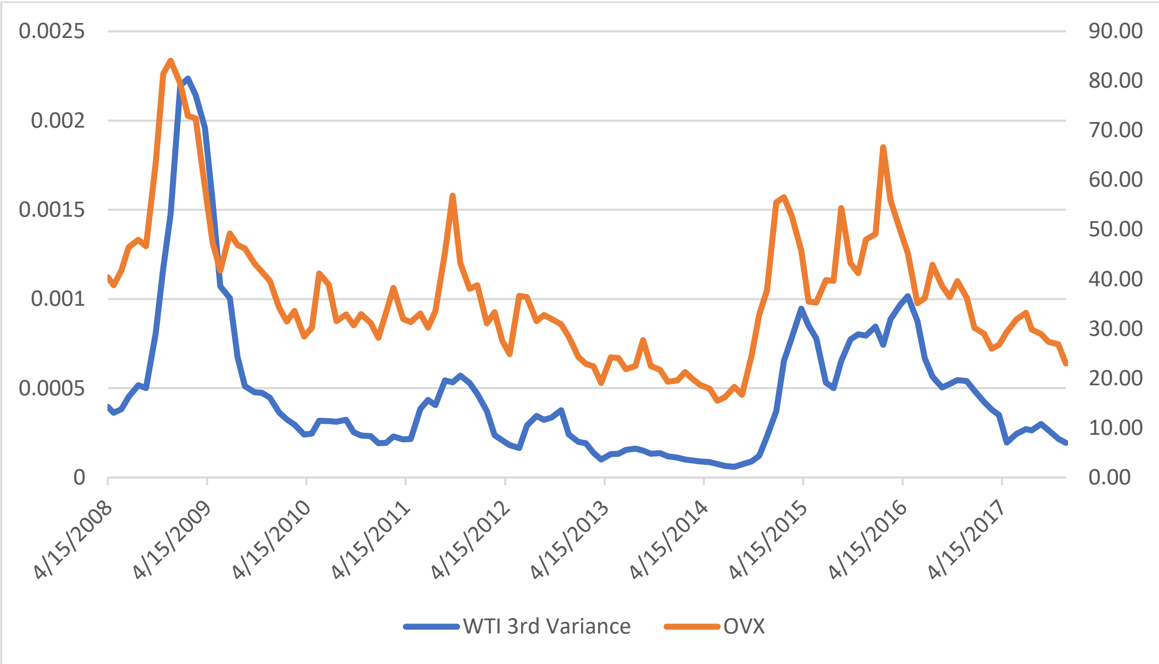

Figure 6: OVX and the variance risk measure. April 2008 to December 2017. OVX price reported on the right axis

Figure 6 shows the Variance risk measure for WTI compared to the OVX. A few things are worth noticing. The overall movements of the two measures follow each other closely, both show an increased price risk when prices are low, especially after large price falls. The OVX seem to take this price risk into account before it is observed in the market. It also looks to overestimate the price risk following smaller price falls, as well as the price risk during periods of smaller price movements.

Commitment of Traders

The commitment of traders (CoT) sorts traders in the futures market into different categories. Broadly we have two main categories in these markets; hedgers and speculators. The hedger portion of the CoT is still just set in one category, in this case called commercials, which are the traders that has a physical position in the underlying asset. This will include producers, refineries and so on.

The speculators are split into four sub-categories. First of we have the swap dealers, these are traders that primarily deals in swaps for a commodity and uses the futures market to hedge risk associated with these trades. Although these traders use this market to hedge out risk, they do not take a physical position in the oil market, and will therefore be classified as a speculator. Next, we have money managers, these are traders engaged in managing and conducting organized futures trading on behalf of clients. This may include a registered commodity pool operator, trading advisor, or an unregistered fund identified by the CTFC. The other reportable category is aimed to capture all other reportable traders that are not captured by the other first three categories. Lastly, we have the non-reportable, as the name suggests these are traders that does not need to report their positions to the CFTC. This post usually consists of smaller individual traders.

The CoT reports are posted on Friday's by the CFTC and displays the trading positions for that week's Tuesday, where it shows both the long and short positioning in all the five categories mentioned above. Some traders use this information to decide which position they should take. The general belief in the market has been that the position should be the opposite of the net positioning of the smaller traders, with a belief that these traders lack the market information to time their investments correctly. Since this thesis' focus is on risk, there will be no further analysis on this particular topic. But further research is encouraged.

Basis

An important part of trading in the future markets of oil, are the sell (short) and buy (long) sides of the market. The two traders hope for different movements in the market. A long trader hopes for a market in Contango (or an increase in the price of the commodity) and a short trader hopes for a backwardation of the market (or a decrease in the price of the commodity). A common way to distinguish a market in contango from a market in backwardation is to look at the *basis* of the underlying commodity. In figure 7 we can see the basis for both of our oils defined as: $Basis_t = F_t - S_t$, where F_t is the price of the given future at time t, and S_t is the spot price at time t. The basis can in many instances be viewed as an indicator to how market participants believe the market will look like t-periods ahead.

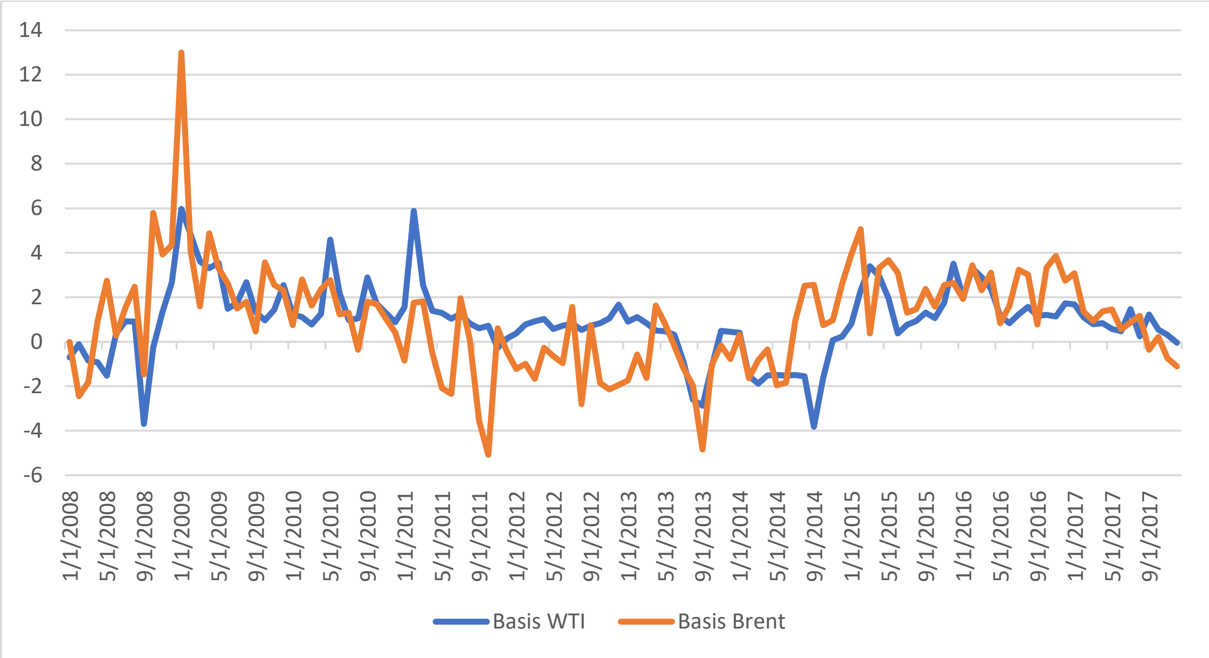

Figure 7: Brent and WTI monthly basis January 2008 to December 2017 for the three-month contracts

Figure 7 shows that throughout most of the sample period we see a market in contango both for Brent and WTI, which is in accordance with the economic theory, suggesting that seller of a commodity will require a premium for storing goods for future consumption instead of selling these in today's market. We do, however, see a few instances where the market is in backwardation. We first see this for Brent in late 2011. The Libyan civil war started the 15th of February this year, effectively knocking out half of the country's 1.6 million barrels a day output. Even though Libya is only accountable for about 2% of the world's oil output, this sudden drop in supply was able to increase the oil prices in the short term. When the war ended a few months later this sent the market into backwardation. After a period of positive basis, we once again see this dip below zero from mid-2013 towards mid-2015. After a climb where the basis briefly breaks the positive, we once again see the basis fall to a new minimum together with the prices in 2014. As previously stated, this was a period with falling demand, and an oversupply in the market.

Open Interest

The open interest (OI) show us the total numbers of open or outstanding future contracts that exist on that day (long or short, but not a combination of the two). We can use the OI to measure the flow of money that comes into, or goes out of, the futures market. In figure 8 the weekly OI is plotted for the period 2008-2017

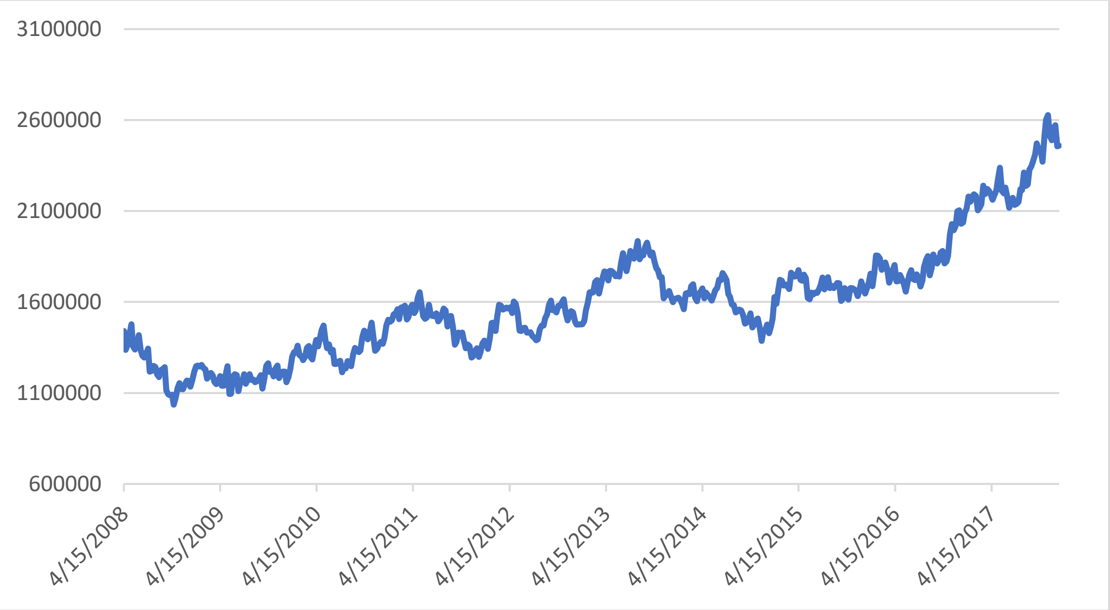

Figure 8: Weekly Open Interest April 2008 to December 2017

Over the last decade, trade in oil has had a large increase. With an overall increase of 70,86% in OI over this sample-period. There is a small growth throughout the financial crisis, which slows down with the prices after 2011. The small period of rising prices in 2013, set of an increase in OI, that would continue until the 2014 price fall. During this period, we see a small decrease in the OI, which is increased further when prices fall again in mid-2015. The number of active contracts increases for the remainder of this year, and remains stable for most of 2016. With start of the price increasing again in 2017, we can see a large increase in OI of 17,52% from the start to the end of this year. As with the risk measure OI seems to be sensitive to price falls, unlike the price risk, it seems to grow in periods of small price movements.

For the coming chapters the CFTC's definition of traders will be used. So that a *producer* is an entity that engages in production, processing, packing or handling of the oils, and uses the futures market to hedge risk associated with this activity. A *swap dealer* is an entity that primarily deals in swaps for the oils and use the futures market to hedge or manage risk associated with this activity. A *money manager* is a registered commodity trading advisor, commodity pool operator, or an unregistered fund identified by CTFC. Every other reportable trader that is not placed into one of the other categories goes under *other reportables*.

Positioning and changes in the oil futures market

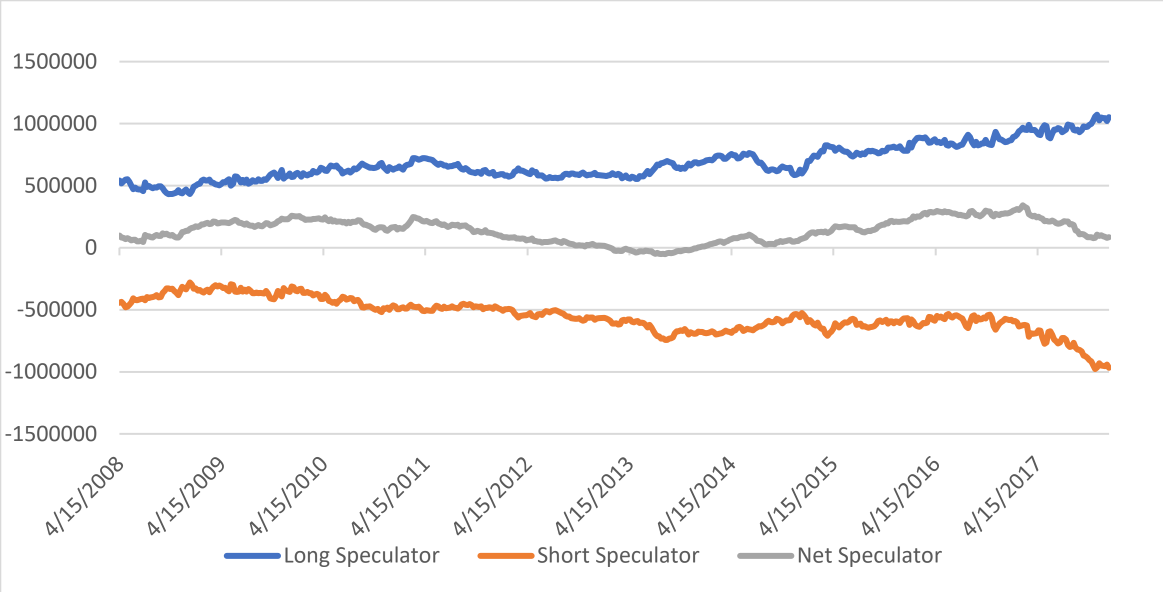

Figure 9: Speculator Positions April 2008 to December 2017

Table 2: Descriptive Statistics for Speculator Position

	Long Speculator	Short Speculator	Net Speculator
	Entire Period		
Average	685 580	-546 565	139 015
Standard Deviation	141 670	135 414	93 716
Minimum	432 020	-977 419	-50 815
Maximum	1 072 092	-279 959	341 911
	Financial Crisis (2008-2010)		
Average	517 352	-362 653	154 699
Standard Deviation	46 670	43 363	57 900
Minimum	432 020	-479 104	46 420
Maximum	627 441	-279 959	257 895
	2014 price fall to 2017		
Average	832 484	-645 831	186 654
Standard Deviation	113 672	105 444	85 448
Minimum	586 374	-977 419	25 021
Maximum	1 072 092	-525 906	341 911

Figure 9 show the positions of long, short and net speculators from April 2008 to December 2017, and table 2 shows key statistics for the same period. The speculative market seems to have flourished in the post-financial crisis area. The speculators have been especially active on the buy side of the market, where contracts of 685,580,000 barrels of oil have been held each week throughout the period, on average. The demand for oil contracts does not seem to slow down, with additional contracts entering the market each week on average for both contracts. From 2008 to 2017 the long and short contracts have grown with 94.67% and 118.52% respectively.

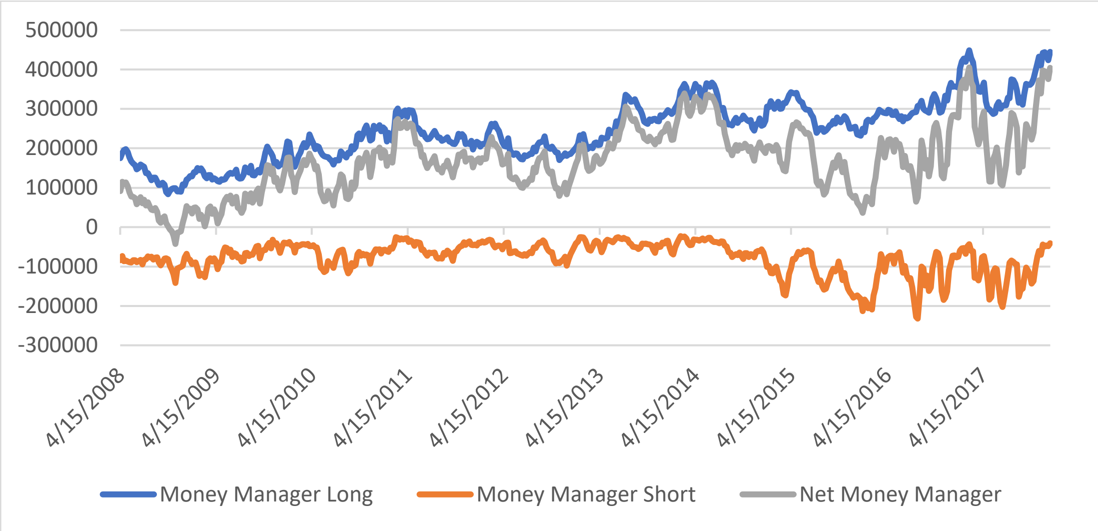

Figure 10: Money Manager Positions April 2008 to December 2017

Table 3: Descriptive Statistics for Money Managers

	Long Money Manager	Short Money Manager	Net Money Manager
	Entire Period		
Average	246 625	-77 979	168 646
Standard Deviation	76 398	40 538	85 015
Minimum	83 540	-232 202	-42 735
Maximum	448 846	-22 797	405 328
	Financial Crisis (2008-2010)		
Average	138 241	-79 660	58 581
Standard Deviation	27 758	20 927	41 577
Minimum	83 540	-141 432	-42 735
Maximum	204 608	-32 332	157 563
	2014 price fall to 2017		
Average	309 698	-109 433	200 265
Standard Deviation	50 533	45 692	79 246
Minimum	231 998	-232 202	36 372
Maximum	448 846	-36 222	405 328

Figure 10 show the positioning in long, short and net positioning for money managers from April 2008 to December 2017, table 3 show key statistics for the same period. Of the four defined sub-categories money managers are the traders that holds most of the long contracts, with an average of 35.97 % of the open longs. At the same time, they are one of the traders that holds the least of the short contracts, with an average of 14.28% of the open shorts. This means that money managers have been net long on average throughout the sample, we can also see that increases and decreases in the long positions that have primarily driven the net. Through the sample money managers have only gone net short on one occasion, this happened during the financial crisis, where long contracts decreased with the falling oil prices of the period. The entire period is identified by much movement in the long positions, while the short side have been comparatively quite up until price fall following the 2014 oil price fall, where many spikes in the positions are observed. Short positioning seems to be moving back to their previous levels when prices start to rise. The number of long contracts seems to be more volatile throughout the period, where they seem to follow the prices closely. Money Managers seem to increase their number of long contracts in periods of prices increasing, and decrease these numbers when they fall, or price movements are small. The long money managers reacted heavily to the financial crisis, where their average number of contracts fell by over 100.000, and overall share of long contracts fell to 26.72%. On the short side the average amount of contracts is higher than what is for the overall period, where Money Managers held 21.96% of the overall number of open shorts. Moving to the last period, the Money Managers average long share increased to 37.2% of the overall long positions, while their share of overall short positions increased to 16.94%. This period also marks the most volatile period for the number of money manager held contracts, for both long and short contracts.This suggests that money managers' activity reacts more to periods with supply and demand issues, and less to periods of economic slowdowns.

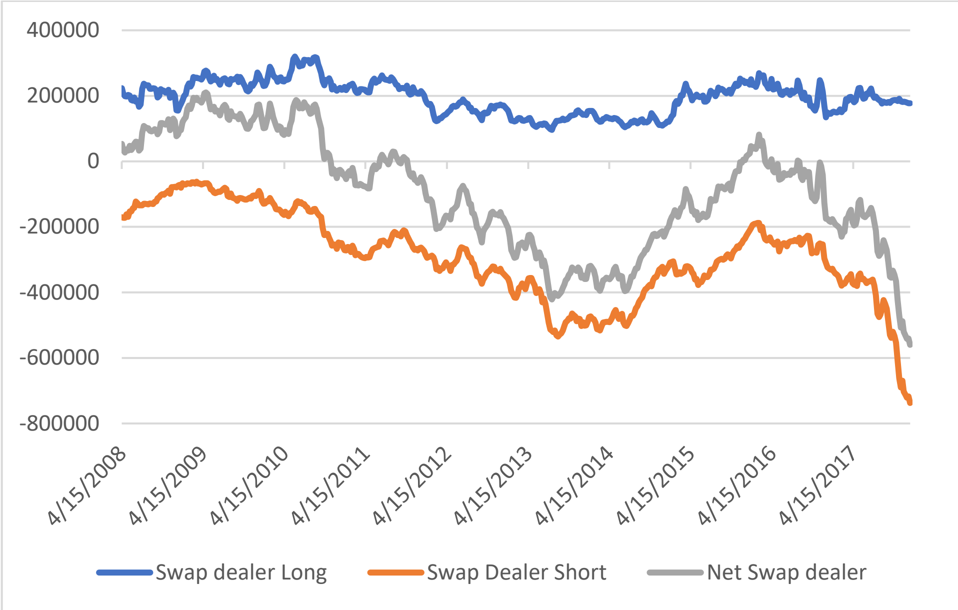

Figure 11: Swap Dealer Positions April 2008 to December 2017

Table 4: Descriptive Statistics for Swap Dealers

	Long Swap Dealer	Short Swap Dealer	Net Swap Dealer
	Entire Period		
Average	195 183	-288 649	-93 467
Standard Deviation	50 497	136 917	176 152
Minimum	95 991	-737 456	-560 037
Maximum	319 892	-62 071	210 415
	Financial Crisis (2008-2010)		
Average	226 203	-103 236	122 967
Standard Deviation	28 337	28 418	46 138
Minimum	155 293	-172 204	26 468
Maximum	277 355	-62 071	210 415
	2014 price fall to 2017		
Average	189 762	-343 049	-153 287
Standard Error	38 514	110 635	131 237
Minimum	108 635	-737 456	-560 037
Maximum	269 405	-187 672	81 733

Figure 11 shows the long, short, and net swap dealers for April 2008 to December 2017, table 4 show key statistics for the same period. This is also a large player in the market, holding 28,47% of the average long positions throughout the sample, while also holding the largest share of short positions, with a share of 52.81% of the samples average short positions. Meaning that Swap Dealers are short on average, we can slo see that long positions are comperatively stable in the period, compared to shorts, meaning that changes in the net is primarly driven by changes in short positions. During the financial crisis Swap Dealers were the biggest players holding 43.72% and 28.46% of the average long and short positions respectivley. Swap Dealers reacted opposite of how we saw the money managers react in the same period. Throughout the crisis we see long contracts grow, with, expcation of a decrease during the periods large negative price shock, while short positions declined. Moving out of the financial crisis we see the long contracts declining, while the number of short contracts increase. This continues until price risk is at its minimum after 2013. After the 2014 price fall we start seeing the same tendencies as during the financial crisis, where long positions start increasing while short decrease. The Swap Dealers where still a large player on both sides of the market, holding 22.79% of the overall averag long contracts and 53.11% of the overall short contracts. Except for a small period at the start of 2016, Swap Dealers held their positions net short also in this last period of the sample. The two sides of Swap Dealers seem to react differently to market situations. Activity on the long side seem to increase during periods of larger price movements, while activity on the short side seems to increase when price movements are low. Especially after large negative price shocks, the net seems to switch to become long.

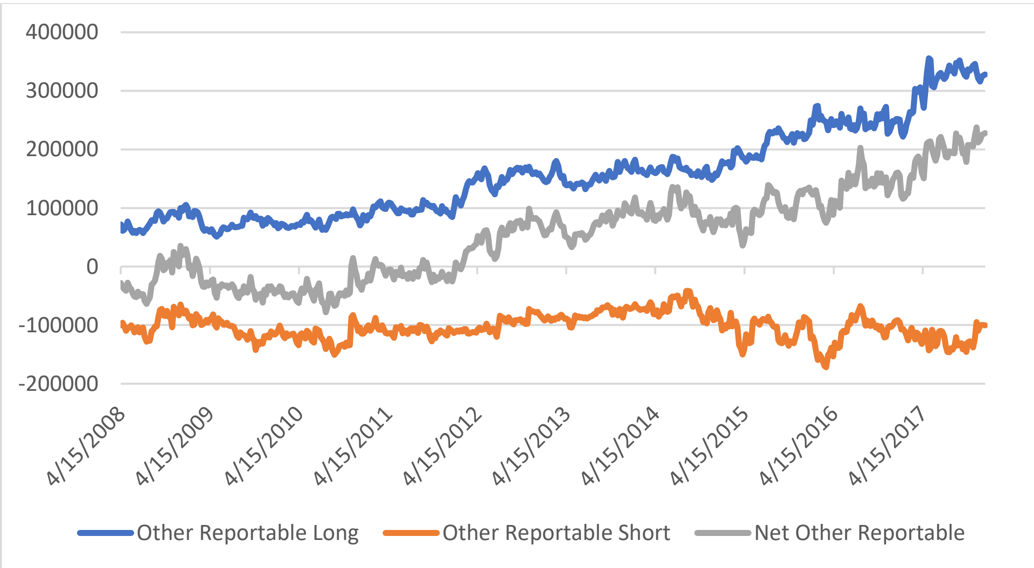

Figure 12: Other Reportable Positions April 2008 to December 2017

Table 5: Descriptive Statistics for Other Repotable Positions

	Long Other Reportable	Short Other Reportable	Net Other Reportable
	Entire Period		
Average	157 149	-103 013	54 136
Standard Deviation	77 727	22 116	77 709
Minimum	51 076	-171 883	-77 986
Maximum	355 574	-41 422	237 586
	Financial Crisis (2008-2010)		
Average	75 671	-101 694	-26 023
Standard Deviation	13 087	17 039	24 330
Minimum	51 076	-142 319	-63 657
Maximum	105 463	-64 850	35 162
	2014 price fall to 2017		
Average	241 558	-108 908	132 650
Standard Deviation	57 035	25 268	48 332
Minimum	147 802	-171 883	35 622
Maximum	355 574	-41 422	237 586

Figure 12 show the long, short and net positioning for other reportable positions for April 2008 to December 2017, table 5 show key statistics for the same period. Throughout the sample Other-Reportable traders have, on average, held a net long position. This category is smaller than the traders discussed above, holding 22.92% of the average long, and 18.85% of the average short speculative contracts. These traders were a larger player on the short side during the financial crisis, where they held 28.04% of the average outstanding short contracts, while also holding 14.63% of the outstanding average long contracts of the period. Meaning that Other-Reportable traders where net short during this period. During this period we can see the net moving into the positives a short period in 2009, coinciding with the large spike in price risk observed in the same period. Moving out of the financial crisis period, short positions remain relatively stable, while long positions grow. Changes in these long position is what seems to primarly be driving the net after this period, with it hitting net long long early 2012, staying on this sign throughout the rest of the period. During the last period, Other-Reportable traders are maintaining a strong net long positioning, holding 29.02% of the total average speculative long and 16.86% of the average speculative short contracts. Although the short positioning remain relatively stable throughout this last period aswell, we see some spikes in held positions, mid-2015, early-2016 and mid-2016 are the most prominent. During these same periods we also see spikes in the long positions. All of these periods corresponds to periods with spikes in oil price risk. This makes it seem that there are an increase in both long and short positions in periods where price risk is high. This is especially prominent after 2014.

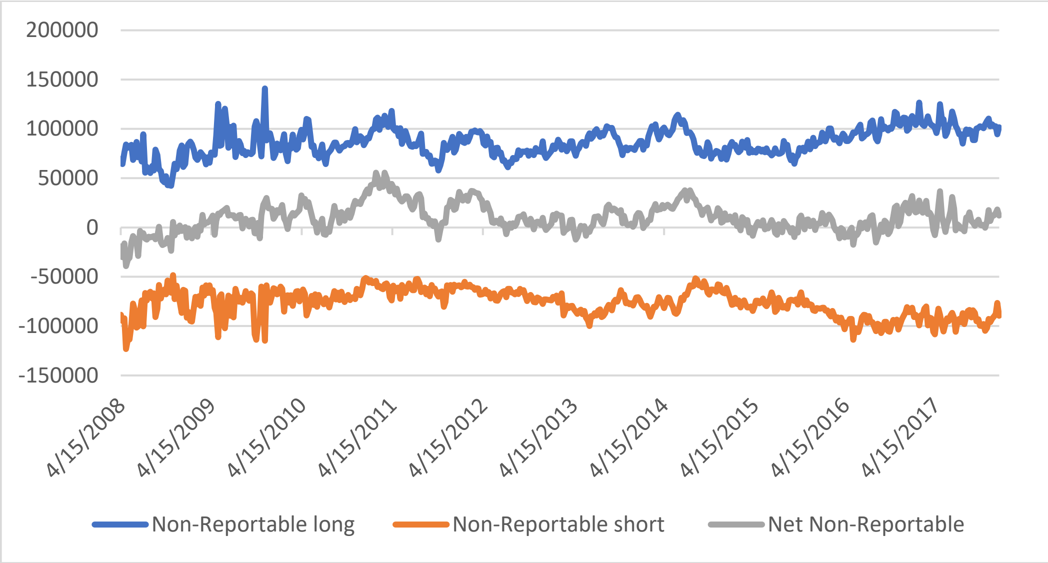

Figure 13: Non-Reportable Positions April 2008 to December 2017

Table 6: Descriptive Statistics for Non-Reportable Positions

	Long Non-Reportable	Short Non-Reportable	Net Non-Reportable
	Entire Period		
Average	86 622	-76 923	9 699
Standard Deviation	14 262	13 821	14 236
Minimum	42 323	-123 194	-39 109
Maximum	141 021	-48 311	55 635
	Financial Crisis (2008-2010)		
Average	77 237	-78 064	-827
Standard Deviation	17 928	16 295	13 936
Minimum	42 323	-123 194	-39 109
Maximum	141 021	-48 311	29 843
	2014 price fall to 2017		
Average	91 466	-84 440	7 026
Standard Deviation	12 998	13 401	10 430
Minimum	64 831	-113 960	-17 340
Maximum	126 631	-51 549	37 650

Figure 13 show the long, short and net positions of Non-Reportable positions from April 2008 to December 2017, table 6 show key statistics for the same period. Since Non-Reportable mostly contains private investors, they also holds the smallest number of contracts. More specifically 12.63% of the average long, and 14.07% of the average short contracts. Both the long and short sides follow each other closely throughout the entire period, with a small bias to being net long on average. During the financial crisis both sides held a higher share of their respecitve contracts compared to their period average. With longs holding 14.93% of the total average, and shorts holding 21.53% of the total average, this large increase in the share of total short contracts, seems to stem from the rest of the market reducing the number of contracts they held, rather than Non-Reportable traders incresing the number they held. Throughout the rest of the period both periods keep following each other closely with the net positioning being close to zero. We do however see theese spiking into the positives, following spikes in the held long positions. These looks to follow smaller spikes in the oil price risk. During the last period of the sample, the average number of held contracts have only had a marginal increase in both the long and short positions, making it so the Non-Reportable traders share of the total contracts have decreased to 10.99% and 13.08% for long and short contracts respectively. The Non-Reportable traders seems to be the categoruy of traders that reacts the least to to changes in oil price risk.

The models

First, we are interested in analyzing if long or short positions of speculators are influencing the oil price volatility for WTI and Brent. Speculator will be defined as the added positions of the speculative traders, given by the CFTC. This means that traders that are mainly interested in trading the financial products associated with the oils will be considered. As discussed in the previous sections, a GARCH(1,1) model will used, given us the following formula.

$$\sigma_{t,i}^2 = \alpha_0 + \alpha_1 \mu_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2 + \Delta Speculator_{n,t} \quad (1.3)$$

Where: μ^2 is the squared daily return of oil i, at time t-1, σ^2 is the variance for oil i, at time t-1, and ΔSpeculator is the changes in speculative positions at time t. The subscript n, denotes if we are looking at changes in long or short positions. Subscript, i, denotes if the analysis is done on the basis of Brent or WTI. $Speculator_t$ is calculated as the sum of the four speculative sub-categories at time t, ΔSpeculator is calculate as: $\Delta Speculator = \ln(\frac{Speculator_t}{Speculator_{t-1}})$. μ^2 and σ^2 are based on weekly price changes, calculated as: $\Delta P = \ln(\frac{P_t}{P_{t-1}})$

Second, an effort to identify if a single group of traders have had an influence on the volatility in the markets in question. These will be split into the four different categories given by the CTFC; Money Managers, Swap dealers, Other Reportables and Non-Reportables. Again, a GARCH(1,1) model will be utilized:

$$\sigma_{t,i}^2 = \alpha_0 + \alpha_1 \mu_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2 + \Delta SD_{n,t} + \Delta MM_{n,t} + \Delta OR_{n,t} + \Delta NR_{n,t} \quad (1.4)$$

Where SD, MM, OR and NR stands for Swap Dealers, Money Managers, Other Reportable and Non-Reportable respectively.

Last, the analysis will be repeated for two sub-periods, to see if a change in the market situation will have an impact. The sample will be split in the middle giving us two periods, one spanning 2008 to mid-2013, and the second spanning mid-2013 to 2017. The same GARCH(1,1) models will be used.

For our OVX-analysis an OLS-based simple regression will be used, where the weekly oil prices for both the WTI and Brent three-month contracts, as well as the weekly position changes in the COT-rapports will be used. Giving us the following general formulas:

$$\Delta OVX_t = \Delta P_{t,WTI} + \Delta Speculator_{t,i} + \epsilon_t \quad (1.5)$$

And

$$\Delta OVX_t = \Delta\, P_{t,WTI} + \Delta MM_{t,i} + \Delta SD_{t,i} + \Delta OR_{t,i} + \Delta NR_{t,i} + \epsilon_t \quad (1.6)$$

Empirical Results and Discussion

*Table 7: Z-values for speculator analysis on WTI. */**/*** marks significance at the 10%/5%/1% levels*

WTI	Speulators L	Speculators S
Z-value	0.07	0.90
	Period 1	
WTI	Speulators L	Speculators S
Z-value	0.60	0.06
	Period 2	
WTI	Speulators L	Speculators S
Z-value	-1.42	-1.07

Table 7 shows the obtained z-values for long and short WTI speculators throughout the three different tested periods [2]. Neither speculator category seems have any significant impact on the oil price volatility, neither the full sample nor the two sub-periods.

[2] The corresponding parameters estimates can be found in the attachments

*Table 8: Z-values for the COT-analysis on WTI. */**/*** marks significance at the 10%/5%/1% levels*

WTI	Money Manager L	Swap Dealer L	Other Reportable L	Non Reportable L
Z-value	-2.67***	1.80	1.24	1.33
WTI	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
Z-value	0.23	-0.35	0.14	1.15
	Period 1			
WTI	Money Manager L	Swap Dealer L	Other Reportable L	Non Reportable L
Z-value	-1.84	2.01**	54.51***	0.12
WTI	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
Z-value	1.35	-0.63	1.12	1.02
	Period 2			
WTI	Money Manager L	Swap Dealer L	Other Reportable L	Non Reportable L
Z-value	-2.73***	1.13	-1.14	1.29
WTI	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
Z-value	0.89	-0.91	0.55	0.86

Table 8 shows the test results for the four sub-categories of traders and WTI. For the entire period, we only see one significant value, namely the long money managers. Surprisingly these traders seem to have an inverse relationship with the oil price risk. Moving into period 1, this result is no longer significant. Long Swap Dealers and Other Reportable are, however. This period includes the financial crisis of 2009, which brought with it large price movements over short periods of time. After removing this period from the sample and re-running the test neither of these are significant (with a z-value of 1.79 and 1.57 for swap dealers and other reportable respectively). Moving into the second period, spanning mid-2013 to 2017, the same result as the first test is found, where long money managers seems to have a negative inverse relationship with oil price risk.

There are no significant values in the total speculator tests, lending support to the theory that speculators do not affect price volatility in the oil market.

As we can see, only the long money manager positions seem to have an impact on oil price risk. This relationship seems to be inverse, meaning that an increase in Money Managers trading activity reduces risk. This relationship seems to be most prominent in the second period, spanning 2013- 2017. This marks a period where we have an increase in both money manager positioning, and an increase in OI. Lending support to the hypothesis that an increase in OI mitigates risk. This also brings support to the observation of Money Managers reacting more to supply and demand factors than economic slowdowns. This also suggest that the criticism against speculators in the market is wrong. The speculators do not drive prices and price risk upwards, rather with an increase in liquidity in the market they bring with them a more stable price picture for both hedgers in the commodity and the end-user of this commodity.

*Table 9: Z-values for speculator analysis on Brent. */**/*** show significant at the 10%/5%/1% levels*

Brent	Speculators L	Speculators S
Z-value	0,15	0.88
	Period 1	
Brent	Speculators L	Speculators S
Z-value	0.17	0.81
	Period 2	
Brent	Speculators L	Speculators S
Z-value	-0.81	1.21

Table 9 shows the results for speculators impact on Brent. As with WTI there are found no significant values, neither for the entire period or the two sub-periods.

*Table 10: Z-values for COT-analysis on Brent. */**/*** shows significance at the 10%/5%/1% levels.*

Brent	Money Manger L	Swap Dealer L	Other Reportable L	Non Reportable L
Z-Value	-2.80***	0.64	0.49	1.61
Brent	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
Z-value	1.12	-1.96*	-0,76	4.39***
	Period 1			
Brent	Money Manger L	Swap Dealer L	Other Reportable L	Non Reportable L
Z-Value	-0,20	1.51	-0.18	1.50
Brent	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
Z-value	1.47	-0.64	0.92	0.35
	Period 2			
Brent	Money Manger L	Swap Dealer L	Other Reportable L	Non Reportable L
Z-Value	-3.03***	0.23	0.06	2.33**
Brent	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
Z-value	1.11	0.86	-0.71	1.67*

In table 10, the results for the four sub-categories are given. As with WTI a negative relationship between long money managers and oil price risk is found, both for the entire period and for the second sub-period, with no significant values for the first sub-period. Again, lending support to support to the findings for WTI, where an increase in this position increases liquidity and helps mitigate risk. A difference appears in the non-reportable category, where short positions are significant down to a 1% significance level. In period 2 this changes to a 10% significance level, while long positions are significant down to a 5% level. Non-reportable do not, as the name suggest, have to report their positions to the government. A large change in these positions might therefore send a signal to other traders that a price change, in either direction, might be expected resulting in other traders buying, or selling contracts. We also see short swap dealers being negative and significant at a 10% significance level. Short swap dealers had a large increase in numbers of contracts between 2012 and 2014, which might be why we do not see any significance in the two sub-periods. The large increase coincides with an increase in the long positions of money managers, signaling that swap dealers might have taken the opposite side of their trade in this period.

*Table 11: t-values for the speculator analysis on the OVX. */**/*** shows significance at 10%/5%/1% levels*

OVX	Speculators L	Speculators S
t-value	2.15**	2.53**
	Period 1	
OVX	Speculators L	Speculators S
t-value	1.29	1.32
	Period 2	
OVX	Speculators L	Speculators S
t-value	1.79*	2.42**

Figure 11 shows the t-values for long and short speculators during the three sample periods. For the entire period both positions are significant at a 5% level, while period 2 shows long positioning significant at 10% while short remain at a 5% level. Neither are significant during period 1. Looking at speculative positioning compared to the OVX, one can see spikes in the data following each other closely. One exception from this is during the financial crisis, where the OVX was increasing while both long and short positioned speculators were falling. After the oil price fall of 2014, we especially see a closely linked short speculative position and OVX prices, which continues until oil prices started rising in late 2016, where short speculative positioning started growing sharply while the OVX fell.

Table 12: t-values for the COT-analysis on the OVX. */**/*** shows significance at the 10%/5%/1% levels

OVX	Money Manger L	Swap Dealer L	Other Reportable L	Non Reportable L
t-value	-0.29	2.97***	1.70*	1.36
OVX	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
t-value	3.90***	-1.04	1.49	0.92
		Period 1		
OVX	Money Manger L	Swap Dealer L	Other Reportable L	Non Reportable L
t-value	-0,55	2.03**	1.78*	0.68
OVX	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
t-value	2.83***	-1.55	1.25	1.03
		Period 2		
OVX	Money Manger L	Swap Dealer L	Other Reportable L	Non Reportable L
t-value	0.33	2.22**	0.08	1.84*
OVX	Money Manager S	Swap Dealer S	Other Reportable S	Non Reportable S
t-value	2.83***	0.35	0.99	0.32

Table 12 shows us the empirical results for the four sub-categories of traders. The results are quite different from what was obtained through the GARCH modelling. Looking at the entire sample short money managers and long swap dealers are found to be significant and positively related to the OVX. Looking at the long swap dealers, the changes in these positions have remained relatively calm throughout the entire period. A sudden change of some magnitude might therefore be seen by the rest of the market participants as a change in the market information held by these traders, that they themselves might not have. We see the same tendencies with short money managers, where changes are relatively small, and large changes are infrequent.

Looking back at figure 5, showing the OVX and WTI three-month futures price. We saw that the OVX reacted heavily to the smaller price drops, when comparing it to the variance measure. Short money managers and long swap dealers are especially interesting to look at and compare to OVX figure. Even though the movements in these periods have been comparatively small we see that movements fit surprisingly well with the OVX figure. Where large spikes in either positions (positive and negative) follows the OVX closely.

For WTI the surprising result of a negative, and significant, relationship between long money managers and was found, both for the entire period and period 2 all the way down to a 1% significance level. Suggesting that an increase in these contracts brings with it increased liquidity to the market, which in turn secures a more of a "fair price" to both hedgers and end-consumers of the commodity. The Brent contract shows us the same results for money managers, however, we also get a few additional significant values. For the entire period it's found that short other reportable positions have a positive significant value at a 1%

significance level, this is found to be changed to a 10% level in period 2, while the long side is significant at a 5% significance level. These additional findings are explained by uncertainty around the traders due to them not being obligated to report to the government. Due to the lower trade number in the Brent oil market, the oil price risk seems to be more sensitive to changes in speculative positioning, especially towards the more uncertain category of non-reportable traders. Since the observed variance risk measure seems to be more affected by a negative price shock, than a positive shock of the same magnitude, arguments can be made that a GARCH-model isn't the best fit for these types of analysis. A possible extension to this thesis might therefore be to use an EGARCH approach, or any other approach that consider that price shocks might influence volatility asymmetrically.

The findings suggest that OVX as a price risk measure picks up on small changes in the market, due to it reacting heavily to small, especially negative, price changes in the market. This is most clearly seen to the significant values for both short money manager and long swap dealer, both significant at a 1% level throughout the period. Due to the OVX being traded on the expected volatility in the market a month ahead, the results might indicate a market expectation that the behavior of these traders will have an impact on the future oil price risk, rather than them necessarily having an impact on the oil price volatility itself.

Part 2: Is a Simple Event Study Methodology Sufficient at Measuring Excess Volatility?

Event studies have become a popular and commonly used form of analysis in financial research. Its popularity stems from the fact that it makes it easy for researchers to pick out single events in a timeseries to further analyze their impact on the market. Being used for analyzing anything from the effect of mergers single events impact on commodity prices, it is a methodology useful for academics in any economical field. Traditionally this type of study has been conducted on returns in the market in question. The surge in popularity of non-linear models in recent times has brought with it criticism for this type of event-studies. Balaban and Constantnou (2006) claims that, since financial markets are proven to be heteroscedastic, a linear model used to explain changes will give t-values that can't be trusted to give correct information.

Comparatively, as far as I can tell, there are few academic papers of event studies on the volatility effects of events. There might be several reasons for this. First, the methodology for an event study on returns is a straight forward approach. Where the researcher simply measures the actual found return in a pre-defined event window, and measures this return towards the expected return based on a pre-defined model, often using OLS parameters. For the volatility analysis, researchers have employed a more complex framework. By using a GARCH(1,1)-type model they are able to find a measure of expected risk (the data's variance), further a likelihood model is employed to find what's called "the cumulative abnormal volatility (CAV)". Especially this last step is an econometrical heavy analysis. And might therefore "scare" off practitioners that is not comfortable employing to much econometrics in their research. An example can be given through Essaddam and Mnsari (2015) where in their study on terrorisms impact on stock market volatility they use a bootstrapping approach to rescale the obtained residuals from an GARCH(1,1) model. This paper will therefore try a simpler approach to the volatility event study. Where the expected volatility will still be based on a GARCH(1,1)-type model, but the actual "observed" volatility will be based on a 400-days rolling variance-window. The rest of the analysis will be based on the simpler event-studies on returns. The study itself will be based on 21 announcements on changes in oil production from OPEC spanning 2007-2017, measured against a benchmark.

Literature on Volatility Event Studies

Bomfim (2003) used the event study methodology to investigate pre-announcement and news on public disclosure of monetary policy influenced the American stock market. Using an event study methodology on the day of policy announcements, as well as on a 5-day basis preceding these announcement days. The findings suggest that the stock market tends have a abnormally low volatility on days preceding regularly scheduled announcement days. The findings were, however, only significant over the last few years before the paper was written, this was attributed to the Federal Reserve's disclosure practice in 1994. Further an analysis on how the actual interest rate influences the stock market volatility. It is found that these announcements significantly boost stock market volatility in the short-run.

Kaminsky and Schmukler (2002) used an event study methodology to investigate the effect of bond rating on risk in financial securities in emerging markets. Their findings suggest that changes in ratings and market outlook affect bond and stock market. Further they find a spillover effect between emerging markets, where a rating change in one triggers a change in both yield spreads and stock returns. These effects are found to be strongest during crisis, and in non-transparent economies.

Aik and Ng (2015) wanted to investigate general elections in Asia impact on stock indexes in the area. This case also utilizes the GARCH(1.1) model to obtain the one day ahead variance estimation. Once again, a more complicated calculation to obtain the CAV estimates are used, which again differs from the rest of the estimates observed in other literature on the subject. Their findings indicate that there is excess volatility in the price data around general elections on the continent.

The Benchmark

As the benchmark Demirer and Kutan (2010) and Lin and Tamvakis (2010) will be used. Both of these theses set out to investigate if OPEC announcements had an impact on oil price returns. Both use a standard Event Study analysis, where they calculate the CAR based actual observed return and estimated expected returns from a linear regression. Both find no significant abnormal returns for OPEC up events. For the constant events both find significant values. For the last event category, their conclusion differs to some extent. Lin and Tamvakis find no significant abnormal returns on down events, while Kutan and Demir find that a signal of a decrease in quotas brings with it an increase in prices. Both theses conclude that the magnitude of these effects depends highly on the overall market situation, where OPEC has more influence on prices when the market has a particularly low, or high price. They also find that the results are dwindling with an increased event window.

Introduction on OPEC and oil production

The Organization of the Petroleum Exporting countries (OPEC) was founded during the Baghdad Conference of 10^{th} to 14^{th} of September 1960, by the five nations Saudi Arabia, Venezuela, Iran, Iraq and Kuwait. Today this number has grown to 14-membering countries, from both South-America, the Middle-East and parts of Africa. According to their own numbers, OPEC stood for 81,5% of the world's total oil supplies in 2016 (equaling 1,216.78 billion barrels) (Organization of the Petroleum Exporting Countries, 2017). Each member-country's proven reserves are given in the figure below.

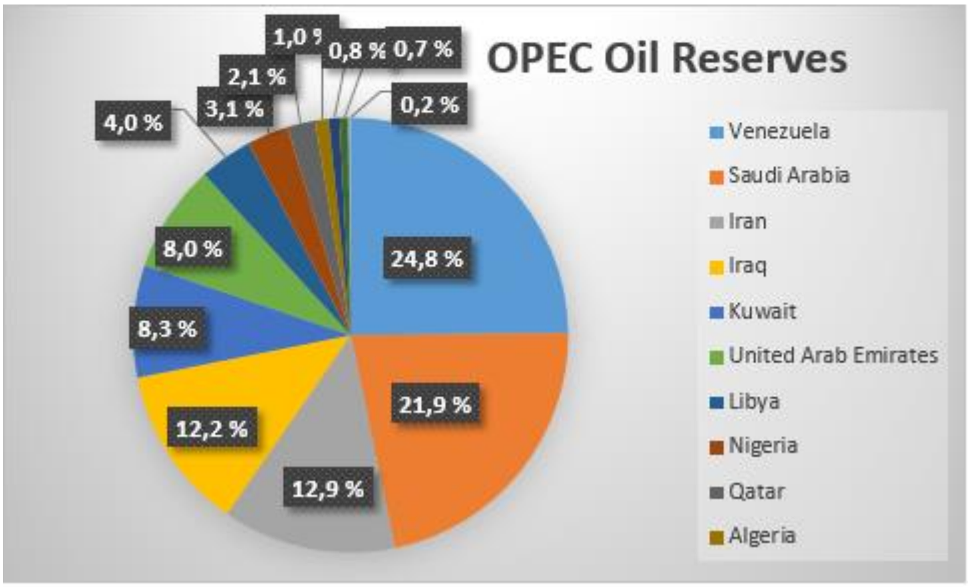

Figure 14: Member-countries share of total proven OPEC oil reserves: Members-countries share of total proven OPEC oil reserves: (Organization of the Petroleum Exporting Countries, 2017)

OPEC, and especially Saudi-Arabia, which is the largest producer of these countries, have been given a large part of the blame for the fall in oil prices of 2014. When the economic boost of emerging markets, like China and Russia, slowed down in the 2010's this resulted in a downward pressure on the oil prices. After years of increasing oil prices and incentivized by the negative effect high oil prices have on their respective economies, the U.S and Canada increased their output of the commodity. In the U.S private companies started extracting oil through fracking in shale formations in North Dakota, while Canada started extracting from the Alberta oil sands. During this period, both nations where able to decrease their imports drastically, putting further downward pressure on the price.

Literature on OPEC and the oil market.

OPEC's effect on oil prices has been thoroughly researched. Kaufmann, Dees, Karadeloglou, and Sanchez (2004) set out to investigate if the real price of oil had an impact on OPEC's oil utilization, their quotas, and cheat over the given quota. They find no proof of the oil prices effecting OPEC's decisions in any significant way. They do, however find that all their variables effect the real oil prices. These findings indicate that that the OPEC countries may be able to interact in a price cooperation, and in this way influence the global prices. Smith (2005) finds evidence to support that OPEC works as a bureaucratic cartel. It is also found that the formal quota system, imposed in 1982, has increased the transaction cost among the member-countries, and therefore, has lowered the efficiency of the cartel. It was also suggested that Saudi Arabia has taken a leading role in the organization. It was not found any evidence to support or reject this possibility. Alhajji and Huettner (2000) disagrees with these statements. According to their study OPEC does not have the necessary systems in place to punish the members that does not produce to their allocated quota, neither do they agree on a oil price. The lack of these factors leads the authors to submit a hypothesis that OPEC lacks the groundworks to function as a cartel. This is further supported by the authors attempt to fit OPEC into a dominant firm model, in which it did not fit. They did, however, find evidence that Saudi-Arabia fits this model, and propose that they use their power to control prices to maximize and reach political goals. The lack of willingness of the participating countries to follow the quotas are further supported by Hamilton (2008), who claims that quotas are moved to support each member-country's stated production goal, instead of the other way around.

Cairns and Calfucura (2012) builds further on the study of Alhajji and Huettner. They reach the conclusion that OPEC is not a cartel. They further suggest that the organization works more as a trust builder, between the oil producers, past the level of trust that exist between the different states on its own.

Bentzen (2007) found using a Vector Error-correction model, that OPEC had an impact on both the WTI and Brent prices. Further he found that the impact has increased in later periods. It is proposed that the organizations change in strategy around, 1999-2000, where focus were changed from quotas and markets shares towards a more direct price targeting policy has influenced the world market for oil, and reduced the benchmark role for WTI and Brent. Mensi, Hammoudeh, and Yoon (2014) find strong evidence that OPEC cut, and maintain announcements are anticipated in the WTI and Brent price changes. These findings are further supported by Schmidbauer and Rösch (2012) research indicate that these impacts are primarily found in the pre-announcement periods. Fattouh and Mahadeva (2013) adds some insight into this finding. Reviewing several other papers, they found that OPEC's impact on oil prices depends on the market situation. Further they claim that even though OPEC's power is visible in the short run, it is less certain that they can maintain their pricing power in the long-run.

Data and methodology

The data collected includes daily data for WTI and Brent three-month future prices. The data goes from February 2006 to the end of December 2017 giving us 3106 points of data for each of the oils. In this study 21 events have been identified from OPEC's own announcements of meetings held between the members. This data is sorted into three categories depending on the signals of production, up signal, down signal and no change signals. This gives us a total of three up signals (2 in 2007 and 1 in 2017), two down signals (1 in 2008 and 1 in 2009) and sixteen no change signals. There will be used three different event windows, t+/- 5 days, t+/- 10 days and t+/- 30 days. Giving us an event window of 11, 21, and 61 days respectively. Both t+/- 5- and 10 days have been used in the benchmark studies. A 30-day event window was chosen in an effort to analyze the effect of the events a month before and after the event took place. This will aid us in determining if other volatility effects will affect the conclusions. The actual observed risk measure will be calculated as 400 days rolling average, which is the same timeframe as the GARCH(1.1)-model will be modeled after.

To estimate the expected volatility at time t, a GARCH(1,1) will be employed. This decision is based on the logistics given in the data chapter of the Commitment of Traders case. This model will still be defined as follows:

$$\sigma_t^2 = \alpha_o + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2.1)$$

Where the estimated variance is based on the one-day lagged squared return as well as the one-day lagged variance. A GARCH model is still chosen on basis of the observations in figure 2.

Conducting an event study using the (G)ARCH-framework does not come without its own challenges though. Since an out-of-sample period will be far away from the later estimations, it does not seem likely that this will hold for all 21 events. For each event day there will be estimated a unique model, based on the 400 observations preceding the event window for each of the oils. Since we are working with three different lengths of windows, this means that 126 different models will be estimated.

To analyze whether the event in question has influenced the volatility or not we need to calculate the abnormal volatility (AV) for each of the days in the event window. Our test will be based on the simple return model, altered to fit to our analysis:

$$AV_{t,q} = \sigma^2_{t,q} - E(\sigma^2_{t,q}) \quad (2.2)$$

Where subscript q denotes which contracts is used.

To further analyze the abnormal volatility from the events we calculate the cumulative abnormal volatility (CAV) for each of the events as the sum of the abnormal volatility, given as:

$$CAV_q = \sum_{t=-n}^{t} AV_{t,q} \quad (2.3)$$

The hypothesis that OPEC announcements has no effect on the volatility of the oil market will be tested using a two-tailed student's t at the 5% level defined as:

$$t = \frac{CAV_i}{\sqrt{K_i} * \sigma(AV)_i}, t \sim K - 2 \quad (2.4)$$

Where K_i is the observed number of AV's in the calculated CAV_i and $\sigma(AV)_i$ is the standard deviation of the AVs. t_i has K – 2 degrees of freedom.

*Table 13: Empirical results for individual CAVs. */**/*** marks significane at a 10%/5%/1% level*

WTI								
	Up			Down				
	CAV 1	CAV 2		CAV 1	CAV 2	CAV 3		
5 Days	-0.89	-1.74		-0.24	-1.62	-0.90		
10 days	-1.13	0.24		-3.62***	-3.61***	-0.39		
30 Days	-2.01**	-1.97*		5.19***	2.74**	1.59		
	No Change Events							
	CAV 1	CAV 2	CAV 3	CAV 4	CAV 5	CAV 6	CAV 7	CAV 8
5 Days	-0.92	-2.03*	4.35***	7.49***	14.87***	2.96**	-0.84	-12.62***
10 days	-1.10	-3.29***	4.38***	5.23***	16.39***	3.06***	0.18	-0.03
30 Days	-4.07***	6.01***	N/A	8.17***	23.19***	9.87***	1.35	1.76*
	CAV 9	CAV 10	CAV 11	CAV 12	CAV 13	CAV 14	CAV 15	CAV 16
5 Days	4.45***	1.83	2.57**	-1.67	-2.32**	-0.76	7.86***	0.95
10 days	4.97***	-100.73***	4.94***	-1.68	-0.25	0.39	3.69***	1.33
30 Days	2.76***	0.31	3.85***	-2.94***	-4.11***	-2.65**	2.24**	20.12***
Brent								
	Up			Down				
	CAV 1	CAV 2		CAV 1	CAV 2	CAV 3		
5 Days	-0.65	-1.16		1.93	-2.20**	-0.94		
10 days	-1.63	-1.10		-4.22	-3.04	-0.37		
30 Days	-1.39	-1.47		5.53***	0.51	1.57		
	No Change Events							
	CAV 1	CAV 2	CAV 3	CAV 4	CAV 5	CAV 6	CAV 7	CAV 8
5 Days	0.12	0.19	-0.87	17.54***	1.70	0.55	0.11	-0.86
10 days	-1.06	3.38***	-3.54***	4.98***	10.04***	-0.40	0.60	-0.45
30 Days	-3.71***	4.57***	N/A	7.69***	17.63***	2.83***	1.34	-0.84
	CAV 9	CAV 10	CAV 11	CAV 12	CAV 13	CAV 14	CAV 15	CAV 16
5 Days	0.06	0.16	0.46	-1.15	0.04	-0.31	0.73	0.27
10 days	5.21***	3.47***	2.76**	-1.82*	-2.55**	0.22	2.93***	1.94
30 Days	2.24**	127.08***	1.92	-3.09***	-3.37***	-2.76***	2.63**	421.20***

Table 13 show the empirical results for each of the calculated CAV in the event study on Brent[3]. As with the Benchmark there is found that Up events do not cause a reaction in the market, except for when looking at the 30-days window, where all values are significant. The Benchmarks found that during announcements of no change that returns were either not

[3] The model was unable to estimate parameters for no change CAV 3 on a 30-days basis both for WTI and Brent, these are therefore removed from the study.

significant or significant and negative for the three month-contracts.The empirical results obtained in this thesis shows a different result. For the 5-days study all CAVs are found to be insignificant except CAV 4 which shows a positive significant value at a 1% level. For the 10-days study all results are found to be positively significant or non-significant, except for CAV 3, CAV 12, and CAV 13

For the down events, the Benchmarks found the CAVs to be significant and positive for all event-windows. For the found CAVs in this analysis, both oils have instances of insignificance, as well as both positive and negative significance in the dataset. Where the 5-days event window finds no significant values, the 10-days event window finds the first and second CAV to be negative and significant, and the 30-days event window find the same CAVs to be positive and significant.

*Table 14: Empirical Results for Added CAVs. */**/*** marks significane at a 10%/5%/1% level*

	5-days		10-days		30-days	
Down	WTI	Brent	WTI	Brent	WTI	Brent
t-value	-1.48	-1.19	-3.13***	-3.23***	3.31***	2.56**
No Change	WTI	Brent	WTI	Brent	WTI	Brent
t-value	-1.59	-2.52**	-2.85***	-1.65	8.08***	0.31
Up	WTI	Brent	WTI	Brent	WTI	Brent
t-value	-1.79	-1.23	-0.57	-1.80	-2.78***	-2.00**

Table 14 shows the empirical results for each of the events in the event study. According to the Benchmark, the significance levels should be diminishing the longer the maturity is. For the results obtained in this analysis, this is not case. Looking at the table, the results seem to remain significant, become significant, or switch signs when moving into the 30-day window. This is especially apparent for the up events, according to the Benchmark this should not be significant at any maturity, yet our results give us negative and significant values for both oil contracts. For both the down and no change events the values changes signs when moving from the 10-day to the 30-day window. Signaling that, using our model, the 30-day event window might also pick up other, unrelated events in the calculations. A possible issue might be the way the out-of-sample period for the GARCH was constructed. Some of the events in the sample was close enough to one another that, using the 30-day window, they overlapped. Looking at the 5-day window, the empirical results for the up events are as expected, with no significant values. The constant events are as expected for the 5-day Brent analysis, with a negative significant value, which becomes insignificant at a 10- and 30-days basis. None of the down events nor the WTI no change events are as we would expect from the Benchmark.

They all start of as insignificant at the 5-days basis, and changes to significant at both the 10-days and the 30-days event-windows.

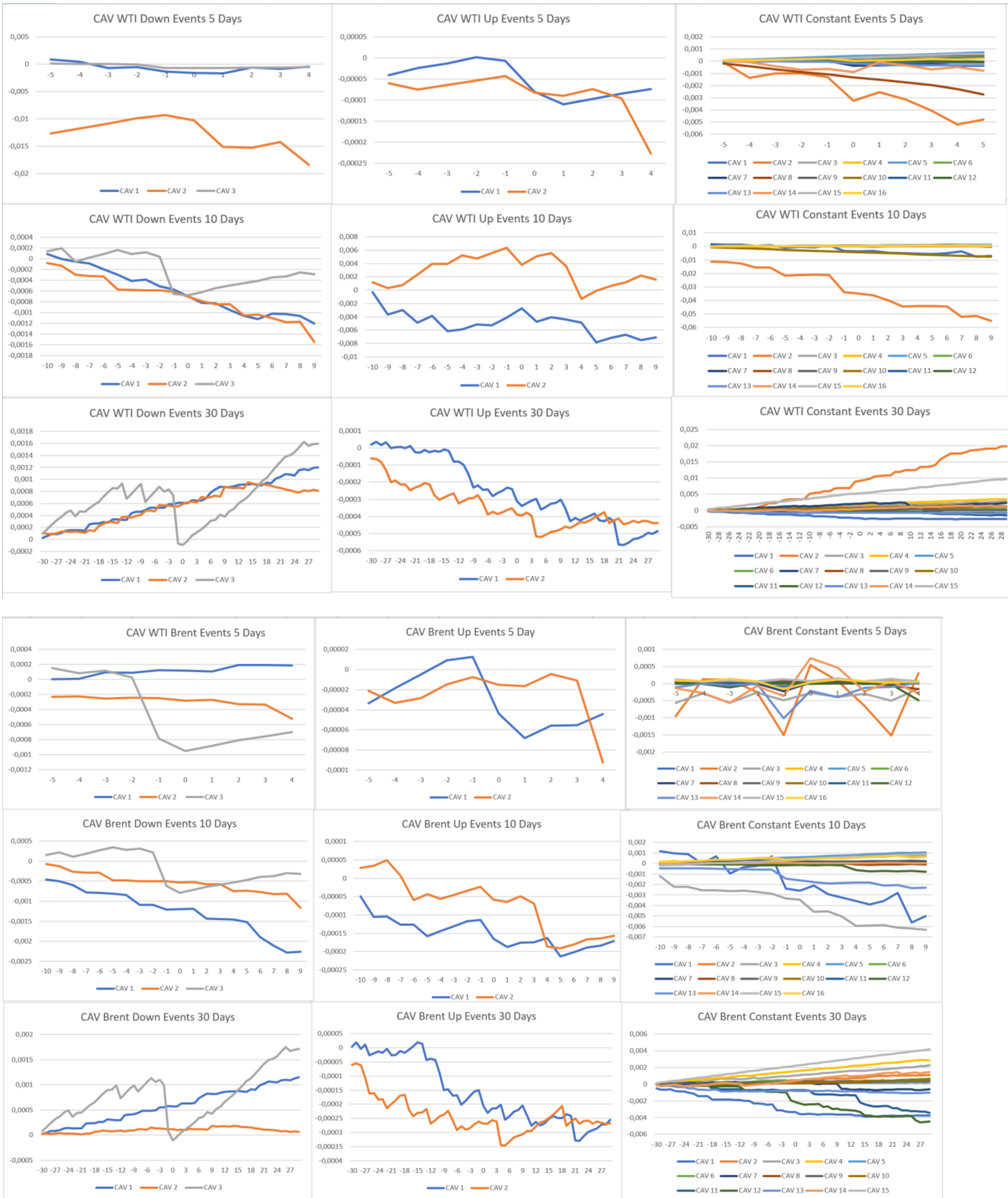

Figure 15: CAVs for each event and event windows

Figure 16 shows the graphed CAV-values for the event study. Looking especially at the 10- and 30-days CAVs seems to follow the oil price changes in their respective periods. These findings are not surprising, but the rate at which they are declining or increasing makes it seems like this simpler model is unable differentiate the overall market situation from what changes are due to the events themselves. To take a deeper look at this, the CAV 1 for the down events with these event windows will be viewed in isolation. These start of the period approximately at zero, to grow linearly throughout the entire event window. This event day occurred on October 24th, 2008, when oil prices started declining and oil price risk was increasing. Due to this and that the out-of-sample period consists of data outside increasing oil price risk, the model might underestimate the expected volatility. Another issue is that many of the estimated GARCH-model have ARCH and GARCH- parameters that adds up to be higher than one. Meaning that the unconditional variance can't be calculated and that the estimated variance will tend to infinity. Another issue is that several of the estimated models had small estimated α and β parameters, with large standard deviations. For the no change CAVs we expected to see negative significant values according to the benchmark, the findings however indicate that these were positive. The explanation looks to be underestimated α and β values, making the model underestimate most of the expected variances. For the down events the issue seems to be the opposite, where the estimated $\alpha_1 + \beta > 1$, meaning that calculated variance estimates will converge towards the average variance in longer term forecasts. An indication of this may be the change from negative significant values, to positive significant values when moving from the 10- to 30-days event window. These findings might be an indication that the model is estimated on too few observations[4]. (e.g Hwang and Valls Pereira (2006)).

For both Brent and WTI the simpler event study does not seem to give satisfactory results. When looking at each individual CAV several significant values are found where they are expected, but according to the Benchmark these are mostly of the wrong sign. The model seems to be underestimating the "no-change" event-windows expected volatility. A reason for this might be that the estimated parameters are too small due to, to short estimation periods. For the "down" events the CAV t-tests gives us contradictory conclusions when moving

[4] Because several GARCH(1.1) models were estimated, the parameters will not be presented in the text. A list of these can be found in the attachments to this thesis.

between the different lengths of event-windows. The issue seems to be the opposite of what we see in the “no-change” events. The estimated parameters add up to give us a value equal to, or above 1, meaning that we have non-stationarity in the variance, where the estimated variance will move towards the average when the forecast horizon increases. Looking to the empirical results for the events as a whole, this issue seems to increase with an increased event-window, with a change in the t-values sign for both the down and constant events when moving to a 30-day event window.

Concluding Remarks

In the first part of this thesis an analysis to investigate speculative positioning’s impact on oil price risk was conducted, in an effort to contribute to the ongoing debate on the relationship between oil price risk and speculators. A GARCH(1,1) model was employed to investigate the impact on volatility, first on a speculative long and short basis, then with the four different sub-categories given by the CTFC. For both WTI and Brent the findings indicate that neither long nor short speculators have had a significant impact. The findings do, however, indicate that the category long money managers have had an impact. This relationship seems to be inverse, meaning that an increase in the number of these contracts will bring with it a decrease in price volatility. This seems to be true in periods with supply and demand issues. This result lends support to studies claiming that an increased open interest mitigates risk. This is often explained by increased activity bringing with it increased liquidity, which again may result in physical hedgers getting a fair price for their product. For both oils this is found to hold true mostly in the period between mid-2013 and 2017. For Brent there is also found that short non-reportable positioning is positive and significant in the same time-frame. As the name suggests, these traders do not have to report to the authorities, a change of some magnitude might therefore send ripples of insecurities to rest of the market. These results indicate that both oils are impacted by speculators, Brent seems to be more sensitive to these positions compared to its counterpart. It is however important to consider the criticism against a GARCH model in this type of analysis. Since this type of model is calculated as if both positive and negative price shocks have the same impact on the price risk arguments can be made that it is not optimal.

Second a simple OLS-based analysis was conducted on COT's influence on the OVX. The findings where quite different from what was found using the GARCH(1.1). The findings indicate that both long and short speculative positions were positive and significant, whereas long positioning were found to be significant throughout the entire period, but not in any sub-period, and short positioning were found to be significant throughout the entire period and from mid-2013 to 2017. For the sub-categories, short money managers, and long swap dealers were found to be significant and positive throughout the entire sample, and the two sub-periods. Reasons for this might be that changes in these positions have been comparatively small throughout the period, a larger shift in these might therefore send a signal to other traders in the market of an expectation of a price increase or decrease.

Although the OVX-analysis is based on an OLS-type model, which does not take into skewness or excess kurtosis in the price data, and on the expectation on future volatility instead of actual observed volatility. It is difficult to base a single conclusion on these two contradicting models, other than that the results obtained are highly dependent on the model used. further research into the subject is therefore encouraged.

For the second part of this thesis, there was an attempt to conduct an event study on volatility changes in the oil market, based on 21 different OPEC announcements in a time frame spanning from 2007 to 2017. After seeing that previous research on the subject employs complicated econometrics to estimate the price volatilities I wanted to see if there is possible to reach the same conclusions using a simpler framework. This test was done by altering the cumulative return test to calculate variance as a proxy of volatility. Volatility estimations where obtained through a GARCH(1,1) model, and the actual observed volatility was estimated as a 400-day running variance on price changes. A longer event window tends to bring other events then what we are interested in, into the model. This problem increases with an increased event-window. Running variance for 400 days might also bring with it some issues, with OPEC announcements being released roughly twice a year, this measure runs through at least one other event, which might taint the calculations. It does not seem like a simple framework for estimation of volatility event studies is optimal. Many of the CAV estimates seem to have the opposite sign of what is expected, this is especially true for the no change events. Looking at these results, it looks like the expected variance is underestimated through much of the sample.

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Attachments

Paramaters for CoT positions, standard deviation in parenthesis.

	Brent			
	Speculators Long	Speculators Short	COT Long	COT Short
α0	0.00002 (0.00002)	0.00003 (0.00002)	0.00003 (0.00001)	0.00004 (0.00002)
α_1	0.12 (0.03)	0.14 (0.04)	0.08 (0.03)	0.10 (0.03)
β_1	0.87 (0.03)	0.84 (0.04)	0.89 (0.02)	0.88 (0.03)
$\alpha1 + \beta_1$	0.99	0.98	0.97	0.98
Δ Speculator	0.00028 (0.0020)	0.00159 (0.0018)		
Δswap Dealer			0.00005 (0.00075)	-0.0015 (0.0007)
Δ Money Manager			-0.00231 (0.00082)	0.0002 (0.00019)
Δ Other Reportable			0.0005 (0.0009)	-0.0004 (0.0005)
Δ Non-Reportable			0.0016 (0.00099)	0.0023 (0.0005)
	Brent Period 1			
	Speculators Long	Speculators Short	COT Long	COT Short
α0	0.00005 (0.00005)	0.00004 (0.00005)	0.00007 (0.00006)	0.0021 (0.0031)
α_1	0.15 (0.06)	0.14 (0.06)	0.09 (0.05)	0.06 (0.11)
β_1	0.83 (0.06)	0.83 (0.06)	0.86 (0.06)	0.57 (0.34)
$\alpha1 + \beta_1$	0.98	0.97	0.95	0.63
Δ Speculator	0.0035 (0.0043)	0.0005 (0.0029)		
Δswap Dealer			0.0021 (0.0014)	-0.0099 (0.0154)
Δ Money Manager				

			-0.0004 (0.0017)	0.0019 (0.0013)
Δ Other Reportable			0.0018 (0.0012)	0.0022 (0.0061)
Δ Non-Reportable			-0.0003 (0.0016)	0.0099 (0.0107)
	Brent Period 2			
	Speculators Long	Speculators Short	COT Long	COT Short
α0	0.00001 (0.00001)	0.00004 (0.00003)	0.00002 (0.00001)	0.0011 (0.0009)
α_1	0.08 (0.03)	0.16 (0.06)	0.09 (0.03)	0.01 (0.04)
β_1	0.91 (0.02)	0.82 (0.05)	0.89 (0.03)	0.61 (0.17)
$\alpha 1 + \beta_1$	0.99	0.98	0.98	0.62
Δ Speculator	-0.0015 (0.0018)	0.0030 (0.0024)		
Δswap Dealer			0.0002 (0.0009)	0.0066 (0.0076)
Δ Money Manager			-0.0028 (0.0009)	0.0020 (0.0018)
Δ Other Reportable			0.00009 (0.0014)	-0.0011 (0.0016)
Δ Non-Reportable			0.0027 (0.0012)	0.0156 (0.0093)

	WTI Entire Period			
	Speculators Long	Speculators Short	COT Long	COT Short
α0	0.00004 (0.00003)	0.00006 (0.00003)	0.00005 (0.00002)	0.0021 (0.0023)
α_1	0.12 (0.03)	0.14 (0.04)	0.1 (0.03)	0.04 (0.06)
β_1	0.86 (0.03)	0.84 (0.04)	0.88 (0.03)	0.59 (0.26)
$\alpha 1 + \beta_1$	0.98	0.98	0.98	0.63
Δ Speculator	0.0002 (0.0022)	0.0017 (0.0019)		

Δswap Dealer			0.0015 (0.0008)	-0.0035 (0.0100)
Δ Money Manager			-0.0025 (0.0009)	0.000421 (0.0018)
Δ Other Reportable			0.0013 (0.0011)	0.0006 (0.0042)
Δ Non-Reportable			0.0014 (0.0011)	0.0110 (0.0096)
	WTI period 1			
	Speculators Long	Speculators Short	COT Long	COT Short
α0	0.00017 (0.00010)	0.00017 (0.00010)	0.00009 (0.00006)	0.0018 (0.0015)
α_1	0.17 (0.07)	0.17 (0.08)	0.08 (0.04)	0.50 (0.24)
β_1	0.76 (0.08)	0.77 (0.09)	0.86 (0.05)	0.54 (0.18)
$\alpha 1 + \beta_1$	0.93	0.94	0.94	1.04
Δ Speculator	0.0038 (0.0063)	0.00025 (0.00399)		
Δswap Dealer			0.0021 (0.0010)	-0.0064 (0.0102)
Δ Money Manager			-0.0024 (0.0013)	0.0067 (0.0049)
Δ Other Reportable			0.0029 (0.00005)	0.0061 (0.0055)
Δ Non-Reportable			0.0001 (0.0012)	0.0070 (0.0069)
	WTI period 2			
	Speculators Long	Speculators Short	COT Long	COT Short
α0	0.00001 (0.00001)	0.000004 (0.000013)	0,00002 (0.00002)	0.00002 (0.00002)
α_1	0.07 (0.03)	0.07 (0.03)	0.06 (0.03)	0.04 (0.03)
β_1	0.92 (0.02)	0.93 (0.03)	0.92 (0.03)	0.94 (0.04)
$\alpha 1 + \beta_1$	0.99	1.0	0.98	0.98
Δ Speculator				

	-0.0027 (0.0019)	-0.0019 (0.0017)		
Δswap Dealer			0.0011 (0.0009)	-0.0011 (0.0012)
Δ Money Manager			-0.0024 (0.0009)	0.0004 (0.0005)
Δ Other Reportable			-0.0018 (0.0016)	0.0005 (0.0008)
Δ Non-Reportable			0.0019 (0.0015)	0.0012 (0.0014)

OVX parameters, standard error in parenthesis

	OVX			
	Speculator Long	Speculator Short	COT Long	COT Short
WTI 3rd	-0.81 (0.07)	-0.81 (0.07)	-0.83 (0.08)	-0.8 (0.08)
Δspeculators	0.32 (0.15)	0.27 (0.11)		
Δswap Dealers			0.22 (0.08)	-0.10 (0.10)
ΔMoney Mangers			-0.02 (0.08)	0.10 (0.02)
Δ Other Reportable			0.12 (0.07)	0.06 (0.04)
ΔNon-Reportable			0.06 (0.04)	0.03 (0.04)
	OVX Period 1			
	Speculator Long	Speculator Short	COT Long	COT Short
WTI 3rd	0.42 (0.17)	-0.67 (0.10)	-0.66 (0.11)	-0.64 (0.11)
Δspeculators	0.24 (0.18)	0.17 (0.13)		

∆swap Dealers			0.23 (0.11)	-0.17 (0.11)
∆Money Mangers			-0.05 (0.10)	0.10 (0.04)
∆ Other Reportable			0.15 (0.08)	0.08 (0.06)
∆Non-Reportable			0.03 (0.04)	0.04 (0.04)
	OVX Period 2			
	Speculator Long	Speculator Short	COT Long	COT Short
WTI 3rd	-1.03 (0.13)	0.12 (0.17)	-1.03 (0.13)	-1.017 (0.12)
∆speculators	0.43 (0.24)	0.44 (0.18)		
∆swap Dealers			0.23 (0.10)	0.07 (0.19)
∆Money Mangers			0.05 (0.14)	0.11 (0.04)
∆ Other Reportable			0.01 (0.14)	0.06 (0.06)
∆Non-Reportable			0.18 (0.1)	0.03 (0.09)

GARCH parameters for OPEC analysis, standard errors in parenthesis.

	5-days		10-days		30-days	
	WTI	Brent	WTI	Brent	WTI	Brent
	UP events					
CAV 1						
α0	0.00018 (0.000017)	0.00016 (0.000016)	0.00002 (0.00002)	0.00002 (0.00002)	0.00002 (0.00002)	0.00002 (0.00002)
α1	0.714 (0.037)	0.059 (0.033)	0.064 (0.036)	0.055 (0.036)	0.070 (0.037)	0.061 (0.034)
β	0.856 (0.097)	0.875 (0.091)	0.859 (0.099)	0.874 (0.099)	0.834 (0.102)	0.856 (0.099)
CAV 2						
α0						

	0.000016 (0.000014)	0.000014 (0.000015)	0.00002 (0.00001)	0.00002 (0.00002)	0.00002 (0.00002)	0.00002 (0.00002)
α1	0.068 (0.035)	0.056 (0.031)	0.070 (0.035)	0.061 (0.033)	0.062 (0.034)	0.057 (0.032)
β	0.866 (0.085)	0.885 (0.083)	0.860 (0.084)	0.868 (0.086)	0.858 (0.093)	0.867 (0.090)
	Down Events					
CAV 1						
α0	-0.0000027 (0.000001)	-0.0000016 (0.0000008)	0.00002 (0.000001)	0.000004 (0.000003)	-0.000003 (0.000004)	-0.000002 (0.000003)
α1	'-0.016 (0.014)	-0.016 (0.016)	-0.025 (0.014)	0.045 (0.020)	-0.012 (0.020)	-0.011 (0.021)
β	1.029 (0.017)	1.027 (0.016)	1.026 (0.011)	0.952 (0.023)	1.021 (0.032)	1.020 (0.030)
CAV 2						
α0	0.0000002 (0.000002)	-0.0000009 (0.000001)	-0.000001 (0.000001)	-0.000001 (0.000001)	-0.000003 (0.000001)	-0.000004 (0.000001)
α1	0.034 (0.016)	0.025 (0.014)	0.027 (0.014)	0.022 (0.013)	-0.013 (0.011)	-0.005 (0.011)
β	0.975 (0.016)	0.985 (0.013)	0.984 (0.013)	0.989 (0.012)	1.027 (0.013)	1.022 (0.012)
CAV 3						
α0	0.000046 (0.00003)	0.00006 (0.00004)	0.00004 (0.00003)	0.00006 (0.00004)	0.00005 (0.00003)	0.00007 (0.00004)
α1	0.101 (0.047)	0.114 (0.056)	0.104 (0.047)	0.118 (0.058)	0.122 (0.053)	0.130 (0.060)
β	0.835 (0.074)	0.795 (0.096)	0.836 (0.075)	0.791 (0.102)	0.809 (0.080)	0.769 (0.103)
	No Change					
CAV 1						
α0	0.0000154 (0.00001)	0.000015 (0.00002)	0.000116 (0.00001)	0.00002 (0.00002)	-0.000002 (0.000002)	-0.000001 (0.000003)
α1	0.061 (0.031)	0.047 (0.028)	0.062 (0.031)	0.062 (0.029)	0.028 (0.014)	0.045 (0.019)
β	0.882 (0.072)	0.898 (0.075)	0.880 (0.072)	0.879 (0.079)	0.983 (0.014)	0.967 (0.021)
CAV 2						
α0						

	0.00000004 (0.0000008)	-0.0000012 (0.0000008)	0.000002 (0.000001)	0.0000009 (0.000001)	-0.0000002 (0.0000007)	-0.000001 (0.000001)
α1	-0.017 (0.016)	-0.013 (0.017)	-0.022 (0.016)	-0.020 (0.018)	-0.018 (0.018)	-0.014 (0.018)
β	1.023 (0.015)	1.022 (0.017)	1.023 (0.013)	1.023 (0.016)	1.022 (0.019)	1.022 (0.019)
CAV 3						
α0	0.000009 (0.000007)	0.00072 (0.0003)	0.000009 (0.000008)	0.000007 (0.000006)	0 (N/A)	0 (N/A)
α1	0.064 (0.025)	-0.091 (0.036)	0.067 (0.027)	0.061 (0.024)	0 (N/A)	0 (N/A)
β	0.929 (0.028)	0.574 (0.22)	0.926 (0.029)	0.934 (0.027)	0 (N/A)	0 (N/A)
CAV 4						
α0	0.000014 (0.00001)	0.000014 (0.000009)	0.00002 (0.00001)	0.00001 (0.00001)	0.00002 (0.00001)	0.00001 (0.000009)
α1	0.067 (0.028)	0.062 (0.026)	0.086 (0.031)	0.075 (0.029)	0.073 (0.029)	0.064 (0.026)
β	0.921 (0.031)	0.926 (0.030)	0.899 (0.035)	0.912 (0.034)	0.912 (0.032)	0.924 (0.030)
CAV 5						
α0	0.0000079 (0.00001)	0.0000087 (0.00001)	0.000009 (0.00001)	0.000008 (0.000009)	0.00001 (0.00001)	0.00001 (0.00001)
α1	0.073 (0.026)	0.067 (0.0025)	0.069 (0.027)	0.063 (0.024)	0.067 (0.028)	0.061 (0.026)
β	0.918 (0.029)	0.923 (0.029)	0.923 (0.030)	0.929 (0.028)	0.921 (0.032)	0.927 (0.031)
CAV 6						
α0	0.0000053 (0.000004)	0.0000029 (0.000003)	0.000002 (0.000003)	-0.00003 (0.000002)	0.000002 (0.000003)	0.000001 (0.000002)
α1	0.056 (0.025)	0.024 (0.016)	0.040 (0.020)	-0.015 (0.007)	0.033 (0.017)	0.018 (0.012)
β	0.931 (0.027)	0.966 (0.019)	0.951 (0,021)	1.015 (0.011)	0.959 (0.019)	0.974 (0.013)
CAV 7						
α0	0.000059 (0.00003)	0.000073 (0.00005)	0.00007 (0.00003)	0.00008 (0.00008)	0.00006 (0.00003)	0.00009 (0.00005)
α1						

	0.181 (0.076)	0.125 (0.073)	0.183 (0.079)	0.129 (0.075)	0.176 (0.077)	0.188 (0.087)
β	0.663 (0.121)	0.629 (0.0218)	0.640 (0.134)	0.615 (0.238)	0.674 (0.123)	0.561 (0.197)
CAV 8						
α0	0.000337 (0.0004)	0.00005 (0.00003)	0.00005 (0.00002)	0.00005 (0.00003)	0.00004 (0.00002)	0.00004 (0.00003)
α1	0.150 (0.203)	0.138 (0.071)	0.166 (0.069)	0.128 (0.067)	0.164 (0.066)	0.145 (0.070)
β	0.600 (0.503)	0.68 (0.158)	0.708 (0.111)	0.704 (0.153)	0.730 (0.102)	0.699 (0.140)
CAV 9						
α0	0.000081 (0.00004)	0.000029 (0.00002)	0.00008 (0.00004)	0.00003 (0.00002)	0.00007 (0.00003)	0.00003 (0.00002)
α1	0.235 (0.085)	0.107 (0.052)	0.231 (0.084)	0.100 (0.050)	0.199 (0.080)	0.112 (0.055)
β	0.533 (0.014)	0.782 (0.109)	0.538 (0.140)	0.789 (0.111)	0.638 (0.127)	0.790 (0.105)
CAV 10						
α0	0.00012 (0.00003)	0.000013 (0.00001)	0.00022 (0.0003)	0.00001 (0.000008)	0.00011 (0.00004)	0.000008 (0.000007)
α1	0.336 (0.104)	0.076 (0.040)	0.150 (0.180)	0.064 (0.035)	0.314 (0.098)	0.063 (0.033)
β	0.159 (0.141)	0.847 (0.084)	0.600 (0.530)	0.876 (0.070)	0.220 (0.156)	0.889 (0.061)
CAV 11						
α0	0.0001 (0.00003)	0.0000073 (0.000005)	0.0001 (0.00003)	0.00002 (0.00001)	0.0001 (0.00003)	0.00005 (0.00002)
α1	0.254 (0.089)	0.071 (0.036)	0.256 (0.090)	0.118 (0.054)	0.305 (0.099)	0.229 (0.093)
β	0.228 (0.167)	0.880 (0.059)	0.239 (0.0166)	0.771 (0.102)	0.187 (0.149)	0.486 (0.186)
CAV 12						
α0	0.000001 (0.000001)	0.000064 (0.00002)	0.000002 (0.000001)	0.00005 (0.00003)	0.00008 (0.00006)	0.00006 (0.00003)
α1	0.021 (0.014)	0.240 (0.117)	0.021 (0.016)	0.223 (0.116)	0.096 (0.070)	0.199 (0.0112)
β						

	0.970 (0.020)	0.106 (0.286)	0.960 (0.019)	0.261 (0.309)	0.207 (0.538)	0.212 (0.322)
CAV 13						
α0	0.000003 (0.000003)	0.000069 (0.00003)	0.00005 (0.00006)	0.00006 (0.00003)	0.0000009 (0.000001)	0.00006 (0.00003)
α1	0.040 (0.024)	0.226 (0.115)	0.013 (0.050)	0.195 (0.113)	0.029 (0.017)	0.217 (0.114)
β	0.937 (0.040)	0.092 (0.279)	0.550 (0.584)	0.203 (0.323)	0.964 (0.023)	0.172 (0.333)
CAV 14						
α0	0.00005 (0.00003)	0.00006 (0.00004)	-0.0000002 (0.000001)	-0.0000005 (0.0000009)	0.0000002 (0.000001)	0.000000005 (0.000001)
α1	0.101 (0.047)	0.115 (0.056)	0.061 (0.023)	0.064 (0.024)	0.057 (0.023)	0.062 (0.025)
β	0.835 (0.074)	0.795 (0.096)	0.950 (0.023)	0.948 (0.023)	0.955 (0.026)	0.949 (0.026)
CAV 15						
α0	0.000044 (0.00003)	0.000059 (0.00004)	0.0004 (0.00003)	0.00006 (0.00004)	0.00004 (0.00003)	0.00006 (0.00004)
α1	0.110 (0.048)	0.113 (0.055)	0.109 (0.048)	0.114 (0.056)	0.113 (0.049)	0.113 (0.055)
β	0.829 (0.075)	0.800 (0.096)	0.833 (0.074)	0.800 (0.097)	0.829 (0.075)	0.801 (0.098)
CAV 16						
α0	0.000018 (0.00001)	0.000026 (0.00002)	0.00002 (0.00001)	0.00002 (0.00002)	0.000014 (0.00001)	0.00002 (0.00002)
α1	0.113 (0.048)	0.138 (0.057)	0.115 (0.049)	0.136 (0.056)	0.109 (0.044)	0.128 (0.050)
β	0.858 (0.062)	0.822 (0.073)	0.855 (0.064)	0.825 (0.072)	0.869 (0.056)	0.840 (0.064)
β	0.858	0.822	0.855	0.825	0.869	0.840

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