MASTER´S THESIS

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"How does the intraday and overnight return, and volatility of Norwegian indexes and stocks behave?"

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Abstract

In this thesis I decompose the total (close to close) return into intraday and overnight returns on two indexes and two stocks on Oslo Stock Exchange over the period 2013 to 2019. By analyzing the indexes and stocks individually I find that overnight returns play a much larger part in the total returns of single stocks than that of the total return of the indexes I find a near zero correlation of the intraday and overnight returns on stocks. Further I find the most appropriate ARIMA, ARCH and GARCH models for modeling the behavior of the indexes and stocks and note that they behave differently, both the overnight and intraday for the single indexes and stocks, but also when comparing them. Lastly, I look for hidden Markov model behavior in the indexes and stocks and find that during calm periods the overnight return for the stocks outperform the intraday both on return and standard deviation.

Preface

This paper is written as the final assignment of my MSc in Finance at Nord University. Over the period of doing this thesis I have used the knowledge and experience I have gained through my studies, especially at Nord University.

The motivation for the problem is a personal interest in financial market and its behavior. Having a more extensive knowledge about financial market behavior is of great interest and could be beneficial in the future.

When choosing the problem I wanted a challenge which could intrigue me on a personal level as well as suit my preexisting skills in quantitative work. The thesis required a large amount of data processing which was aided using R, and to a smaller extent Microsoft Excel. During my studies at Nord University I have learned to use R, although not as well as I wish I could. This has given me some extra challenges when working on the thesis. Fortunately, R is a widely used program which has given me the opportunity to find help from others online.

I would like to extend a large thank you to my supervisors Oleg Nenadic and Irena Kustec for insightful input and aid during the period of the thesis.

Nord Universitet, 02.06.2020

Vegard Sørensen

Vegard Sørensen

Sammendrag

I denne oppgaven dekompnerer jeg den totale avkastningen på Oslo Børs til intradag- og overnattenavkastning på to indekser og to aksjer over perioden 2013 til 2019. Analysen av indeksene og aksjene individuelt viser at overnattenavkastning har en stor vekt på totalavkastningen til aksjene, i motsetning til intradagavkastningen. For indeksen derimot er det intradagavkastningen som spiller desidert størst rolle. Jeg finner korrelasjonen til intradag og overnatten til å være tilnærmet lik null for aksjene. Videre finner jeg de ARIMA, ARCH og GARCH modeller som passer best til å modellere avkastningenes bevegelse og noterer at det er stor forskjell mellom hver enkelt indeks og aksjer, i tillegg til at det er forskjell på intradag og overnatten. Til slutt ser jeg etter hidden Markov model oppførsel for indeksene og aksjene og finner at under rolige perioder er avkastningen for overnatten bedre enn intradag, i tillegg til at standardavviket er lavere.

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1. Introduction

The advancements of technology over the last decades have made important information easily accessible for the whole world. In addition to this, the possibility to make financial transactions worldwide has become easier, cheaper, and quicker than ever. This has also improved the stock markets possibilities to react rapidly. Since the development of the Efficient Market Hypothesis (EMH) it was widely accepted that security prices should reflect all information. Securities should have the ability to integrate news into the price without delay. During the last decades there have, however, been a multitude of what is called anomalies that are inconsistent with the EMH, i.e patterns of return which contradict the behavior of an efficient market. Some examples are: The January Effect, The Weekend Effect, The Day of the Week Effect and The Holiday Effect.

In more recent studies there has been presented evidence pointing out an anomaly in the relationship between returns during trading hours and non-trading hours. When the market closes the price changes are not continuous, which causes new information not to be included in the stock price. This difference in information at the prior day's closure and the next day's opening hours has implications for the stock prices.

The purpose of this paper is to look at and model the attributes of the intraday and overnight returns and volatility on the Norwegian stock market. The Norwegian stock market is a small stock exchange, which could impact the behavior of the stocks. The analysis is accomplished using ARIMA, ARCH/GARCH models on daily stock prices and searching for Markov processes. These models help reveal what attributes the returns and volatility display. Seeing as an increase in volatility is an increase in risk, getting a better understanding of the market behavior can help investors make better investment decisions.

Working title

"How does the intraday and overnight return, and volatility of Norwegian indexes and stocks behave?"

2. Literature review

Some of the earliest work done on researching and modeling patterns in non-trading hours is the work done by McInish, Ord and Wood (1985). They used high frequency data, minute-by-minute returns to examine the characteristics of returns and trades. Here they find that the return and standard deviations are higher at the start and end of the trading day. When removing these start and end of day observations they observed a strong reduction in autocorrelation of the time series. This indicates that there is a connection in the way a stock moves right after and before non-trading hours.

Further research on the topic, done by French and Roll (1986) find that stock returns are more volatile during the normal trading hours than non-trading hours of the weekend. Something which they note as strange, and they cite: "Asset returns display a puzzling difference in volatility between exchange trading hours and non-trading hours." (French & Roll, 1986, p. 23) They find that the open-to-close variance of returns in an average trading day to be six times higher than that of the close-to-open variance over the weekend. Even though the weekend lasts eleven times longer. This indicates that the volatility of returns is much higher during opening hours, than during the non-trading period of the weekend. French and Roll argue that the reason for this higher volatility during the week could be due to the difference in information flow.

Hong and Wang (2000) studied how market closures affect investor's trading policies and the corresponding return-generating processes and find similar characteristics with previous empirical findings. A number of these discoveries relate to overnight and intraday returns. Firstly, they note that there exists a U-shaped pattern for the mean and volatility of returns over trading periods. Secondly, they note that the activity around the opening and closure of the market are higher than the rest of the time. Thirdly, the returns when the market is open are more volatile than when it is closed. Fourthly, the open-to-open returns are more volatile than that of the close-to-close returns. Lastly the returns are higher over trading periods than non-trading periods. Longstaff (1995)however presented a theoretical model where he predicted high returns over non-trading hours, due to the illiquidity investors would face by holding a stock overnight. This would be rewarded with a premium and therefore the overnight return would yield a positive return.

There are different studies which discuss the role of returns during the night and which impact it has on the overall returns. One of the first studies empirically documenting that overnight returns outperform the intraday return is done by Cliff, Cooper and Gulen (2008). In their study they find that the excess return on the S&P 500 from 1993 to 2006 is due to the overnight return, while the intraday returns over these years are close to zero, and sometimes negative. They also look at securities listed on NASDAQ, NYSE, AMEX Inter@ctive Week Internet Index and Chicago Mercantile Exchange, these also have strong positive returns while the market is closed. Further they use detailed tick data to divide the intraday return into intervals during the time the market is open. Here they find that the largest negative return stem from the "AM-hour" which is from 08:30 to 09:30, the opening hour of the market. Further out in the day the time intervals they created would improve and the performance of their securities would be at the peak near the closing of the market. The overnight returns would outperform the intraday across weekdays, as well as most months and years, and this would hold not only for indexes, but also other securities such as ETFs and E-Mini Futures.

Another study by Clark and Kelly (2011) looked at the intraday and overnight returns of different US ETFs, which yield similar results to previous studies. "Yet ultimately, the fact that our study and Cliff et all (2008) document similar results while using different methodologies suggest that our rather surprising findings are real." (Clark & Kelly, 2011). Using these returns they estimate Sharpe ratios, they found that the overnight Sharpe ratios constantly exceeded the intraday Sharpe ratios. This indicates that the premium one gets by taking on risk is higher overnight than during the day. In addition to this they found that the overnight return was positive when the intraday return was negative. One argument explaining this they presented could be the presence of day traders. According to Clark and Kelly (2011), a semiprofessional day trader who usually perform more than 25 transactions a day accounts for a large amount of the trades done on the US stock exchanges. The amount of trades done by these day trades causes a liquidation effect and not wanting to hold stocks over a non-trading period, unable to settle their positions would cause the day trades to buy in the morning and sell at close. Prices increase by the buy and decrease by the sell patterns and cause positive overnight returns.

The study done by Cai and Qiu (2013) looks at the presence of overnight and intraday returns in 31 international stock markets. In 20 of these countries the same phenomenon exists, these are a mixture of developed and emerging markets. The strongest overnight returns are documented on exchanges which allow short selling. They cite: “Our findings suggest that investors are generally better off buying at close but selling at opening, especially so on those markets that have high level of information asymmetry and short selling is not commonly practiced.” (Qiu & Cai, 2013, p. 1). This means that an investor should have a long position overnight and short position during the day. After this they find the volatilities to differ, with the overnight return to be less volatile than intraday return and conclude that the superior overnight return is not justified by a risk-return trade off. Low volatility overnight means investors are not compensated with a higher return due to taking on a greater risk during these non-trading hours.

Branch and Ma (2012) researched the relationship between overnight and the ensuing intraday returns. During the years 1994 to 1999 and 2000 to 2005 they found negative correlation between the returns on NYSE, AMEX and NASDAQ. Further analysis revealed the relation to hold with the lagged intraday and overnight returns. In addition to this the overnight returns are discovered to be positively correlated with the lagged overnight and negatively correlated with the lagged intraday. After this they divide the markets into different sizes and find that the correlation is strongest in the low cap stocks. To use these finds for prediction they started a regression analysis where they regress the intraday on the independent variables overnight, lagged overnight and lagged intraday. Results show that the overnight could predict the next intraday movements, which also held for lagged variables. The movement in the overnight and lagged overnight would predict the ensuing intraday to move in the opposite direction, and the lagged intraday would predict the ensuing intraday to move in the same direction. These finds go against the weak form of efficient market hypothesis and the theory of random walk. Branch and Ma (2012) present three explanations for the behavior of the overnight and intraday returns. First, they explain that the market makers push the price up during the auction hours when opening their assigned stocks, which would result in a positive overnight return. Second, they talk about the bid-ask bounce where a stock closing at bid after a non-trading period, to then open at ask would result in a positive overnight. Even with no movement in the stock during the non-trading period. Third, is the specialists who put their funds at risk. Specialist are interested in allowing their stocks to open away from the previous close.

3. Theoretical framework

3.1 History of financial volatility

Volatility can be described as uncertainty or fluctuations in financial assets and may prove difficult to calculate. Financial volatility is something which has been researched for a long time and it almost seems like the more knowledge we get the more questions we get. What we do know however is that volatility has an important role in finance due to its part in valuation, profitability analysis and risk assertion. Constant volatility was assumed for a long period, even in famous research such as Mertons (1969) portfolio diversification theory and Black & Scholes (1973) option pricing theory. This was because constant volatility was not affected by time.

To improve the results of volatility, research a model which could take in to account a change in volatility over time was highly sought after. Robert Engle (1982) introduced such a model which was called the autoregressive conditional heteroskedasticity, also known as ARCH, which became the first popularized model to consider time varying volatility. ARCH filled a void in calculating financial volatility, but it turned out it was difficult to use. This led to an extension of the ARCH by Tim Bollerslev (1986) called generalized autoregressive conditional heteroskedasticity, also known as GARCH, which was a more versatile model for use on time series. Both models will be explained in some more detail.

3.2 Autoregressive conditional heteroskedasticity – ARCH

The ARCH model was first introduced by Robert Engle (1982). In traditional econometric models the conditional variance of the dependent variable does not depend on its previous value, it was assumed to be constant. To improve on these traditional models Engle (1982) introduced ARCH, a model which described the variance as a linear function of the previous squared error terms where there is a difference between conditional and unconditional variance. ARCH allows the conditional variance to change over time as this function of previous squared errors.

The ARCH model is described to have these properties, where ε_t is a random variable, which has a mean and an expected value determined by F_{t-1}. First, $E\{\varepsilon_t|F_{t-1}\} = 0$, and second, the conditional variance $h_t = E\{\varepsilon_t^2|F_{t-1}\}$ (Andersen, Torben, Davis, Richard, Kreiß, & Mikosch, 2009).

An ARCH(q) model can be written as (Chen, 2013):

$$r_t = \mu_t + \varepsilon_t$$

$$\varepsilon_t = z_t\sqrt{h_t}$$

$$z_t \xrightarrow{i.i.d} N(0,1)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 = \alpha_0 + \alpha(L)\varepsilon_{t-1}^2$$

Where r_t is the regression of returns, and h_t is the variance in period t.

The use of ARCH models in finance is highly relevant and have yielded good results, especially in terms of asset pricing models and dynamic hedging strategies (Bollerslev, Chou, & Kroner, 1992).

3.3 Generalized autoregressive conditional heteroskedasticity – GARCH

GARCH was introduced as an extension to the ARCH model introduced by Robert Engle (1982) by Tim Bollerslev (1986). The goal was to be able to implement a longer memory and a more flexible lag structure instead of the fixed structure which is used in ARCH.

The GARCH(p,q) process is given by (Bollerslev, 1986):

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

$$\mathrm{h_t} = \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{t-1} = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t$$

When p = 0 the GARCH(p,q) process is equal to the ARCH(q) process, and when p = q = 0 ε_t is simply white noise. The main difference between the models is that GARCH allows for lagged conditional variances to enter the function. The simplest model, which often yields best results, is the GARCH(1,1) model.

3.4 Hidden Markov models

HMM is a statistical Markov model in which the distribution that generates an observation depends on both the state of an underlying and unobserved Markov process. In the HMM, the state is not directly visible, but we can observe the output, which includes the effects of these hidden states. In other words, HMM helps model the most likely hidden sequence or the most likely model that produces the observed sequence.

Different market regimes should then be characterized by different means and standard deviation values which would mean they have different risk–return profiles. During a financial crisis, the stock market experiences a strong negative mean return, and the standard deviation, used as a proxy of risk, is large. During more stable phases, stock returns fluctuate around a constant mean, and the standard deviation of the index value is lower

4. Data collection

In this thesis I collect data over the period of June 2013 to June 2019. Daily data from 6 years gives me an opportunity to observe the behavior of returns during the day and night over a longer period, in addition to different market conditions. These six years include the oil price shock of 2014 and onwards which has an impact on the Norwegian market due to the large and important role oil has had in the economy.

I have chosen two indexes and two stocks to look at in this thesis. The two indexes are the OBX Total Return Index (OBX) and the Oslo Børs Benchmark Index (OSEBX). OBX includes the 25 most liquid companies on the main index of the Oslo Stock Exchange based on six months turnover ratings. The companies on the index are rotated twice a year. The OSEBX in an index which comprises the most traded shares listed on Oslo Stock Exchange. It is semiannually revised, with the changes taking place on 1. December and 1. June.

The two stocks I have chosen are the largest stocks within the sectors “financials” and “materials”. These stocks are DNB and Yara International. DNB is Norway's largest financial services group and offers financial products and services, including loans and deposits, mutual funds and asset management, life insurance and pension savings, payment and financing services, real estate broking and services related to the money and capital markets. Yara is a Norwegian chemical company with its largest business are being the production of nitrogen fertilizer. Yara delivers solutions for sustainable agriculture and the environment.

I chose these stocks for a couple of reasons. Firstly, I chose stocks which has been on the Oslo Stock Exchange for a longer period. This causes my dataset to not be affected by listing effects. Kadlec and McConnell (1994) document abnormal behavior in returns of newly listed stocks, they perform substantially stronger after initial listing. Secondly, I wanted stocks which were highly liquid, to determine this I chose two stocks with a large market cap and a large number of daily trades.

The prices are collected from two databases. OBX is collected from TITLON which is a database with financial data from Oslo Stock Exchange available for universities in Norway. Due to some technical issues I was not able to collect the data on OSEBX, Yara and DNB from TITLON, they were therefore collected from investing.com. From these datasets I use the opening price, which represents the first possible trade of the day, and the closing price, which is the last trade of the day. The active trading days over this six-year period is 1507 days, which approximately calculates to 252 trading days a year.

I analyze the intraday and overnight returns in a multitude of ways. Starting of I do simpler tests to check for correlation and the structure using acf and pacf plots. Moving on to more sophisticated models starting with finding the best ARIMA models and further on analyzing which ARCH or GARCH processes fit the structure of the returns best. The last thing I do is check for Markov processes in the returns, which could help get a better understanding of how the returns behave and perform under different circumstances.

4.1 Computation of daily, overnight, and intraday returns

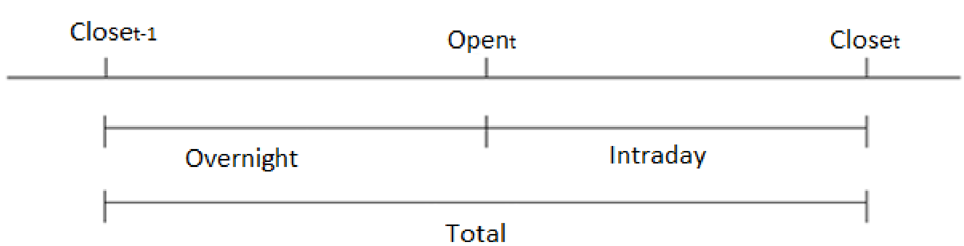

Figure 1: Visual representation of return decompositions

In figure 1 you can see how I decompose the total return in to overnight and intraday returns. Overnight return is defined as the difference between the previous close and current open. Intraday return is the difference between current open and current close. Total return is the difference between current close and previous close. These returns are calculated as logarithmic returns, using this method we can easily add up the intraday and overnight returns to get the total. The total returns can then be written as:

$$Total\ return_t = Overnight\ return_{t-1} + Intraday\ return_t$$

When doing the decomposition, I calculate the return as natural log returns times 100, which causes all my return numbers to be the daily percentage return, using the following formulas:

$$Overnight\ return = 100\ x \ln\left(\frac{Open_t}{Close_{t-1}}\right)$$

$$Intraday\ return = 100\ x \ln\left(\frac{Close_t}{Open_t}\right)$$

$$Total\ return = 100\ x \ln\left(\frac{Close_t}{Close_{t-1}}\right)$$

In table 1 the descriptive statistics of my collected data is summarized, here we can see some differences in the returns, especially from the individual stocks. The indexes have positive means for both the intraday and the overnight returns, whilst the stocks have negative intraday and positive overnight returns. The correlation between the returns for the stocks are also very low, and in the case of DNB it is not significant according to its t statistic.

	OBX		OSEBX		DNB		Yara	
	Intraday	Overnight	Intraday	Overnight	Intraday	Overnight	Intraday	Overnight
Observations	1506	1506	1506	1506	1506	1506	1506	1506
Mean	0.0407	0.0005	0.0389	0.0021	-0.0086	0.04881	-0.0059	0.04178
Standard deviation	1.0089	0.0511	0.9571	0.033	1.2284	0.8241	1.3633	0.9194
Min	-4.9692	-0.6062	-5.3235	-0.3016	-6.2926	-9.6247	-6.0938	-6.6399
Max	4.4335	0.4137	4.1755	0.5829	5.7994	5.6367	8.2708	6.5257
Correlation	0.2608		0.1877		0.0019		-0.0607	
T-stat for correlation	10.478		7.4104		0.0736		-2.3582	

Table 1: Descriptive statistics for selected indexes and stocks

5. Results

The result section of the paper is divided into three parts. The first part is connected to the descriptive statistics and creates a more detailed overview of the data and its attributes. I present the means, standard deviation, and correlation of the returns. The second part is about the ARIMA, ARCH and GARCH models, which better incorporates the nonlinear movements of the returns. Here I show which models fit the different returns best. The third part analyzes if there exists Markov processes on the returns, and where they exist which attributes these possess.

Due to the time-additive properties of logarithmic returns I do not lose any information during the decomposition of the total returns (Campbell, Lo, & MacKinlay, 1997). Therefore, I can write the string of returns, or total returns as:

$$\sum_{i=1}^{n} R_i = R_1 + R_2 + R_3 \ldots \ldots + R_n$$

It is important to note that these graphs of cumulative returns do not take into consideration the transaction costs, only the growth of returns.

5.1 Overview over returns

The eye test on the cumulative returns of the OBX and OSEBX in figure 2 and figure 3 reveal that they are very similar in structure, which is understandable seeing as all the 25 OBX stocks are included in the 67 OSEBX stocks. The intraday returns are accountable for close to all the returns on these indexes, which can be explained due to most speculation happening when the market is closed regards single stocks. The means for intraday returns and overnight returns on the OBX are 0.0458, and 0.0005, respectively. With a corresponding positive correlation of 0.2605, and the t statistic for the correlation being 10.465. For the OSEBX index the intraday and overnight return means are 0.0389 and 0.0021, respectively, with the low positive correlation being 0.1877, and t statistic for this correlation being 7.4104.

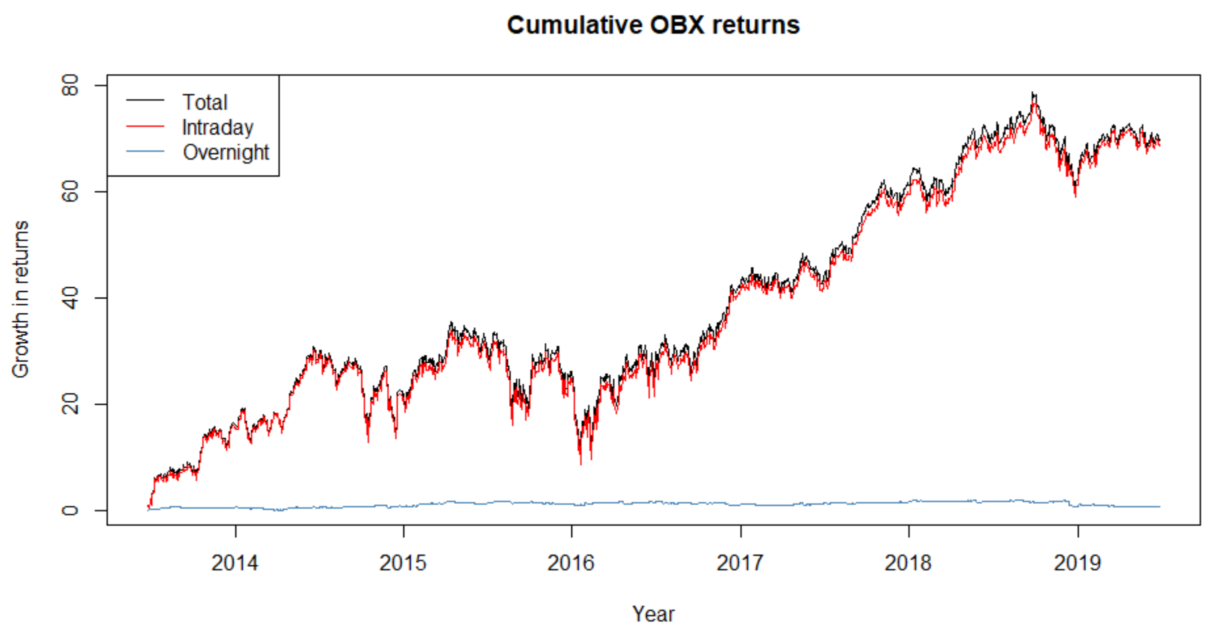

Figure 2: Cumulative OBX Returns

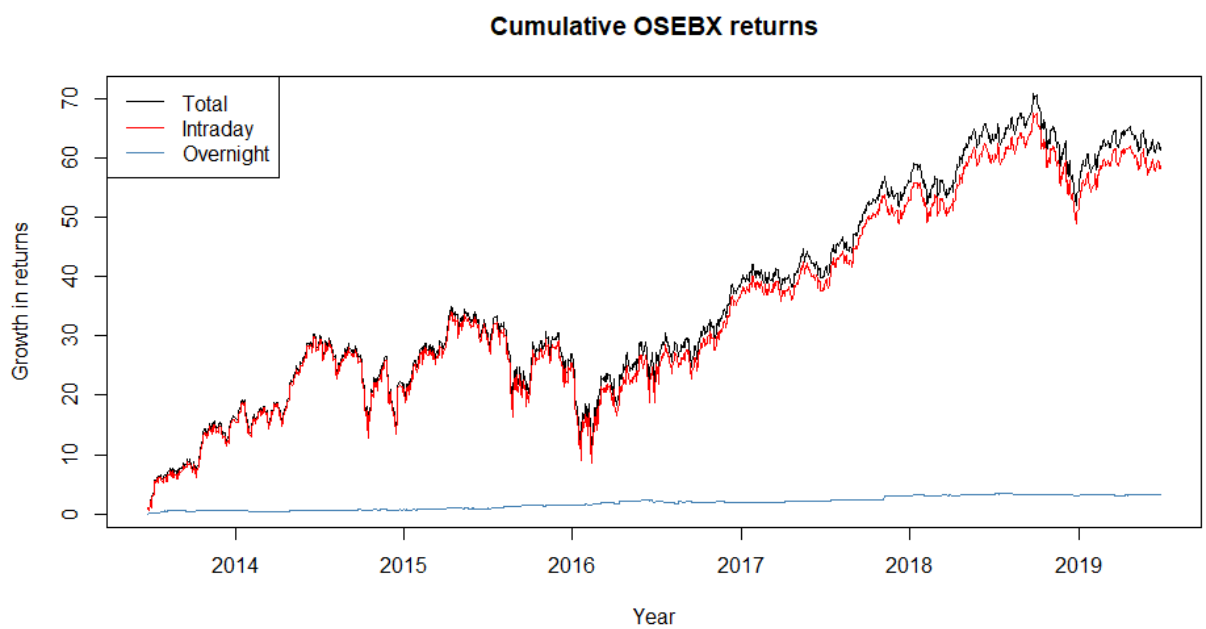

Figure 3: Cumulative OSEBX Returns

When looking at figure 4, the cumulative returns of Yara, one can see that the intraday and overnight returns has a significantly different structure compared to the indexes. A similar occurrence happens with the DNB stock which I will show later. This indicates that single stocks behave very differently when compared to larger indexes. Here we can see that the overnight returns, especially until the mid-2016, have a near constant growth. The intraday returns however have a slow decline over the same period, except for a steep increase in early 2015. This indicate that the overnight returns are the driving factor behind the total return of the Yara stock. When looking at the descriptive statistics from table 1 we can see that the mean intraday and overnight returns on the Yara stock are -0.0059 and 0.04178 respectively which is reflected in the cumulative return structures. The intraday and overnight returns are very weakly correlated, at -0.0607, but the t statistic for the correlation is significant.

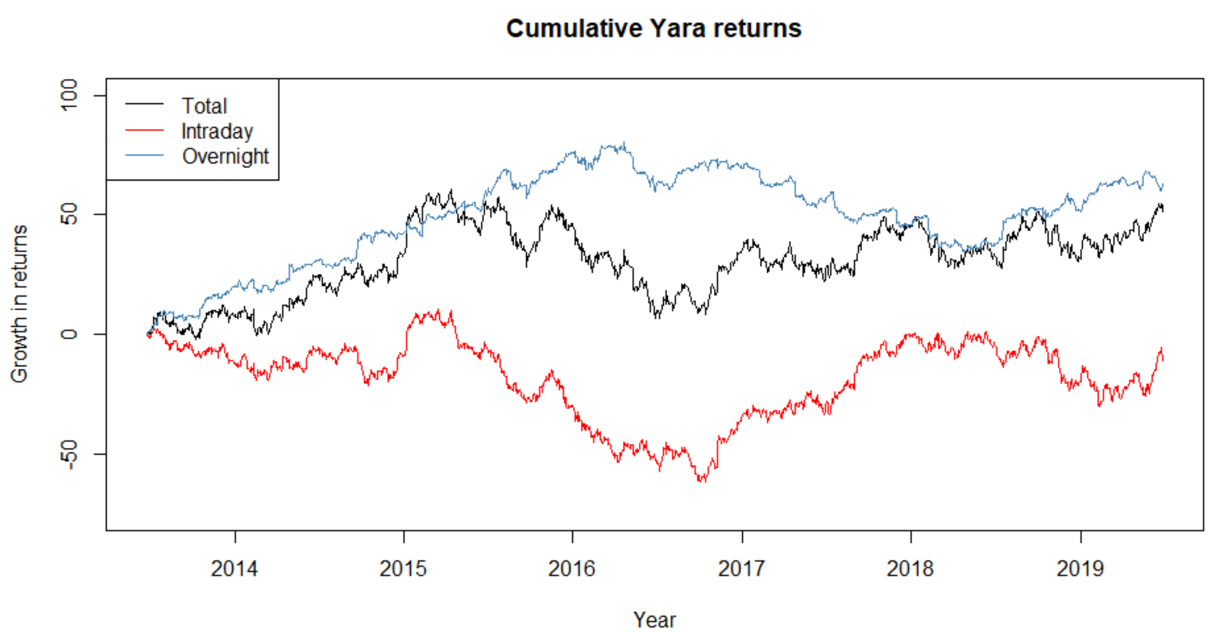

Figure 4: Cumulative Yara Returns

In figure 5 you see the structure of the cumulative DNB returns. Here we see a similar kind of structure to that of the Yara stock, where the overnight returns have a near constant growth. Intraday returns however vary, and over longer periods of time, from mid-2015 to mid-2016, experience a large decline. Such as the case was with Yara, the overnight returns seem to be the driving factor behind the total returns of the DNB stock. The mean intraday return is -0.0086, while the mean overnight return is 0.0488. When it comes to the correlation between the intraday and the overnight returns on DNB, we can see from table 1 that they have a very low positive correlation. This correlation is however not significant according to its calculated t statistic.

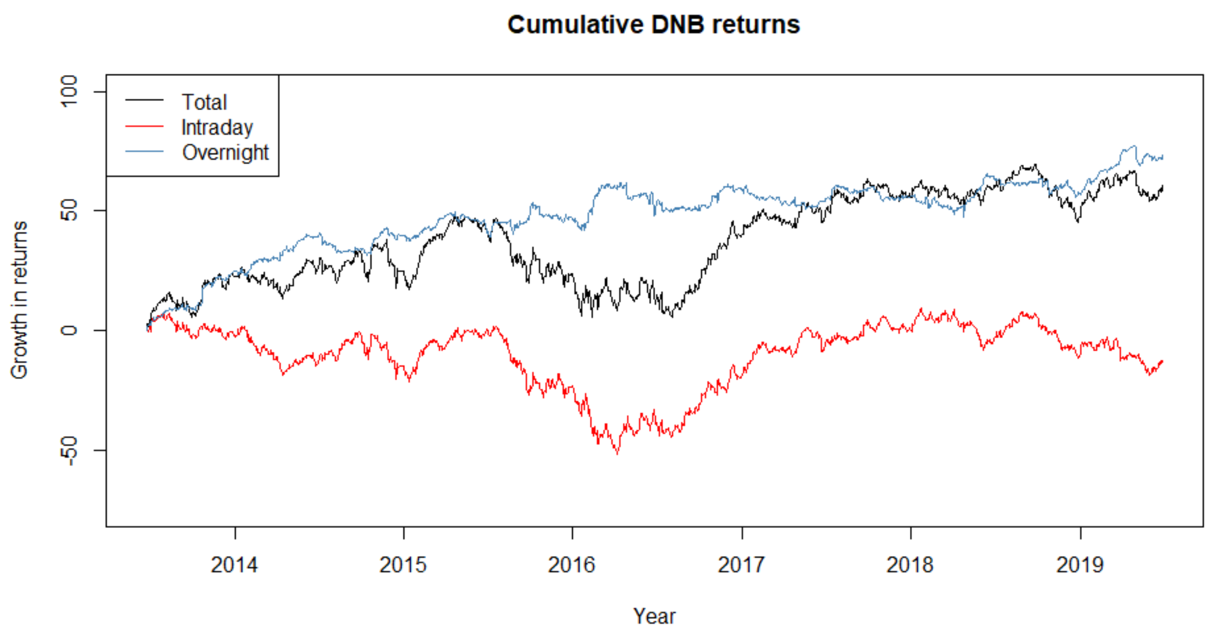

Figure 5: Cumulative DNB Returns

Both the Yara stock and the DNB stock have a period of negative returns around the beginning of 2016, lasting almost until 2017. These negative returns could be an outcome of the 2010s oil glut, where prices stooped, and in January of 2017 the price of oil was at the lowest it had been in 13 years.

According to Clark and Kelly (2011), who found that the Sharpe ratios of overnight returns constantly exceeded that of the intraday returns Sharpe ratio, the premium one gets by taking on risk is higher overnight than during the day. Volatility is a common measure of risk and is often represented by the standard deviations of returns. By using this logic, the overnight returns on Yara and DNB, which show a higher, and positive return, should have larger standard deviations. From table 1 however, we can see that for both stocks, the standard deviation of the overnight return is lower than the intraday return. The standard deviations for intraday and overnight returns on Yara is 1.3633, and 0.9194, respectively, and for DNB the standard deviations are 1.2284 and 0.8241 on the intraday and overnight returns. In figure 6 and figure 7, which is the log returns squared, we can see that the variation of intraday returns has a higher fluctuation than that of the overnight returns. For the two indexes, I have added the squared return figures in the appendix as figure 10 and figure 11, but due to the structure where intraday is by far the majority cause of the total returns, there is little to gain from comparing these variations. These results on Yara and DNB suggest that a higher overnight return is not necessarily associated with a higher risk during this market close. Evidence which contradicts both the theory of risk-return trade-off and Clark and Kelly's findings.

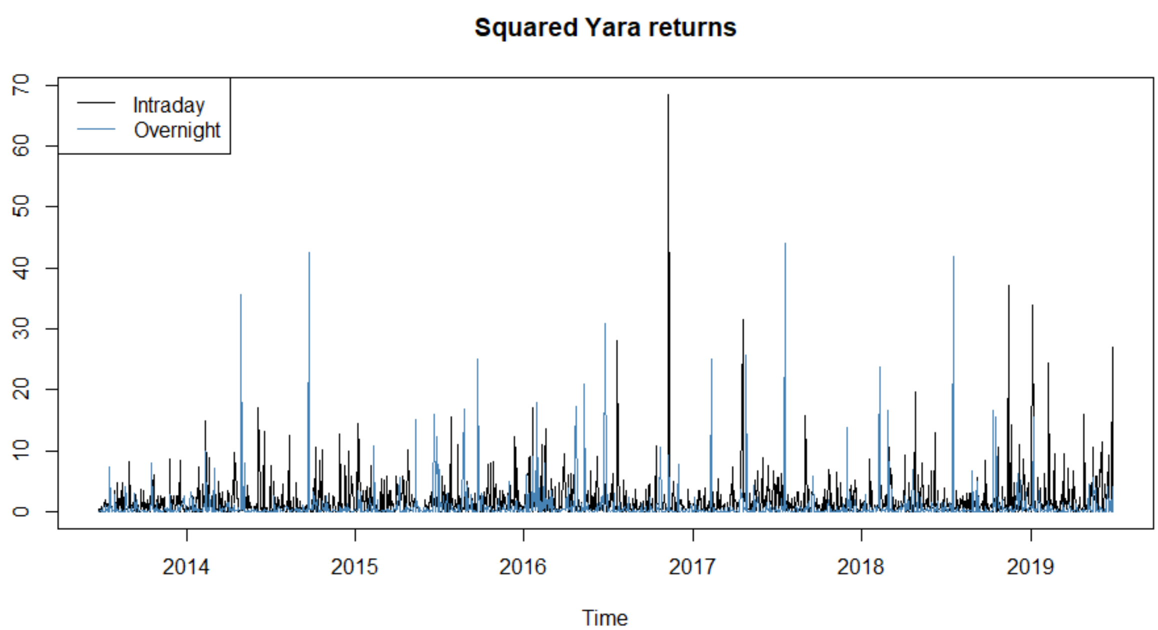

Figure 6: Squared Yara returns

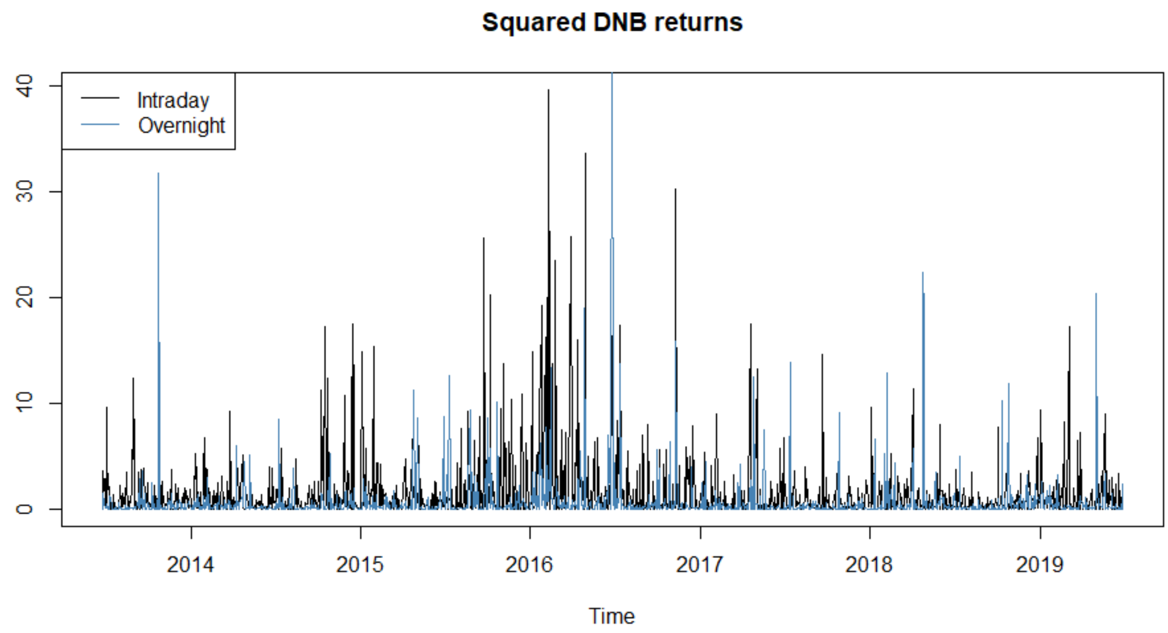

Figure 7: Squared DNB Returns

5.2 ARIMA, ARCH & GARCH

From the «eye test» and the simple descriptive statistics where we see low correlation, some significant others not, I move on to look at the behavior of returns and their volatilities. The goal being to see if there is a pattern in the movements which could possibly be beneficial in for example a trading strategy. Firstly, I use ARIMA, ARCH and GARCH models to look for structure. Then I move on to look for Markov processes in the returns by looking for hidden Markov models.

I started off looking at the autocorrelation plots (acf) and partial autocorrelation plots (pacf) to make sure the return data has stationarity. The easiest way to see this is to make sure these plots have the structure of a white noise, and you can see from figures 12-15 in the appendix how the acf and pacf plots look for the indexes and stocks. The augmented Dickey-Fuller test for unit roots performed on the return vectors reveal that no unit root exists. After making sure the returns have stationarity, I moved on to determining which ARIMA model fit the returns best. Using the function auto.arima in R I got the ARIMA models presented in table 2 as the best fit for each return, both intraday and overnight. The overnight return for Yara exhibited non stationarity, causing the function to express the best ARIMA function for the return to be ARIMA(5,1,0). The simplest way of transform the data, and causing it to have stationarity is by differencing it, which was done, and caused the best result to be ARIMA(5,0,0). Two of the overnight returns, namely OSEBX and Yara behave like the non-zero parameter says. OSEBX overnight return has the structure of a MA(2) model, whilst Yara overnight return has the structure of a AR(5) model. As we can see from table 2 the OBX and OSEBX have some similarities in their overnight and intraday returns, not when compared to each other, but when looking at them individually. Both the intraday and overnight for OBX has an AR(1) process, but deviate in the MA() process, whilst the OSEBX has a common MA(2) process, but differ its AR() process. For the individual stocks there is little similarities in the ARIMA model. Yara has an MA(0) process for both intraday and overnight, that is the only common denominator for the single stocks returns.

	Intraday	Overnight
OBX	ARIMA(1,0,1)	ARIMA(1,0,3)
OSEBX	ARIMA(2,0,2)	ARIMA(0,0,2)
Yara	ARIMA(0,0,0)	ARIMA(5,0,0)
DNB	ARIMA(2,0,2)	ARIMA(0,0,0)

Table 2: Best ARIMA models for the returns

To find out which ARCH or GARCH process fit the data best I used the Akaike information criterion (AIC) as the determining factor. AIC estimates the relative amount of information lost by model, which means the less information loss in a model, the better it is. I manually ran through all possibilities up to GARCH(3,3) for both indexes and stocks, the results for the best ARCH and GARCH models are presented in table 3. Where negative AICs occur, the largest negative is the most appropriate, not the absolute value. The best models according to AIC are colored in green to ease the search when looking at the table. Interestingly for the overnight OSEBX return the

ARCH(1) and GARCH(1,0), the two best models, have the same AIC down to the third decimal. In the ARCH(1) only the intercept itself is significant, not the parameter, and in the GARCH(1,0) all I get is NA values. Could this indicate that none of the simplest ARCH or GARCH models fit the return structure of the overnight volatilities with significant parameters?

	OBX		OSEBX		Yara		DNB	
ARCH Models	Intraday	Overnight	Intraday	Overnight	Intraday	Overnight	Intraday	Overnight
ARCH(1)	4186.365	-4674.203	4013.628	-5981.550	5202.839	4011.568	4858.010	3679.014
ARCH(2)	4146.884	-4683.721	3977.393	-5978.935	5204.539	4010.260	4844.785	3657.754
ARCH(3)	4107.987	-4681.353	3934.714	-5972.778	5206.742	4007.887	4820.826	3652.313
ARCH(4)	4100.652	-4672.535	3924.882	-5966.040	5212.136	4007.989	4805.672	3579.686
ARCH(5)	4089.622	-4695.099	3913.985	-5935.470	5215.830	4004.694	4787.303	3550.851
GARCH Models								
GARCH(1,0)	4305.825	-4674.203	4144.614	-5981.550	5207.920	4024.954	4891.932	3697.934
GARCH(1,1)	4061.822	-4672.203	3886.833	-5979.544	5204.848	4009.607	4754.049	3590.458
GARCH(1,2)	4164.639	-4682.630	3899.859	-5977.808	5206.352	4010.036	4754.337	3581.482
GARCH(2,1)	4048.432	-4666.113	3871.432	-5972.598	5204.034	4009.173	4752.611	3588.844
GARCH(2,2)	4068.992	-4679.933	3875.121	-5974.890	5207.631	4011.106	4838.941	3583.494
GARCH(3,1)	4162.442	-4662.528	3869.916	-5970.373	5203.751	4010.628	4750.974	3598.234
GARCH(1,3)	4139.925	-4679.750	3966.952	-5973.683	5208.382	4009.678	4765.434	3580.720
GARCH(2,3)	4131.431	-4696.545	3958.469	-5967.343	5209.498	4011.047	4813.988	3582.833
GARCH(3,2)	4050.028	-4686.859	3873.594	-5972.342	5207.033	4011.837	4831.810	3579.434
GARCH(3,3)	4125.196	-4699.576	3948.658	-5965.930	5210.826	4013.436	4813.665	3581.737

Table 3: Best ARCH and GARCH models

In addition to finding out which model fits best it is important to check the residuals for structure. When assessing model quality, it is important that the residuals do not have any structure. The idea is that the deterministic portion of a model, which is the parameters, is so good that the only remaining errors are the intrinsic randomness of the real world. If there exists any explanatory or predictive power in the residuals you know that the model failed in catching all the systematic elements in your data.

The corresponding plotted residuals for the best models for the two indexes are in figure 8. Here we can see that the residual errors do not exude any clear structure.

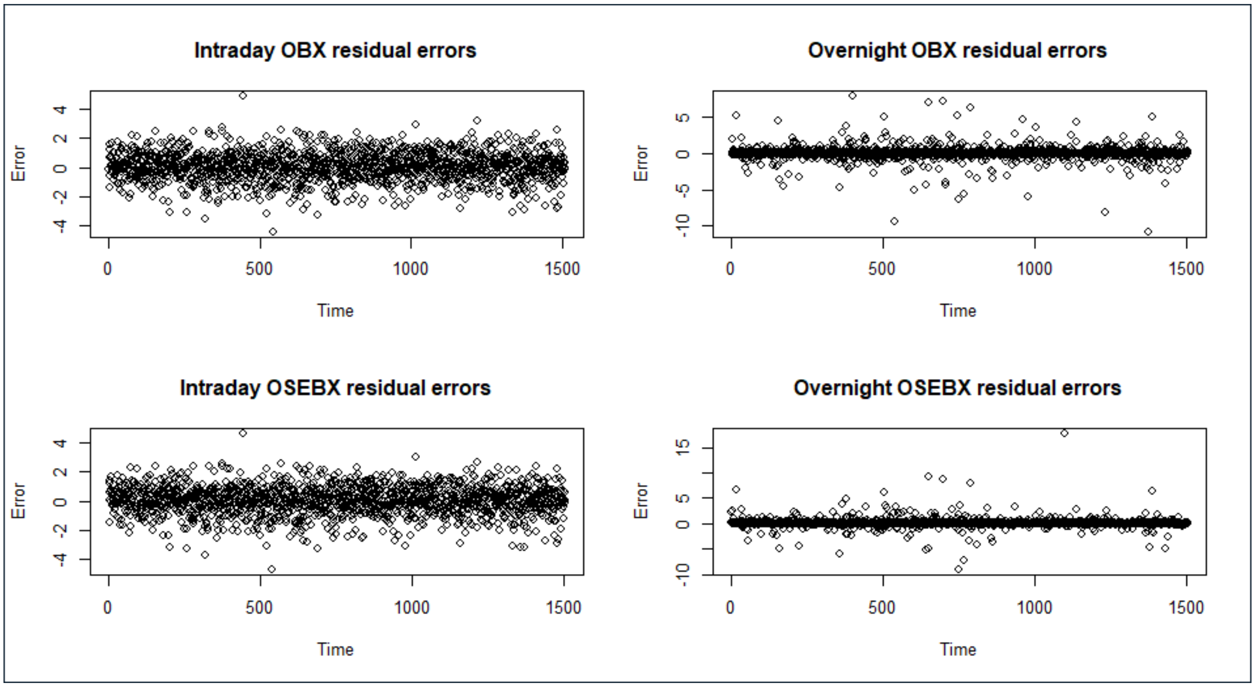

Figure 8: Residual error plots for indexes

The corresponding plotted residuals for the best models for my two stocks are in figure 9. Here we can also see that the residuals do not seem to have any clear pattern or structure.

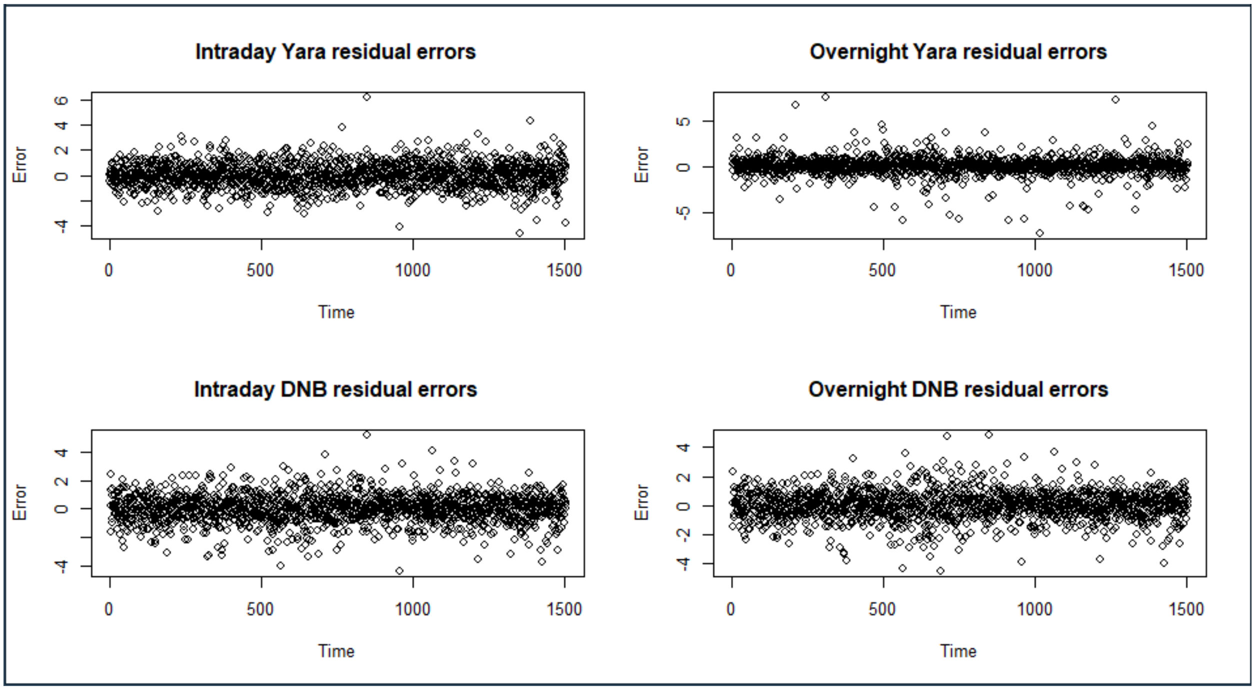

Figure 9: Residual error plots for stocks

5.3 Hidden Markov models

From the plots of the squared returns, in figure 6 and figure 7, we can see that there could exist different states. There are periods where the variation is larger than others, which indicate that there are calmer periods and more volatile, or nervous periods. This could be what is known as volatility clustering, which is the tendency for volatility in financial markets to appear in clumps. In other words, large returns, both positive and negative are expected to follow large returns. Same goes for smaller returns. According to Brooks (2014) an explanation for this phenomenon is that the timing of the information published which drive price changes themselves occur in bunches rather than being evenly spaced over time. This seems to be close to a universal feature of asset returns in finance. If that is the case, it is of interest to know how the indexes and stocks perform in these periods. Using the function depmixs4 in R to detect possible hidden Markov models I find that for some of the returns these periods do exist, and others it does not. The results are presented for each index and stock in this section. State 1 represents the nervous, more volatile period, this can be seen both from the larger standard deviation and looking at the squared return figures. State

2 then represents the calmer period. The probability matrix of moving from one state to another is also included, where State 1 and State 2 is shortened down to S1 and S2 for simplicity.

OBX

On the OBX index there appears to be Markov processes for both the intraday returns and the overnight returns which can be seen in table 4.

Looking at the transition matrix for the intraday returns there appears to be an incredibly small chance on going from one state to the other. This could indicate that the returns follow a very similar pattern which rarely changes.

When looking at both the intraday returns and the overnight returns we can see that the standard deviations in both states are very large compared to the returns

	OBX Intraday	
	State 1	State 2
Starting	1	0
Mean	-0.079	0.07
Standard deviation	1.683	0.772
	Transition Matrix	
	To S1	To S2
From S1	0.946	0.054
From S2	0.012	0.988

	OBX Overnight	
	State 1	State 2
Starting	1	0
Mean	-0.001	0.001
Standard deviation	0.096	0.009
	Transition Matrix	
	To S1	To S2
From S1	0.266	0.734
From S2	0.284	0.716

Table 4: Markov processes for OBX

OSEBX

For the intraday returns on the OSEBX there does not appear to be a structure moving accordingly to a Markov process. This is represented in table 5 under the OSEBX Intraday where there is no starting state and then no mean in these. The overnight returns, however, do look like they have the properties of a Markov process, and as mentioned before, state 1 refers to the more nervous period.

	OSEBX Intraday			OSEBX Overnight	
	State 1	State 2		State 1	State 2
Starting	0.5	0.5	Starting	1	0
Mean	0	0	Mean	0.008	0.001
Standard deviation	1	1	Standard deviation	0.072	0.001
	Transition Matrix			Transition Matrix	
	To S1	To S2		To S1	To S2
From S1	0.5	0.5	From S1	0.213	0.787
From S2	0.5	0.5	From S2	0.202	0.798

Table 5: Markov processes for OSEBX

YARA

The Yara stock contain Markov processes on the overnight return, but not the intraday return. Looking at table 6 we can see that the overnight returns start in state 2, the calm period. The return is much larger, and the standard deviation is much lower in the calm period.

From the transition matrix it seems like the calm state is the dominant one, seeing as there is a low chance at 12.1% to go from state 2 to state 1. Moving from state 1 to state 2 has a much higher probability at 58.5%, which could indicate that the nervous periods are usually shorter in time.

	Yara Intraday			Yara Overnight	
	State 1	State 2		State 1	State 2
Starting	0.5	0.5	Starting	0	1
Mean	0	0	Mean	-0.016	0.054
Standard deviation	1	1	Standard deviation	1.954	0.477
	Transition Matrix			Transition Matrix	
	To S1	To S2		To S1	To S2
From S1	0.5	0.5	From S1	0.415	0.585
From S2	0.5	0.5	From S2	0.121	0.879

Table 6: Markov processes for Yara

DNB

Like the Yara stock, there only exists Markov processes for the overnight return, shown in table 7. The overnight returns start in the calm period (State 2), and the return in the calm period is notably larger than the nervous period (State 1). Another likeness to the Yara stock is the overwhelming probability of staying in state 2 when already being in state 2, from the transition matrix see a 90.9% probability of staying.

	DNB Intraday			DNB Overnight	
	State 1	State 2		State 1	State 2
Starting	0.5	0.5	Starting	0	1
Mean	0	0	Mean	-0.024	0.067
Standard deviation	1	1	Standard deviation	1.63	0.432
	Transition Matrix			Transition Matrix	
	To S1	To S2		To S1	To S2
From S1	0.5	0.5	From S1	0.633	0.367
From S2	0.5	0.5	From S2	0.091	0.909

Table 7: Markov processes for DNB

In nervous periods (State 1) the overnight returns on the stocks are much lower than the calm period returns. Nervous periods most likely coincide with turbulent times for the market, which could be the result of many things, be it political, financial, military, or other major forces. The information flow for single stocks will then be constantly changing causing the returns to fluctuate. A lower, and negative return in addition to the much larger standard deviation in the nervous state could be caused by leverage effects. Leverage effects is the tendency for volatility to increase more following a larger price fall than that of a price increase of the same magnitude.

With the information flow being constant, and easily accessible all hours of the day, it is reasonable to assume the overnight return will be heavily affected by nervous periods, since it is twice as long as the open market on regular weekdays. That is without counting the closed market over the weekends.

Conclusion and limitations

This thesis looks at the behavior of returns on the Oslo Stock exchange by decomposing the total return of two indexes and two stocks in to overnight and intraday returns from 2013 to 2019. After studying the overnight and intraday returns it is evident that the overnight returns have an important role on the performance on single stock, but not on indexes. The overnight and intraday returns have little to no correlation for the stocks, but a low positive correlation for the indexes. This could be due to the behavior of day traders who decide to sell their positions at market closure due to them not being able to trade when closed, which causes the stocks to behave differently during the open market and closed.

Using ARIMA, ARCH and GARCH models to see which model fit the behavior of the indexes and stocks I find that there are little to no similarities in the behavior of the indexes and stocks. The intraday and overnight returns within the stocks also behave very differently from each other. There are a few similarities between the indexes, which is to be expected seeing as the OSEBX index contains all the stocks from the OBX in addition to 42 others.

With the global economy going through different crises over the years, it is of interest to see if the returns move between states where there are higher or lower returns. If these states exist it is advantageous to know and will be of interest when for example making an investment decision. Looking for Hidden Markov models I find that there exist Markov processes for the overnight returns, but only one intraday return. In these overnight return states I find that the calm state is the predominant one, and the returns are larger in this state for all but the OSEBX overnight return. The standard deviations are also much lower, which is to be expected seeing as it is the calmer period.

For a future possible expansion of the study it would be beneficial to expand the list of indexes and stocks to try to determine if there exists behavior within different sectors. Incorporating more advanced GARCH models could yield improved results as well. Trying a similar trading strategy to Qiu & Cai (2013) of long-overnight short-intraday could be interesting to see if it would be a yield positive returns. One possible weakness with determining which ARCH and GARCH models fit the best in my thesis is that I only use AIC as the only determining criteria, though I do check for structure in the residuals it could be beneficial to check other quality estimators.

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Appendix

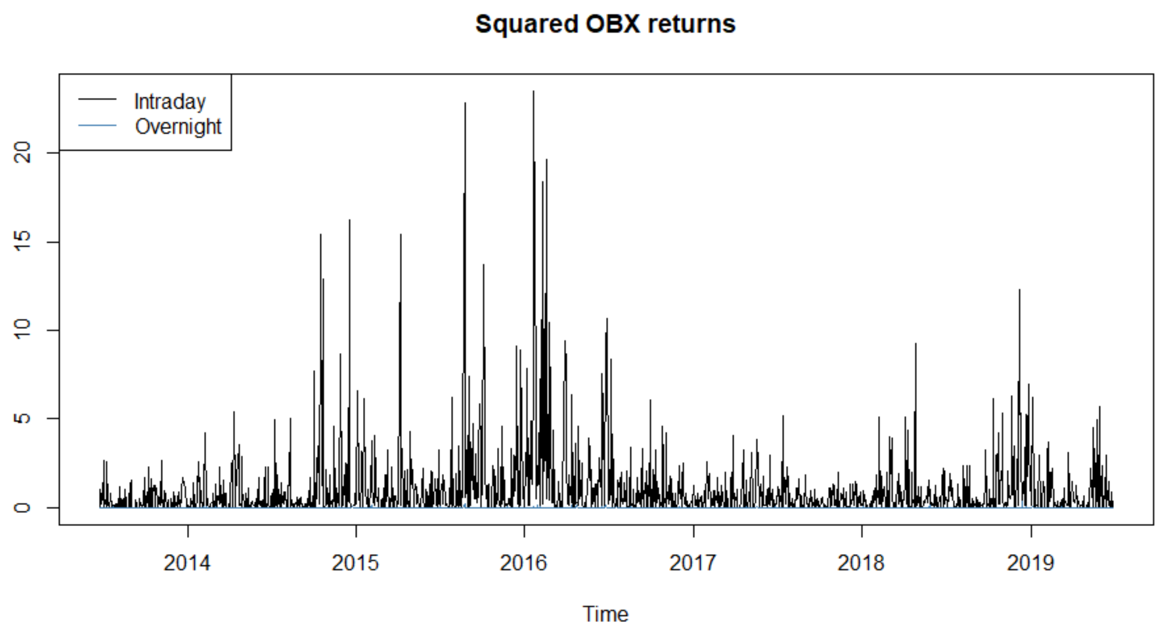

Figure 10: Squared OBX returns

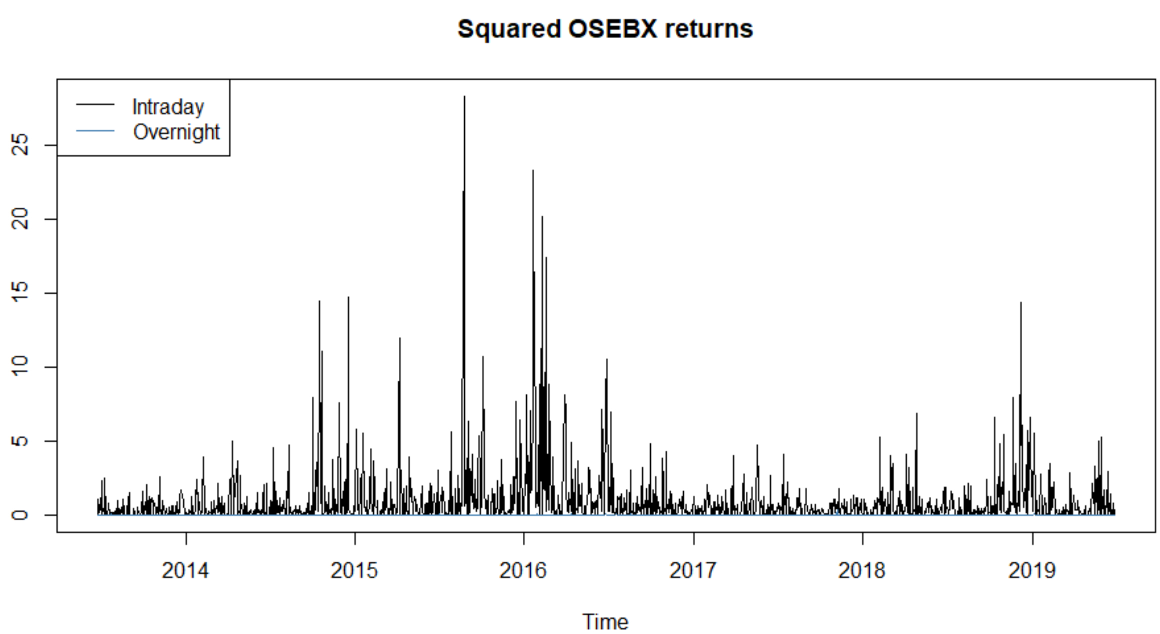

Figure 11: Squared OSEBX returns

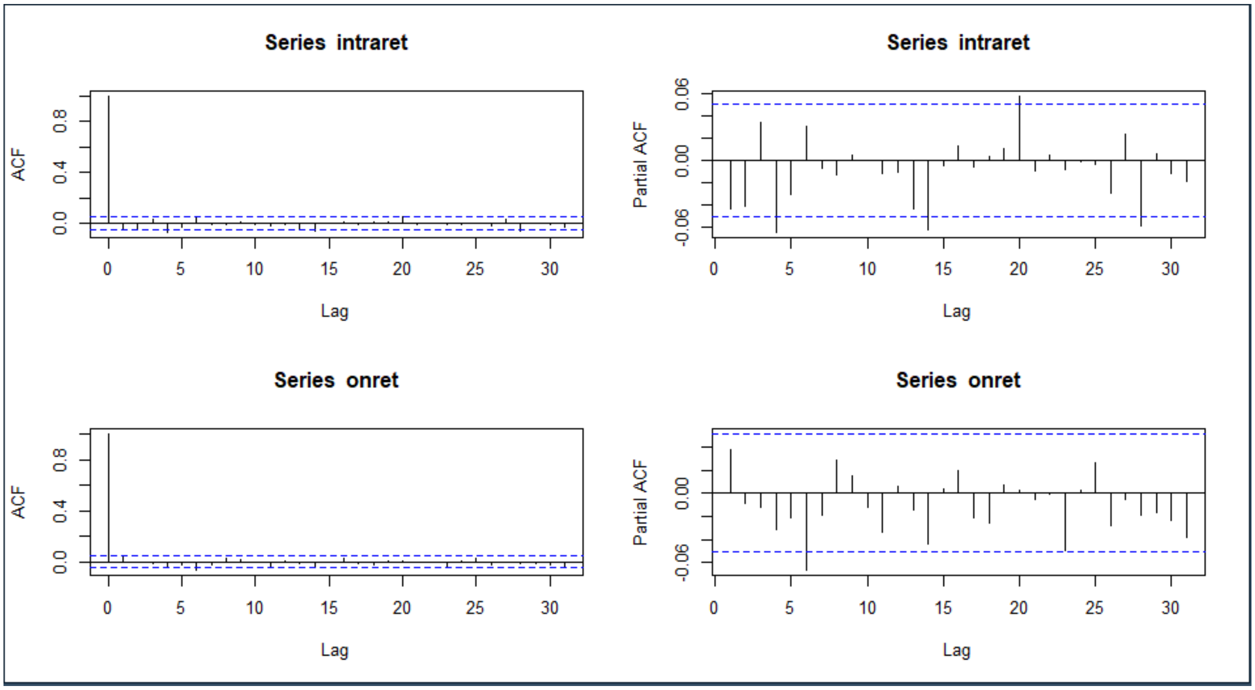

Figure 12: ACF and PACF for OBX

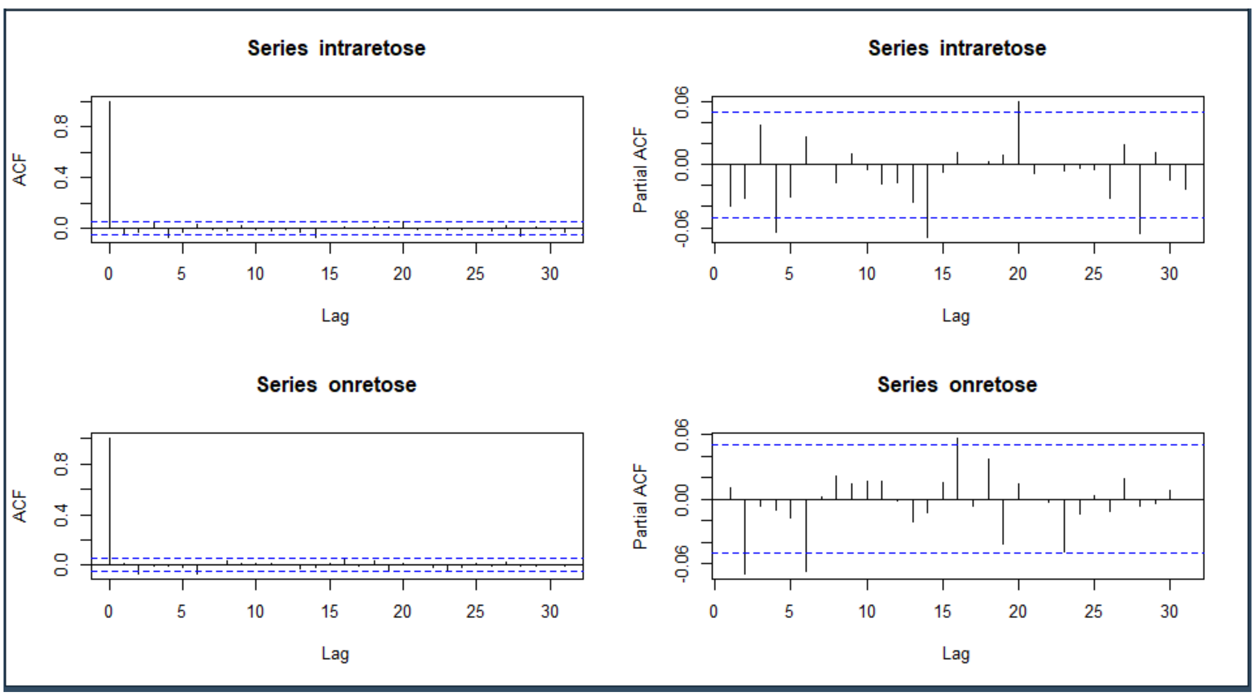

Figure 13: ACF and PACF for OSEBX

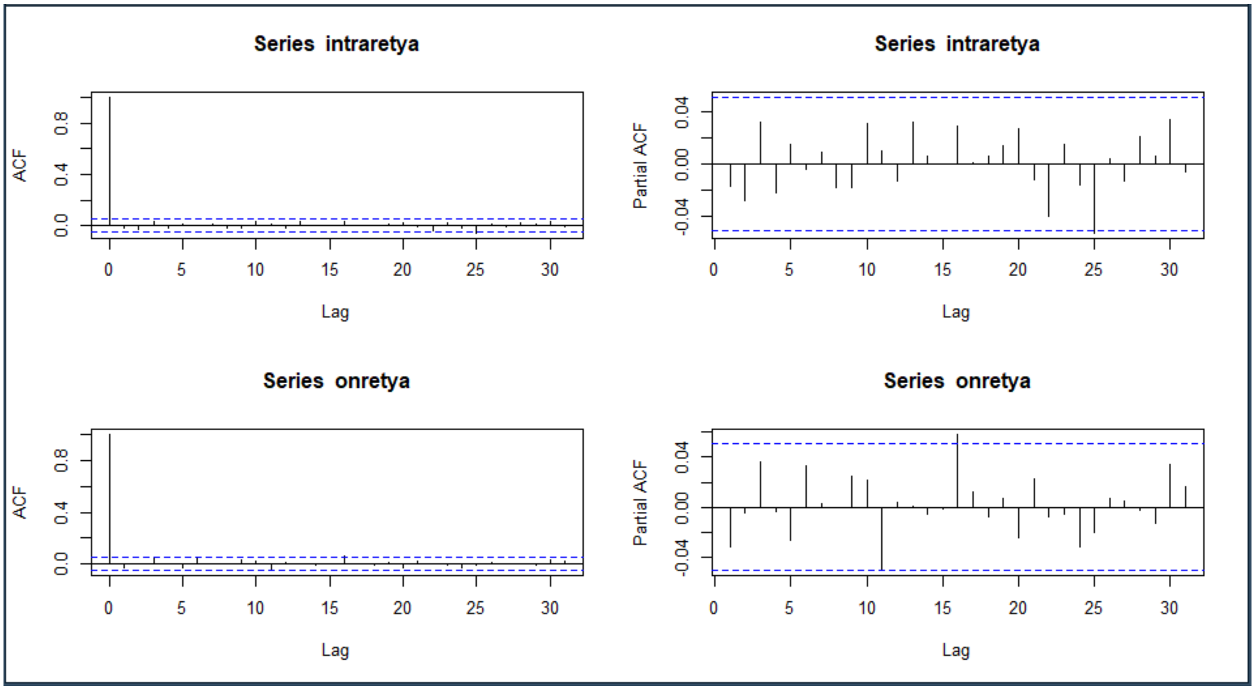

Figure 14: ACF and PACF for Yara

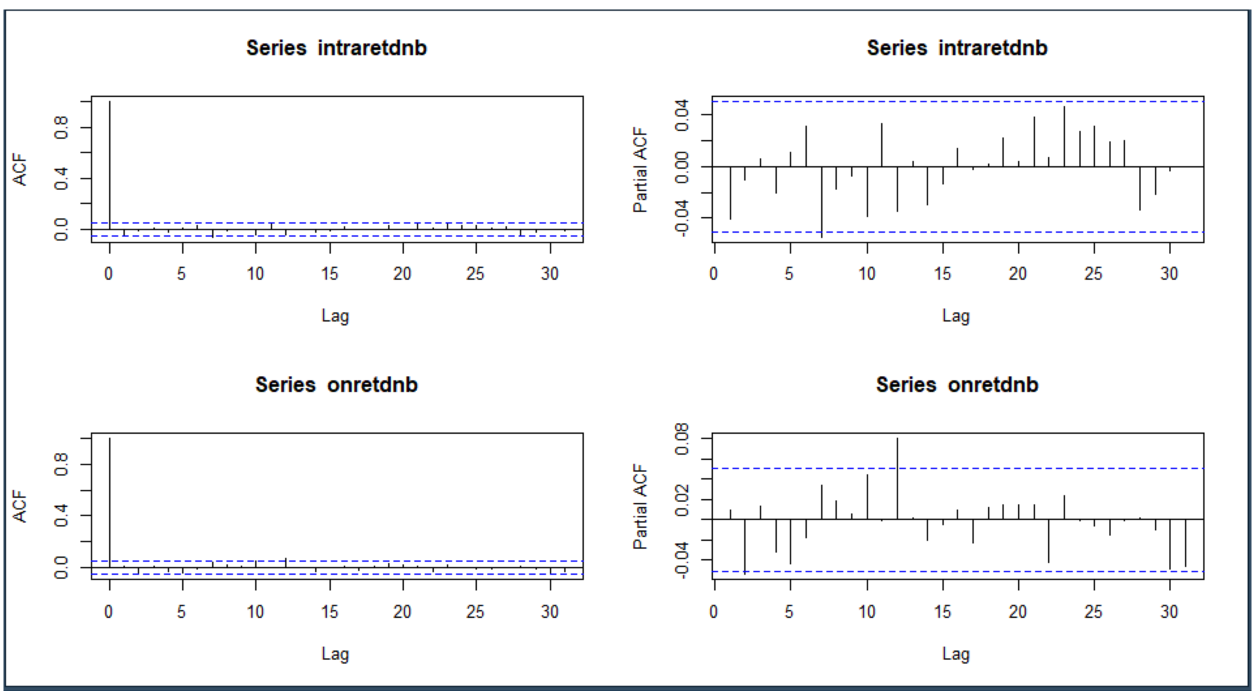

Figure 15: ACF and PACF for DNB