UNIVERSITY OF GOTHENBURG
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Master Degree Project in Finance

# Earnings Announcements and Intraday Volatility

A study of Nasdaq OMX Stockholm

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## Table of Contents

# Abstract

In this study, we investigate how the trading and its corresponding volatility appear after the release of financial reports. The focus is whether financial reports released on trading time appears to have a higher volatility relative to reports released off trading time; this makes the efficient market theory developed by Fama (1970) a cornerstone throughout this study. We investigate the volatility at the immediate time window (first 15 minutes) after earnings announcements are released, using the Realized Volatility approach. The study aims at investigating all companies and all trades listed on the Nasdaq OMX Stockholm Stock Exchange. Two different data sets are used, namely a Tick Time Data set and a Minute Data set. The results regarding Tick Time Data supports the assumption that the volatility is higher on average for reports released on trading time compared to reports released off trading time. For our Minute Data set the inclusion of overnight return violates the assumption, whereas by excluding the overnight return, the volatility after reports released on trading seem to be higher throughout this study with just a few quarterly exceptions.

# 1. Introduction

The purpose of this study is to investigate the relationship between return volatility and the release of the company's earnings announcements for the companies listed on NASDAQ OMX Stockholm Stock exchange. We will further investigate if companies releasing their reports during off trading hours appear to have lower return volatility than companies releasing their reports during on trading hours. The approach that will be applied throughout this study when estimating return volatility is the concept of realized volatility. The realized volatility model is the square root of the sum of squared returns over a given time horizon and it is a model-free approach for estimating return volatility. The realized volatility model is applied for high frequent data and the model has gained in importance in recent years.

The previous work within the disclosure of news announcement and its impact on return volatility is extensive but the contribution of this report, in contrast to earlier research, is that it has its origin in the regulation regarding the release of financial reports. According to the Swedish law, Aktiebolagslagen (2007:528), it is announced that a public company should release its quarterly report as soon as possible after the quarter is finished but at latest two months after. However, there is no legislation concerning any specific time in the day when the company are obliged to publish their earnings announcements. What are the consequences of the absence of a time specified regulation in terms of trading volatility?

Company events, such as quarterly and annual reports, give uninformed investors a good source of where to find information regarding a specific company in order to get conversant on the performance of that company. In Sweden there is a regulation that requires public companies to release four quarterly reports per annum. Since quarterly reports contain extensive information which, until the release, is unknown for the large majority of people, it generally creates a lot of activity on the stock market immediately after the announcement. After the disclosure of the reports, investors have received new information to trade their stocks on and consequently the new information is anticipated in stock prices. The efficient market theory developed by Fama (1970) cover this and suggests that share prices adapt quickly to the new information that the quarterly report brings. Still, the market takes some time to clear on a new price. When a stock is actively traded with small price movements it can signal that the traders have homogenous believes and have agreed upon an efficient price. Conversely, in the opposite scenario when the price movements are high, it might signal that investors have not agreed upon an efficient price and that they trade the stock at different information levels, hence resulting in higher volatility. When new information is released to the market, investors must take this new information into account which may cause an immediate reaction in the price movements.  In this study we will pay attention to the fact that some companies release their quarterly reports when the stock market is open whereas a majority of the companies release their reports when the market is closed, and if this choice of time of disclosure might affect the return volatility of stocks. Are there any complications regarding this and is there any differences in trading volatility for stocks that release their reports during the stock markets trading hour’s relative to those who announce their results when it is closed, during non-trading hours? That is what we intend to investigate closer in this paper.

# 2. Literature Review and Theory

## 2.1 Literature Review

In this paper we intend to analyze intraday volatility on trading after quarterly reports are released for the companies listed on the OMX Stockholm Stock Exchange. In Sweden companies are allowed to release their reports throughout the day and as a result some companies announce their earnings when the stock market is closed and some companies when the stock market is open. This fact attracted our interest to investigate what the implications are depending on the timing of the release of financial reports. The focus is to be placed on how and if the return volatility on stocks differs between reports that are released on trading day relative to off trading day.

In the study by French and Roll (1986), focus is paid on the timing of information and assumption is made that asset prices tend to be more volatile during trading hours when the market is open in comparsion to off trading hours, when the market is closed. The paper discusses different reasons for this phenomenon and among them the impact of arrival of public information. The study is based on the daily returns for all common stocks listed on the New York and American Exchanges over the years 1963 to 1982, of which the variance for each individual stock is calculated. The main finding is that the asset returns seems to be more volatile during trading hours than during non-trading hours, which here is explained to be due to the more frequent release of new information during trading hours. The positive relationship between arrival of new information during trading hours and the return volatility gives support to the Efficient Market Hypothesis; market participants becomes more willing to trade as more information becomes available to them however they have not yet agreed upon an efficient price resulting in higher volatility.

In another study by Clark and Kelly (2011) they point out the context of how risk-adjusted returns between trading hours and off trading hours might differ. Relating back to previous studies (e.g. Stoll and Whaley (1990), Hong and Wang (2000)) the difference in return and volatility is find to be U-shaped; the stock showing a higher return during weekdays compared to weekends, and a higher volatility during trading hours relative to off trading hours.  Clark and Kelly further relate this concept to market efficiency which assumes that the return between on trading and off trading hours should be approximately the same. In the study Clark and Kelly compare the returns of a group of exchange traded funds (ETFs) between daytime (‘open-to-close’, (OC)) and nighttime (‘close-to-open’, (CO)) for the years

1999-2006. The main findings of the study are that the risk-adjusted returns held overnight (CO) exceed the risk-adjusted returns held during day time (OC), with lower volatility for the CO risk premium than the volatility of the OC risk premia. Furthermore the risk premia is estimated to be positive during night and negative during day. An explanation to this, according to Clark and Kelly, might be that active traders usually hold undiversified portfolios and that they fear negative, stock-specific, news during night that might impact the stock price or the liquidity of the stock and as a result of this a large number of traders liquidate their undiversified portfolios at the end of the day and then reestablish their positions in the morning the next trading day; hence these trades lower OC returns and increase CO returns. The authors suggest that the risk adjusted return between on trading and off trading hours should be indistinguishable but the findings of this study shows evidence to the contrary indicating that the market is not fully efficient.

A paper that focuses on how to treat overnight returns is the study by Ahoniemi and Lanne (2013). The study addresses the problem of how to deal with overnight returns when modeling realized volatility in financial markets. As information available to investors accumulates all around the clock, yet the markets are only open a limited time a day, this will affect how information is incorporated and how investors make their decisions. New information that is disclosed when the market is closed will be reflected in the price the next trading day and depending on the information the impact on the overnight return and its corresponding volatility might be high. Thus, the importance of how to deal with overnight returns is of significance and therefore the focus of their study is to investigate how to best deal with overnight returns when modeling realized volatility. The study is based on intraday returns on the S&P 500 index and the thirty equities included in the Dow Jones Industrial Average. To address the issue regarding overnight returns the study uses proxies. A proxy that is used in the study is constituted by the first five minutes of each day; the return from the previous close up until 9:35 AM. This proxy is validated since trading does not begin directly at the opening time, 09:30 AM. In the study various RV measures are compared and the methodology showed to be most satisfactory when measuring realized volatility for the S&P 500 index is the weighted sum of the squared overnight returns and the sum of intraday squared returns.

In the paper by Theobald & Yallup (2005), the focus is on how volatility changes during a day and they measures the speed of adjustment and the intra-daily volatility of UK FTSE100 and FTSE250 indices by hourly data based on a GARCH approach. They find that the total volatility is higher at opening of the trading-day relative to the closing time. Their results follow the efficient market hypothesis and are explained by an overall overreaction at the beginning of the trading day, interpreted as overconfidence, but where the prices eventually adjust to its intrinsic value throughout the day.

Another study performed by Patell and Wolfson (1984) measures the speed of adjustment and the intra-daily variance of stock prices on individual stock level, from Large Cap stocks listed at the NYSE. In the study the impact on stock returns from earnings announcements and dividend declarations from the firms included in the study are investigated. From their intra-daily minute data, Patell and Wolfson create a hypothetical and simplified trading strategy that invests in stocks whose earnings announcements over performs the expectations and sells stocks that under performs the expectations. They compare time intervals at every 30 minute period after the announcement is published and finds excess variation in the 30 minute period following the time at which the announcement is published, where most of this effect is found in the first 15 minutes of this time interval. The findings are significant at a 1 % significance level. For time intervals following the first 30 minute period they find no such significance. Further, Patell and Wolfson discovers a clear difference in price variation between earnings announcements and dividend declarations, where earnings announcements yields a much larger price variation which they explain by that earning announcements in general includes much more information relative to dividend declarations that in general only consists of a “one-sentence press-release”. Patell and Wolfson also conclude that the price variation found, most likely would be greater if also Small Cap stocks were to be included in the data which would be in line with efficient market theories as well since the information transparency in general is lower for that group of companies.

In a study by Muntermann and Guettler (2007) they study intra-daily market data on German stocks around company events and investigate how efficient the market incorporates new information from company specific announcements. In contrast to Wolfson and Patell, Muntermann and Guettler also include Small Cap companies in their study and finds abnormal price variation for this group in the first 15 minutes after the announcement is made. However, Muntermann and Guettler only include announcements that are published during the trading-day and exclude all companies that publish their announcements outside the trading day. Further, they also investigate the share price reactions before an announcement is published to try determining if an insider effect is present, but find no such effect in their study.

Warren et al.(2003) takes another approach and perform a study of intra-daily volatility and market activity around company events from a regulative perspective based on a regulation that was implemented in the US, called the regulation fair disclosure (REG FD). They investigate if the new law that forces companies to immediately announce company news to all market participants has had any effects on lowering insider trading activity, but find no such significant effect in the sense of return volatility. They do however find abnormal trading activity measured by trading volume after REG FD was implemented. The fact that market volume went up after the new law was implemented may give evidence to the Efficient Market Hypothesis in the sense that the market participants were willing to trade more when more timely information was available to them.

#### 2.1.2 Contribution of this report

The research regarding volatility estimation around company specific events is well studied and some papers of importance are presented here, but in contrast to earlier research we have a perspective that has its origin in the regulation regarding the release of reports. This perspective make this report to stand out in a sense and in addition, we have not seen a similar study reported based on Swedish market data at individual stock level. Our attention is on how the market reacts in the immediate period (first 15 minutes) after the release of financial reports. We investigate whether there is an effect on return volatility arising from the timing of the reports. Further we compare if there is any differences depending on what list on OMX Stockholm Stock Exchange (Large, Mid or Small Cap) the companies are listed on as well as by what quarterly report (i.e. Q1-Q4) that is released.

#### 2.1.3 Delimitations

Even though the underlying scope of this study might be closely related to the concept of Behavioral Finance, such as overconfidence, framing and overreaction, and its impact on trading of irrational investors, this subject is not dealt with in this study. As such, we leave to the reader to draw their own conclusions regarding the impact on trading considering the aspects of Behavioral Finance and the potential impact it might have on this topic.

Further we limit this study to only cover the Swedish stock market, this because it is of interest to investigate whether the Swedish stock market might benefit from imposing a regulation.

## 2.2 Theory

The Efficient market theory lies at the core of this study and is described in detail below. Further in this section, we go through some of the most used models for estimating asset volatility, followed by a description of the realized volatility model and its implications, which is the model to be used in this study.

### 2.2.1 Efficient Market Hypothesis

In this particular study the Efficient Market Hypothesis (EMH) is of high significance and the theory is a cornerstone throughout the study. The foundation to the theory took its beginning in the mid mid-1960s when Eugene Fama published the paper *"The Behavior of Stock Market Prices"* (1965). In the paper Fama describes stock prices to be unpredictable and to follow a random walk. The random walk of stock prices is by Fama described as a situation where price changes are assumed to be independent. As a result one cannot, given available information, predict future prices of the stock. Fama remarks that the independency of stock prices supports the existence of an efficient market for securities. Fama states that: *"… given the available information, actual prices at every point in time represent very good estimates of intrinsic values"* (pp. 90). By this the Efficient Market Hypothesis is a theory that states that all relevant information already is incorporated in asset prices, indicating that stocks are traded at their fair value. As a result, investors should not be able to outperform the market since all available information already is reflected in market prices. Consequently, excess return should only be possible to gain by taking riskier positions, according to the EMH.

In 1970, Eugene Fama published the paper "*Efficient Capital Markets: A Review of Theory and Empirical Work*", a study that extended the primary EMH. The EMH was now described to appear in three forms of efficiency; the weak-form, the semi-strong-form and the strong-form. The weak form efficiency states that the information available is built on historical prices. Second. the semi-strong form efficiency tests if new publicly available information is incorporated into asset prices. Finally, the strong-form efficiency states that stock prices should reflect all available information, both publicly and privately.

### 2.2.2 The value of Information and adjustment

The efficient market theory assumes that markets adapt quickly to new information. Why the process of incorporating new information cannot be made instantaneously is due to for example information and transactions costs. An example of when new information arrives to the market is the announcement of quarterly reports. When a corporation discloses their quarterly results, market participants have new information to trade that corporation on and it is reasonable to believe that it takes some short time-interval for the participants to agree upon a new price due to the implications mentioned above. The term *speed of adjustment* is frequently used for such a time horizon, and is investigated upon in for example Patell and Wolfson (1984) and Muntermann and Guettler (2007). Patell and Wolfson who investigate the speed of adjustment after earnings and dividend announcements by companies find that most of the price adjustments occurs within the first 15 minutes after the announcements is made. Muntermann and Guettler find abnormal trading activity within the first 30 minutes after the announcements are published. The information and importance of company specific announcements differ, and as Patell and Wolfson suggest earnings announcements do in general include much more information than a dividend announcement do, hence it is reasonable to assume that the time span until the market clears is longer for earnings announcements than for dividend announcements.

### 2.2.3 Relevance of the timing of reports

According to the Swedish law, Aktiebolagslagen (2007:528), regarding quarterly reports, it is announced that a public company should release its quarterly report as soon as possible after the quarter is finished but at latest two months after. However, there is no legislation concerning any specific time in the day when the company are obliged to publish their earnings announcements. This makes the company free to choose at what time in the day they will publish their report. If a company releases their earnings announcements when the market is closed it will give market participants time to evaluate the announcement before entering the market relative to a company that releases the earnings announcement during trading hours. This timing of reports might result in differences in trading activity and its corresponding volatility between these two groups.

### 2.2.4 Modeling Return Volatility

In order to model the financial volatility there are several approaches that can be applied and commonly, multivariate (G)ARCH or stochastic volatility models are used. In this section we pay special attention to the Autoregressive Conditional Heteroskedaticity (ARCH), Generalized Autoregressive Conditional Heteroskedaticity (GARCH) and Realized Volatility models. Later we explain why Realized Volatility is chosen and why this model is superior to the others for the purpose of this study.

#### 2.2.4.1 Autoregressive Conditional Heteroskedaticity model, ARCH

A commonly used approach when modeling financial volatility is the ARCH model. The ARCH model was developed by Robert Engel in 1982 and has, since then, become a widespread model. An important feature of the ARCH model is that it assumes a non-constant variance of the error term, $u_t$. Also the ARCH model assumes the conditional variance of the current error term, $u_t$ , to be positively correlated to the level of the previous periods' squared error terms, this known as "Volatility clustering", Mandelbrot (1963). The model is estimated as:

$$r_t = \mu + \beta' x_t + u_t, \qquad u_t \sim N(0, \sigma_t^2) \tag{2.1}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_q u_{t-q}^2 \tag{2.2}$$

*Where*: $u_t$ is a random variable, $\sigma_t^2$ is the conditional variance of $u_t$, $u_{t-q}^2$ is the lag *q* of the error term.

The ARCH model is estimated with maximum likelihood which might be a drawback of the model, since when the number of lags, *q*, becomes large, the maximum likelihood function often becomes complex. Thus, another issue with the model is to decide how many lags, *q*, of the squared error term to include. Since the value of the conditional variance, $\sigma_t^2$ ,must be strictly positive, this might according to Brooks (2008) cause a problem when estimating a large number of parameters; the more parameters added to the model the more likely it is that one of them will take on a negative estimated value.

#### 2.2.4.2 Generalized Autoregressive Conditional Heteroskedaticity model, GARCH

The GARCH (*p*,*q*) model is an extension of the ARCH model and was introduced in 1986 by Tim Bollerslev. In the GARCH model the conditional variance is a function of *q* lags of the squared error terms and *p* lags of the conditional variance, thus the conditional variance $\sigma_t^2$ is function of its own previous lags. The model is estimated as follows:

$$r_t = \mu + \beta' x_t + u_t, \qquad u_t \sim N(\sigma_t^2) \tag{2.3}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \cdots + \alpha_q \mu_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots \beta_p \sigma_{t-p}^2 \tag{2.4}$$

*Where*: $u_t$ is a random variable, $\sigma_t^2$ is the conditional variance of $u_t$, $\mu_{t-q}^2$ is the lag *q* of the error term, $\sigma_{t-p}^2$ is lag *p* of the conditional variance.

GARCH is, just like ARCH, estimated by maximum likelihood, which relates to the same problem as in the ARCH model; that is how the value of the lags ($p$ and $q$) of the squared error term should be decided. However, the GARCH model has an advantage to ARCH in the sense that it captures the variation in the error term with fewer parameters which simplifies the estimation, Hjalmarsson (2013).

In common for the (G)ARCH models are that they cannot utilize the information from high frequent intra-day data, which according to Andersen et al. (2003) make them incapable in capturing intra-day volatility movements sufficiently well. Also, according to Brooks (2008), the importance of deciding a proper number of the lags $p$ and $q$ aggravate the usage of the ARCH and GARCH models in this particular study and hence speaks in favor of Realized Volatility, which is the model to be used in this study.

#### 2.2.4.3 Realized Volatility

The Realized Volatility model is a non-parametric model which in recent years has gained importance for estimating return volatility. The Realized Volatility is calculated as the square root of Realized Variance which in turn is the sum of squared returns. The Realized Variance is given by:

$$RV_t = \sum_{i=1}^{n} r_{i,t}^2 \tag{2.5}$$

In order for the Realized Volatility model to be applicable, high-frequency data is required, Hjalmarsson (2013). Theoretically, the modeling of the return volatility using $RV_t$ will be unbiased and consistent as $n \to \infty$. However, in reality, the $RV_t$ might be affected by "market microstructure noise", indicating that if sampling to often on illiquid assets, the true economic variation in prices are not picked up, but instead price variations that are due to market mechanisms. Therefore a drawback with the model, according to Hjalmarsson (2013), is that the estimate might be biased if one sample too often; how often sampling can be made mainly depends on how liquid the asset is.

Andersen et al (2001) remarks that using squared asset returns can give good estimation about volatility, however, the authors are also fast to point out that squared returns are noisy estimates of volatility, which implies that the sampling frequency is of high importance. Andersen et al. argue that high frequency returns play a critical role in order to justify their results, and as a result makes them to use only the 30 stocks in the Dow Jones Industrial

Average index (DJIA), which showed a median duration of 22.1 seconds between trades in their study.

Since the Swedish stock market is not as liquid as the US stock markets, one can raise questions whether it is liquid enough to get good estimates when applying the Realized Volatility model. However, during times when earnings announcements are published it is reasonable to believe that trading increases in the majority of stocks, which in turn makes the Realized Volatility model applicable. As the sampling frequency is of high importance and might result in bias this extends to the concept of the market microstructure, such as the bid ask bounce, which will be discussed in the next section.

### 2.2.5 Statistical distribution and market microstructure using RV

The term market microstructure covers the trading mechanism which for example includes the bid-ask bounce. The bid-ask bounce is the difference in price between what a potential seller is willing to sell the asset for minus what a potential buyer is willing to give for that asset. Since the bid-ask bounce may have significant impact on asset prices in the short term; this is something that must be controlled for when estimating the volatility of asset prices over short horizons. This to be able to get a picture of how much of the price changes that comes from an efficient price mechanism relative from the bid-ask bounce.

Since RV is a model free estimate, Andersen et.al (2001) claims that the usual procedure when estimating the market microstructure noise in high frequent data by using RV is to outline the distributions of the data in order to determine its statistical properties. The distribution of the sample is outlined by estimating the “fourth moments” of volatility, which are the mean, standard deviation, skewness and kurtosis.

Through calculating the skewness of the data, the statistical distribution can reveal if the data is symmetrically shaped from the center or not. If the dataset is asymmetrically shaped the data is skewed to the right or to the left of the middle. The symmetry of the data can be revealed by setting the mean in relation to the median value of the data set. The skewness of the data is calculated as:

$$Skewness = \left(\frac{1}{n}\right)\left(\frac{\sum_{t=1}^{n}(x_t - \bar{x})^3}{s^3}\right) \tag{2.6}$$

If the value of the skewness is zero the data is considered to be normally distributed. If the value of the calculated skewness is negative, the median is larger than the mean value, and the data is thus skewed to the left. If the skewness takes a positive value the mean is larger than the median and the data is said to be right skewed. In the literature of high frequent stock market data, it is well known that the distributions usually exhibit a positive skew. One study that points this out is the study by Andersen et.al, (2001) who find the variances of the returns to be clearly right skewed, which, they claim, is a result from the market micro structure noise.

Another measure used in order to distinguish if the data is normally distributed is to estimate the Kurtosis. Kurtosis is a statistical property which outlines if the data is peaked or flat, hence providing a measure of the weight in the tails of a probability density function. Kurtosis is estimated as:

$$Kurtosis = \left(\frac{1}{n}\right)\left(\frac{\sum_{i=1}^{n}(x_t-\bar{x})^4}{s^4}\right) \qquad (2.7)$$

A Kurtosis of three indicates the dataset to be normally distributed. A Kurtosis above three indicates the data to be peaked and a Kurtosis below three indicates the data to be flat in relation to a normal distribution. A Kurtosis above three is called Leptokurtosis and indicates that the possibilities for having extreme outcomes are high, where the curve has fat tails and a peaked top. A Kurtosis below three is called Platykurtosis indicating the data to have a flat top (Newbold et al. 2010).

By estimating Skewness and Kurtosis one can reveal the distribution of the data and thereby outline its statistical properties. In the study by Andersen et.al, they find the variances of the intraday returns to be non-normally distributed with fatter tails than in a normal distribution and also heavily right skewed. A right skewed distribution depends in general on autocorrelation in the error term and is well-known to be found in intraday return estimations, known as market microstructure noise. In order to adjust for the market microstructure noise, Andersen et.al, also estimate the distributions of the logarithmic standard deviations of the returns. Their results from this approach show that their returns are almost normally distributed, with a kurtosis close to three and skewness close to zero, which are the properties of a normal distribution.

Another supplementary approach, regarding the issue of optimal sampling frequency to solve for noise in realized volatility, is the theory about sampling schemes. This theory has gained more importance in scientific work due to its property to potentially solve the problem of optimal sampling frequency and is discussed next.

### 2.2.7 Sampling schemes

Sampling schemes are the theory about what data points to use in the sample and addresses the problem of optimal sampling frequency by instead use the optimal data sampling scheme. According to Oomen and Griffin (2008) realized volatility has no requirement on a specific sampling scheme that has to be used, as long as one follows the general procedure they claim. The most common one is probably calendar time scheme that uses some specified time intervals, i.e. one minute or five minute intervals. However, there are a lot of different sampling schemes to choose between. In their paper from 2008 Oomen and Griffin choose to compare two of the more recent and common schemes, in exception of the calendar time scheme, when estimating intra-daily data. These are the *tick time data scheme* and the *transaction time data scheme*. With *tick time data scheme* only the relative price changes in the transactions are included, which in our particular study would mean an exclusion of all trades that were traded at the same price as the previous recorded one and only include the transactions that had another price than the previous recorded one. For the case of *transaction time data* all transactions within the estimation period are included, which essentially means that all trades that took place during the chosen time window are included when the volatility are estimated. Using this method for our study would imply that we use all transactions that are made within the 15 minute time window. In their paper from 2008, Oomen and Griffin shows that *tick time data* scheme is superior to other schemes in solving for market microstructure noise using realized volatility. The same result is given in a paper from Fukasawa (2010) who finds that *the tick time data* scheme gives robust results to market microstructure noise in his estimation of realized volatility.

# 3. Data & Methodology

This section describes the data and the method used to estimate the intra-daily volatility around reports of the Swedish stock market. The study covers all listed companies at present per 2014-01-01, in Sweden on the Large, Mid and Small Cap lists. This section outlines how the data is received and the procedure for estimating volatility by the realized volatility model.

## 3.1 Data description

In this paper we estimate the behavior of companies stock market prices at the immediate period (first 15 minutes) after their earnings announcements are released. We compare the return volatilities for companies that release their reports on trading hours relative to companies that release their reports during off trading hours. As a result we create two groups; on trading reports and off trading reports, for each list; Large, Mid and Small Cap. We compare the two groups to see if the market agrees more efficient upon the price when it has more time to evaluate the reports. This leads us to collect data for the first fifteen minutes after the release of a quarterly report. For the companies that publish their announcements when the market is closed we estimate the volatility from the close the previous day up until the first 15 minutes the next trading day.

The decision to use only a 15 minute time window is based on the findings in Patell and Wolfson (1984), and Muntermann and Guettler (2007) who found the largest impact on return volatility during the first 15 minutes after reports. Also since we are interested in holding the time window as short as possible in order to evaluate what the implications on trading are when investors have limited time to go through a report and to see if there possibly arises abnormal price reactions that potentially arrives from for example hazardous trading, we propose to estimate the volatility of the 15 minute time period after the announcement is made. In addition, another reason for using only a 15 minute window arises from that we have reason to believe that some of the small and more illiquid companies in our sample that are listed in Sweden are excessive traded during a short time period after their earnings announcements are presented and where this effect drop out after a while. And in order to be consequent we use a 15 minute window for all companies.

As a result, the exact time at when the earnings announcements are released is of outmost importance. Since a large majority of the companies listed on Nasdaq OMX Stockholm send their reports to Nasdaq OMX in the first instance we are able to find all these times at the

Nasdaq OMX portal. We manually collect the times for all years and all companies in our sample, which consists of all companies listed on the Large, Mid and Small Cap in Sweden. The data of this study is constituted by observations in trade for the first 15 minutes after the release of quarterly financial reports. The shares listed on the Large, Mid and Small Cap lists amount to approximately 250 in total. The data is constituted by historical tick and minute data in trade for each company during the period 2011-2013, quarterly.

The dataset is built up by panel data indicating that for each cross-sectional company there is a time series; we collect financial information for each company on Stockholm Stock Exchange over a three-year period. The panel dataset of this study will be unbalanced since there will be limited number of trades for some of the companies during some quarters in the study, which will, as a consequence, be omitted.

### 3.2.1 Data restrictions

For those companies issuing more than one class of equity, we chose only to include the class of shares with the highest frequency in trade. This leads us to exclude the least traded share among the different classes from the dataset. The importance of having dataset consisting of observation points with high frequency is a requirement in order to be able to apply the formula for Realized Volatility when modeling the return volatility. The relevance of having high frequency data is because volatility is highly persistent; hence high frequency data will provide us with more accurate and better estimates of volatility. If the frequency of sampling is to low the estimates will be less precise; which leads us to exclude the companies' class of shares that are less frequently traded.

In order to reduce seasonality patterns in trade, only companies with a fiscal year ranging from January 1 to December 31 are included in the study, indicating that those companies having a different fiscal year are omitted from the study. This since the data might be skewed if companies with a different fiscal year are included in the study and by omitting companies with different fiscal years it will provide us with more accurate estimates. In addition we want to investigate if there is any differences depending on what quarter the quarterly reports are announced, therefore we won't compare different quarterly reports, even though the dates match, between companies with different fiscal years.

In this study we assess that cross listed companies should be included in the study. This assessment is made because most of the companies listed on other stock exchanges abroad release their reports when the market place is closed, and taken different time zones into consideration we observe that for our sample the market place is closed both in the Swedish Stock market as well as in the foreign stock market, where the stocks are traded. In regard of this, the market participants won't start trading on the new information on another stock market before the Swedish Stock market opens, indicating that that it won't affect the data we intend to study.

We believe the above listed adjustments to be necessary in order to fit our data with the proposed method of estimating realized volatility, as well as being able to more accurately compare our results. Since the adjustments only comprise a few companies, the effect on our results will be of negligible art.

### 3.2.2 Data Collection

After we have made the above adjustments, we are ready to start collecting the data, which is done in Bloomberg for the most recent reports ( i.e Q3,Q4 2013) and from the trader application Autostock for earlier ones. An implication we face is that the data in Autostock are reported minute by minute and not in real-time as in Bloomberg. However, since Bloomberg do not provide more the 140 days of historical real time data and we are not able to receive more real time data due to limited resources, we decide to create two data sets. The first consists of real time data and covers the two last quarterly reports in 2013 (i.e. Q3-Q4 2013) for all our companies. The second data set downloaded from Autostock covers the whole period of quarterly reports from 2011 to 2013 (i.e. Q1- Q4 2011-2013). Data available in Autostock requires far more work to be applicable for this purpose but are manageable. The fact that we have two data sets covering both real-time and minute data for a period of time will be to our favor later on, since we will be able to compare two different sampling schemes estimated on the same period.

For companies disclosing their interim reports during off trading hours, 17:30-08:59, the overnight return is treated as the closing price up until the first 15 minutes the next trading day, 09.00-09.15. For companies announcing their interim reports during on trading hours, 09:00-17:29, the trades are observed for the immediate 15 minutes after the release of each report.

The dataset is built up by panel data indicating that for each cross-sectional company there is a time series; we collect financial information for each company on Stockholm Stock

Exchange over a three-year period. The panel dataset of this study will be unbalanced since there will be a limited number of trades for some of the companies during some quarters in the study, which will, as a consequence, be omitted. Our decision to omit companies with only a few trades is in line with the study from Andersen et.al. (2001) concerning realized volatility on the Dow Jones stocks (30 largest stocks in the US), they find the median time duration between trading for their full sample to be 23.1 seconds, ranging from a low of 7 seconds for the most liquid company up to a high of 54 seconds for the least liquid company between each trade. Following their suggestions on only using highly liquid stocks makes us insert a minimum trading-limit for the companies in our sample to be included in the study. We set the limit in our tick time data set to only include stocks that after each quarterly report have been traded a minimum of once every minute or at least 15 times in total during our time window of 15 minutes. This decision makes our estimations more reliable since we do not want companies with only a few trades to be included and potentially change the picture of the results. The total number of companies and trades at this stage are summarized in the tables below, separated into tick time data, minute data as well as between lists.

| **LARGE CAP** | | **Number of Companies & Trades** | | | |
|---|---|---|---|---|---|
| **Tick Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2013** | Q3 | 15 | *14149* | 40 | *32112* |
| | Q4 | 12 | *9799* | 35 | *30304* |
| **Total** | | 27 | 23948 | 75 | 62416 |

| **MID CAP** | | **Number of Companies & Trades** | | | |
|---|---|---|---|---|---|
| **Tick Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2013** | Q3 | 6 | *894* | 40 | *3787* |
| | Q4 | 8 | *504* | 42 | *4298* |
| **Total** | | 14 | 1398 | 82 | 8085 |

| **SMALL CAP** | | **Number of Companies & Trades** | | | |
|---|---|---|---|---|---|
| **Tick Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2013** | Q3 | 16 | *403* | 48 | *4103* |
| | Q4 | 15 | *921* | 47 | *3649* |
| **Total** | | 31 | 1324 | 95 | 7752 |

**Table 3.1**. Tick data: Number of companies releasing their reports on trading day vs. off trading day, for Large, Mid and Small Cap respectively.

| LARGE CAP | | Number of companies & Trades | | | |
|---|---|---|---|---|---|
| **Minute Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2011** | Q1 | 26 | *304* | 30 | *509* |
| | Q2 | 14 | *272* | 39 | *663* |
| | Q3 | 15 | *240* | 42 | *712* |
| | Q4 | 20 | *320* | 36 | *629* |
| | | | | | |
| **2012** | Q1 | 20 | *320* | 37 | *629* |
| | Q2 | 14 | *224* | 42 | *711* |
| | Q3 | 16 | *256* | 40 | *680* |
| | Q4 | 19 | *304* | 37 | *714* |
| | | | | | |
| **2013** | Q1 | 18 | *290* | 38 | *646* |
| | Q2 | 14 | *224* | 42 | *714* |
| | Q3 | 14 | *224* | 42 | *714* |
| | Q4 | 13 | *208* | 42 | *611* |
| **Total** | | 203 | 3186 | 467 | 7932 |

| MID CAP | | Number of Companies & Trades | | | |
|---|---|---|---|---|---|
| **Minute Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2011** | Q1 | 22 | *208* | 31 | *662* |
| | Q2 | 18 | *304* | 37 | *541* |
| | Q3 | 13 | *208* | 41 | *690* |
| | Q4 | 15 | *240* | 36 | *606* |
| | | | | | |
| **2012** | Q1 | 20 | *352* | 31 | *523* |
| | Q2 | 16 | *288* | 37 | *618* |
| | Q3 | 14 | *224* | 38 | *643* |
| | Q4 | 16 | *256* | 35 | *594* |
| | | | | | |
| **2013** | Q1 | 19 | *320* | 32 | *521* |
| | Q2 | 13 | *256* | 39 | *623* |
| | Q3 | 12 | *192* | 39 | *662* |
| | Q4 | 10 | *160* | 40 | *680* |
| **Total** | | 188 | 3008 | 436 | 7363 |

| **Small CAP** | | Number of Companies & Trades | | | |
|---|---|---|---|---|---|
| **Minute Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2011** | Q1 | 50 | *800* | 38 | *632* |
| | Q2 | 32 | *510* | 62 | *1026* |
| | Q3 | 28 | *447* | 67 | *1107* |
| | Q4 | 24 | *381* | 65 | *1097* |
| | | | | | |
| **2012** | Q1 | 46 | *733* | 44 | *727* |
| | Q2 | 24 | *384* | 64 | *1079* |
| | Q3 | 24 | *382* | 69 | *1170* |
| | Q4 | 25 | *399* | 68 | *1151* |
| | | | | | |
| **2013** | Q1 | 47 | *752* | 48 | *809* |
| | Q2 | 26 | *414* | 68 | *1152* |
| | Q3 | 21 | *336* | 70 | *1186* |
| | Q4 | 17 | *272* | 72 | *1222* |
| **Total** | | 364 | 5810 | 735 | 12358 |

**(*Note: The columns On trading refer to companies releasing their reports during trading-time and the column Off tradingrefer to companies releasing their reports outside trading.*)**

**Table 3.2**. Minute data: Number of companies and trades for companies releasing their reports on trading day vs. off trading day

The data summarized in the tables above must then be adjusted in order to fit with our chosen method of estimating the realized volatility as is discussed next.

### 3.2.3 Data adjustments

Realized volatility is a model free estimate and in its most simple form it is the square root of the sum of the squared returns. The outlook of the model is simple but the implications are to prepare the data set to be applicable for the model which is a complex issue. Theoretically the model gives unbiased and consistent estimates as the sampling frequency reaches infinite speed as $n \rightarrow \infty$ and is estimated as:

$$RV_t = \sqrt{\sum_{i=1}^{n} \left(\frac{p_t - p_{t_{-1}}}{p_{t_{-1}}}\right)^2} \qquad (3.1)$$

However, when using high frequency data in reality, the returns will most likely be biased by market microstructure noise. Since high frequent data is used we need to be aware of the effect from market microstructure noise in order to be able to distinguish between what of the price change that comes from an efficient price mechanism relative from market microstructure noise. Using observed log prices of trading the process looks;

$$\log P\ (t) = \log\ P^*\ (t) +\ \varepsilon(t) \tag{3.2}$$

*Where*: $P^*$ can be thought of as the efficient price change and the term $\varepsilon(t)$ as the market microstructure component.

The market microstructure noise, as essentially is serial correlation in the error term, arises most importantly from the bid-ask bounce which may have a major impact on this type of high frequent data. The distributions of intraday returns are often found to be non-normally distributed. In the paper by Andersen et al. (2001) the returns are found to be heavily skewed to the right and with fatter tails than in a normal distribution. Therefore one important decision to be made is to decide what sampling scheme to apply in the study. The choice of sampling scheme may solve some of the autocorrelation in returns that comes from the market microstructure noise. In this paper we follow the procedure suggested to be superior by Griffin and Oomen (2008) as well as by Fukasawa (2010), by using a tick time data scheme. This implies that we only use price changing transactions in the estimation and exclude all trades with zero returns. Griffin and Oomen explains this approach as when excluding transactions with zero returns, the ask price moves to the bid price and back, implying that the price change to a larger extent comes from an efficient price adjustment than would be the case with transaction time data for estimating RV. This leads to that we exclude all transactions that follow at the same trade price i.e. all zero return transactions and only keep transactions that changed the price to the latest recorded one. In their paper Oomen and Griffin reduce their data points by 90% when using this procedure, implying that 90% of the trades in their sample of the 30 Dow Jones stocks were zero return trades. Since this method is only applicable for tick data we are only able to make this adjustment for the tick time data set. However, since adding zero returns will not affect the realized volatility results, it does not affect our numerical results and comparisons, but only has distributional effects on trying to soften the market microstructure effects. Even if the chosen tick time data scheme will solve some of the market microstructure noise, we still need to be aware of its implications on this type of data. Another feature that must be taken into account is the one regarding overnight returns; we do this by including the closing price of the previous trading day to the report. Overnight returns are in our study only of relevance for the group of companies that announce their earnings outside the trading day and are therefore only collected for that group of companies. Our complete and final tick-time data set adjusted for our chosen sampling schemes of which the realized volatility will be estimated on are listed in the tables below.

| **LARGE CAP** | | **Number of Companies & Trades** | | | |
|---|---|---|---|---|---|
| **Tick Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2013** | Q3 | 15 | *5126* | 40 | *7743* |
| | Q4 | 12 | *3502* | 35 | *8003* |
| **Total** | | 27 | 8628 | 75 | 15746 |
| **MID CAP** | | **Number of Companies & Trades** | | | |
| **Tick Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2013** | Q3 | 6 | *291* | 40 | *997* |
| | Q4 | 8 | *196* | 42 | *1345* |
| **Total** | | 14 | 487 | 82 | 2342 |
| **SMALL CAP** | | **Number of Companies & Trades** | | | |
| **Tick Data** | | On trading | *Total Trades* | Off trading | *Total Trades* |
| **2013** | Q3 | 16 | *205* | 48 | *1368* |
| | Q4 | 15 | *256* | 47 | *1037* |
| **Total** | | 31 | 461 | 95 | 2405 |

**Table 3.3**. Tick data: Number of companies releasing their reports on trading day vs. off trading day considering data requirements

To get a better picture of the data, table 3.4 below shows the average of trades per company and the average of price-changing trades per company. In the last row, the rate of price-changing trades to total trades per company are shown and as can be seen the rate are distinct higher for companies releasing their trades during trading than for companies releasing outside the trading day in our sample. Also note that our rate of price-changing trades seems to be clearly higher compared to the data in the study by Oomen and Griffin (2008) who found that only 10% of the trades changed the price in their study.

| **Tick Data** | **Average number of Trades per Company for Q3 & Q4 2013** | | | | | |
|---|---|---|---|---|---|---|
| | **Large Cap** | | **Mid Cap** | | **Small Cap** | |
| | On trading | Off trading | On trading | Off trading | On trading | Off trading |
| Trades/Company | 887 | 832 | 100 | 99 | 43 | 82 |
| Price-Changing Trades/Company | 320 | 210 | 35 | 29 | 15 | 25 |
| % of Price Changing Trades | 36% | 25% | 35% | 29% | 35% | 30% |

**Table 3.4**. Tick data: Average of trades per company and average of price-changing trades per company.

With all data in place, we prepare our sample in order to estimate the returns. Since we are not interested in specific company’s volatilities but rather in the overall effect of the market distinguished by index and quarter, we need to create indices from our sample. We use equally weighted index in this study which implies that all stocks are treated equally. The reason for using this approach is because we are interested in the overall effect of the timing of reports from a regulatory perspective and not on individual stock level. For every quarter in our study we create six indices, consisting of one “trading-time index” and one “off-trading-time index” for small, mid and Large Cap respectively. For the quarters Q3 and Q4 in 2013 we create six additional indices for our tick time data received from Bloomberg. From all these indices we then calculate the logarithmic returns that are used to estimate the realized volatility. Regarding how to incorporate the overnight returns, we follow a similar approach as Ahoniemi and Lanne (2013) by taking the squared return from the closing price of the last trading day relative to the opening price of the reporting day. The impact of the overnight return will be analyzed separately in order to determine how the market reacts when it is already incorporated in the price. The estimations of realized volatility are model-free estimates of the volatility and we will get six estimates of the volatility for each quarterly report in this study (twelve for Q3,Q4 2013). Since the chosen method is model free, we will further outline the distributions of our results in order to try to outline what impact the market microstructure may have on our results. The distribution of the sample is outlined by estimating the “fourth moments” which is the mean, standard deviation, skewness and kurtosis. Through calculating the Skewness and Kurtosis of the data, the statistical distribution can reveal if the data is symmetrically distributed or not.

# 4. Results

In this section the results of return volatility after earnings announcements are presented when using the Realized Volatility (RV) approach. The results are further separated into the two different sampling schemes that are used; with tick data as the first and minute data as the latter. Later in this section we outline the standard deviations of trading for each of the fifteen minutes after a financial report is released. The section finishes up with statistical distributions of the intraday minute data.

## 4.1 Estimation of Realized Volatility using Tick data

Considering the first sampling scheme when using tick data, data is available for the two most recent quarters, Q3 and Q4 2013. The Realized Volatility is here calculated as an equally weighted index for Large, Mid and Small Cap on the Stockholm Stock Exchange.

Graph 4.1 shows the 15 minute Realized volatility for the companies releasing their reports during on trading hours, off trading hours and off trading hours when excluding the overnight return.

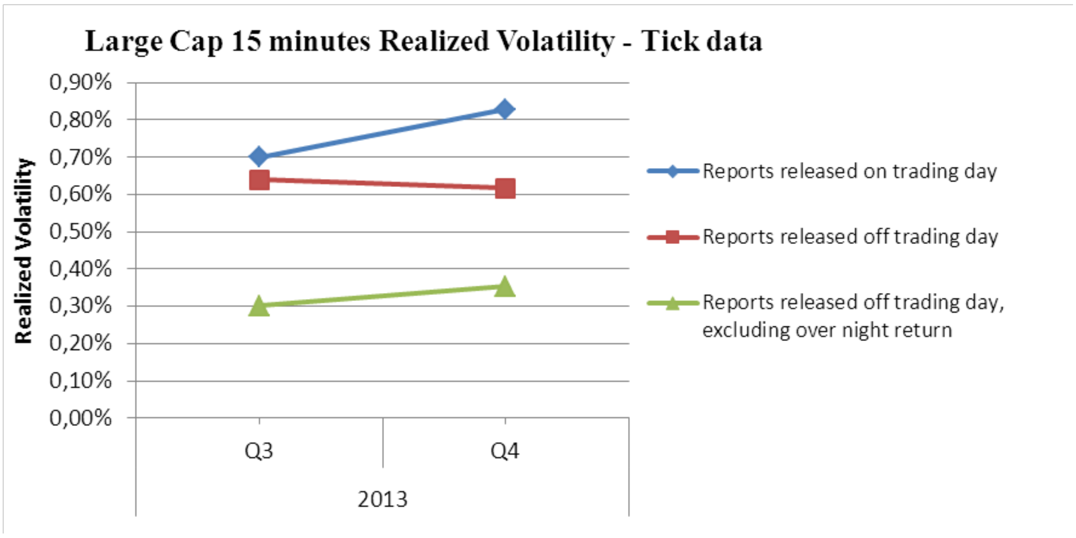



**Figure 4.1** Large Cap: Fifteen minutes return volatility for on trading, off trading and off trading excluding overnight return based on Tick data

From figure 4.1 it can be seen that the Realized Volatility for the companies releasing their reports during trading hours appear to have a higher return volatility than the companies releasing their reports during non-trading hours. The equally weighted RV for companies releasing their reports during on trading hours is estimated to be 0,70 % for Q3 and 0,83 % for Q4. The estimated RV for companies releasing their reports during off trading hours are

0,64% and 0,62%, respectively. If excluding the overnight return when estimating the off-day return volatility it is obvious that the Realized Volatility decreases significantly, from 0,64% to 0,30 % for Q3 and from 0,62% to 0,35 % for Q4 (see Appendix 2 Table 1-2). This indicates that the overnight return constitutes approximately 50 percentage points of the total off-day return for the companies releasing their reports during non-trading hours.

The same estimations regarding Realized Volatility is made for the companies listed on Mid Cap. The results are presented in figure 4.2 below.

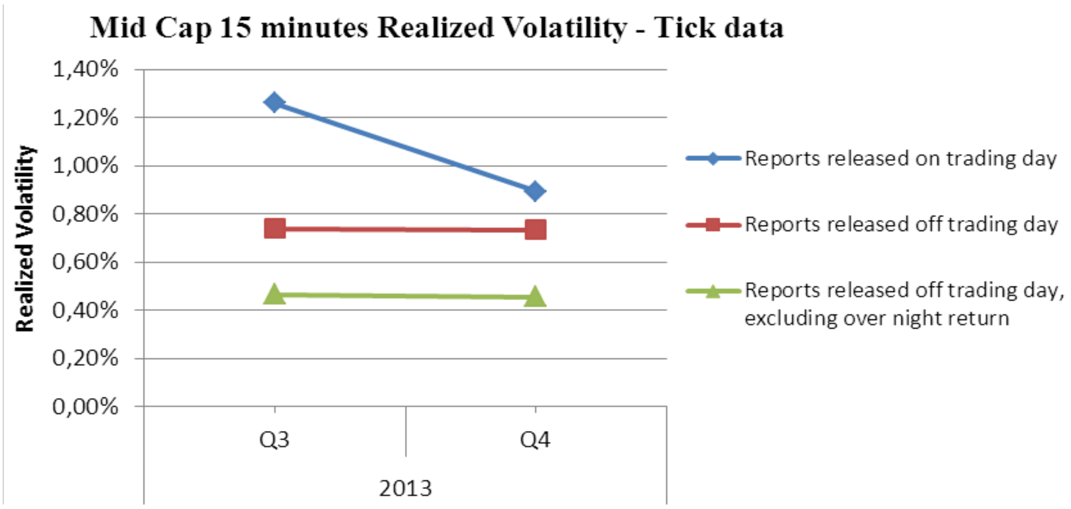
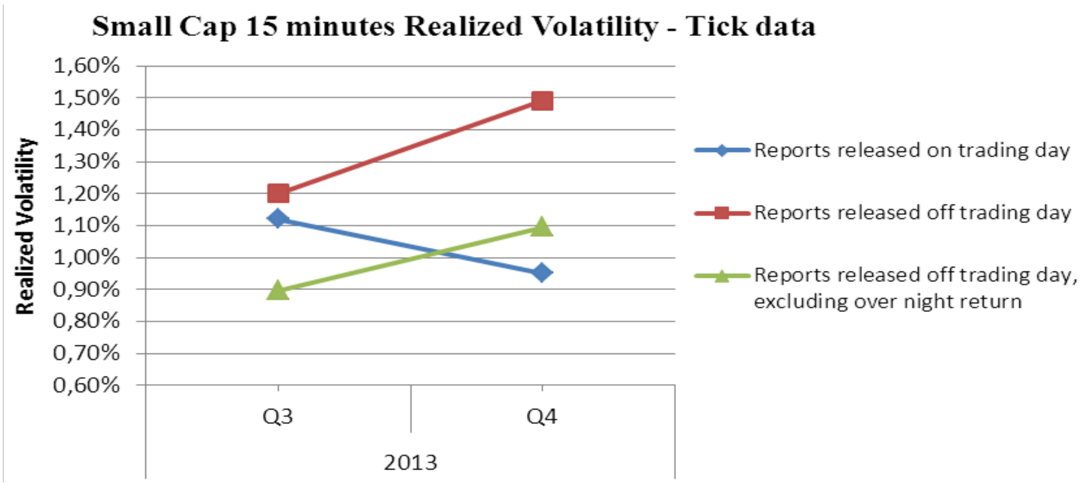



**Figure 4.2** Mid Cap: Fifteen minutes return volatility for on trading, off trading and off trading excluding overnight return based on Tick data

Apparent from the graph is that the realized volatility is higher for the companies announcing their quarterly reports when the stock market is open compared to the companies releasing their reports when the marketplace is closed. The estimated RV for companies releasing their reports during trading hours is 1,26 % for Q3 and 0,89% for Q4. The RV for companies releasing their reports during non-trading hours is 0,74 % for Q3 and 0,73 % for Q4. If excluding the overnight return from the return when estimating the Realized Volatility for companies that releases their reports off-trading hours the realized volatility decreases extensively to 0,47 % for Q3 and 0,46 % for Q4 (see Appendix 2 table 2.1).

The estimations regarding the 15 minute Realized Volatility for the companies listed on Small Cap are performed in the same manner as for Large and Mid Cap. The results are presented in figure 4.3 below.




*(Note: The y-axis starts at 0,6%)*
**Figure 4.3** Small Cap: Fifteen minutes return volatility for on trading, off trading and off trading excluding overnight return based on Tick data

For the companies listed on Small Cap the estimated realized volatility for the companies releasing their reports during trading hours is 1,12 % for Q3 and 0,95% for Q4. The RV for companies releasing their reports during non-trading hours is 1,20 % for Q3 and 1,49 % for Q4. If excluding the overnight return from the return when estimating the overnight return the realized volatility decreases to 0,89 % for Q3 and 1,10 % for Q4 (see Appendix 2 table 3-4). Considering the results concerning the companies listed on Small Cap the outcome is different to the results for Large and Mid Cap. The realized volatility for companies releasing their reports during off trading hours appears to be higher for both quarters, Q3 and Q4 2013. If excluding the overnight return from the estimation, the realized volatility is higher for companies releasing their reports during trading hours for Q3. For Q4, the realized volatility is higher for reports released off-trading, even when the overnight return are excluded. A different result to what was shown for Large and Mid Cap.

## 4.2 Estimation of Realized Volatility using Minute data

In the second sampling scheme we apply minute data when estimating return volatility. For each quarter, Q1-Q4, for the period 2011-2013 we calculate the Realized Volatility for each list; Large, Mid and Small Cap, using an equally weighted index. The Realized Volatility for Large Cap is presented in figure 4.4 below.

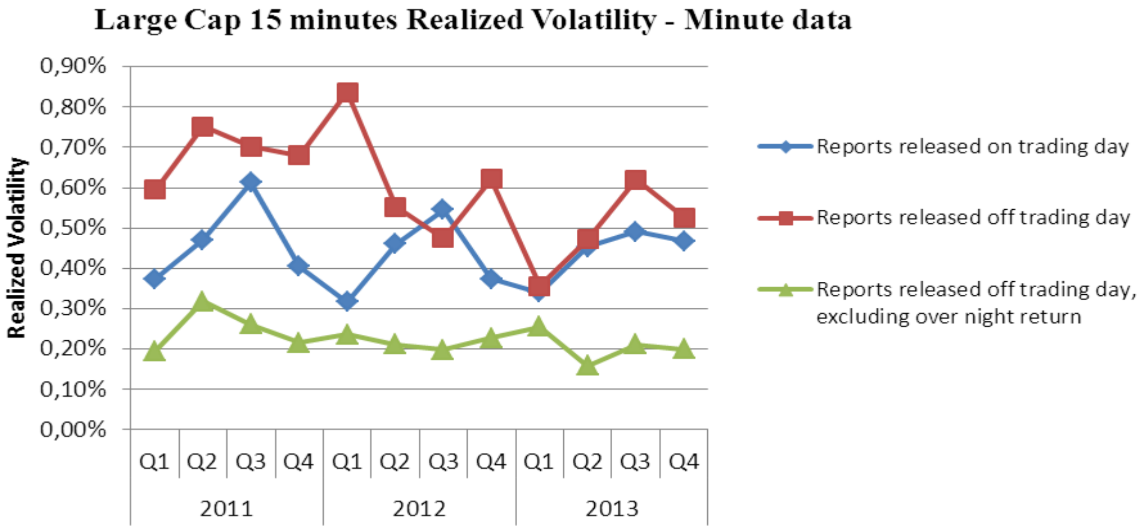



**Figure 4.4** Large Cap: Fifteen minutes return volatility for on trading, off trading and off trading excluding overnight return based on Minute data.

From figure 4.4 it appears that the return volatility for companies announcing their reports during non-trading hours is higher than the return volatility for companies releasing their reports during trading hours. The Realized Volatility for on trading is in the range 0,32 % (Q1 2012) to 0,61% (Q3 2011) and the Realized Volatility for off trading is in the range 0,36% (Q1 2013) to 0,84 % (Q1 2012) (see Appendix 2 table 2.2). However, when excluding the overnight return, the return volatility is higher for companies releasing their reports during day. Excluding overnight return when estimating off day realized return, results in estimates in the range 0,16%(Q2 2013) to 0,32% (Q2 2011) (see Appendix 2 table 2.2).

The same estimations regarding Realized Volatility based on minute data is made for the companies listed on Mid Cap. The results are presented in figure 4.5 below.

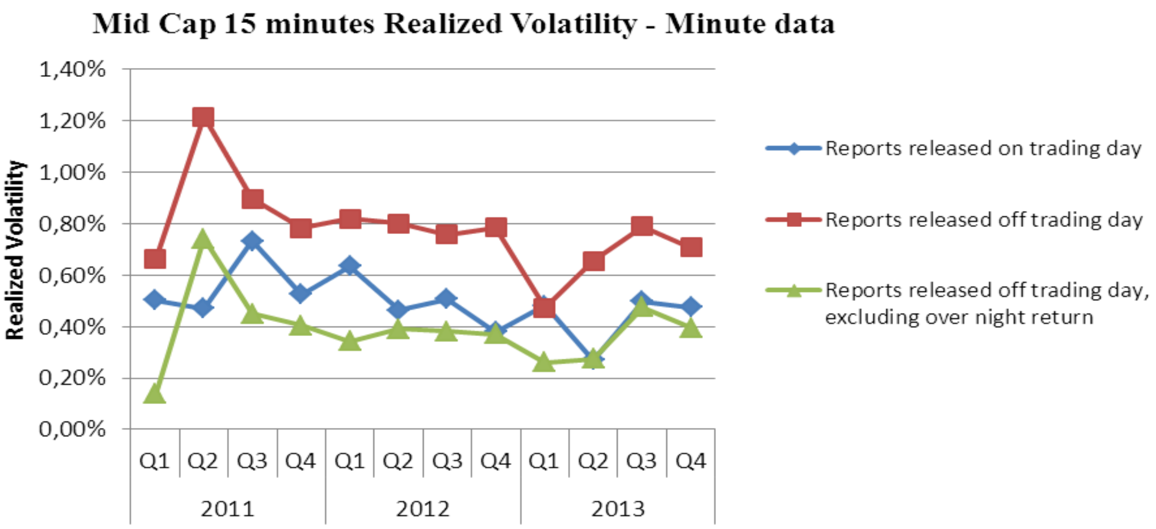



**Figure 4.5** Mid Cap: Fifteen minutes return volatility for on trading, off trading and off trading excluding overnight return based on Minute data**.**

Studying figure 4.5 the results regarding Realized Volatility for the companies listed on Mid Cap seems to follow a similar pattern as the results regarding the companies listed on Large Cap. Hence, the return volatility for companies announcing their reports during non-trading hours appears to have a higher volatility when the return volatility for companies releasing their reports during trading hours. The realized volatility for on trading is in the range 0,27 % (Q2 2013) to 0,73% (Q3 2011) and the realized volatility for off trading is in the range 0,47% (Q1 2013) to 1,22% (Q2 2011). When excluding the overnight return the results changes significantly and the Realized Volatility is higher for companies releasing their reports during on trading hours than for companies releasing their reports during off trading hours. Excluding overnight return when estimating off day realized return results in estimates in the range 0,14% (Q1 2011) to 0,74% (Q2 2011) (see Appendix 2 table 2.2 for further details).

Graph 4.6 shows the estimations regarding Realized Volatility based on minute data for the companies listed on Small Cap.

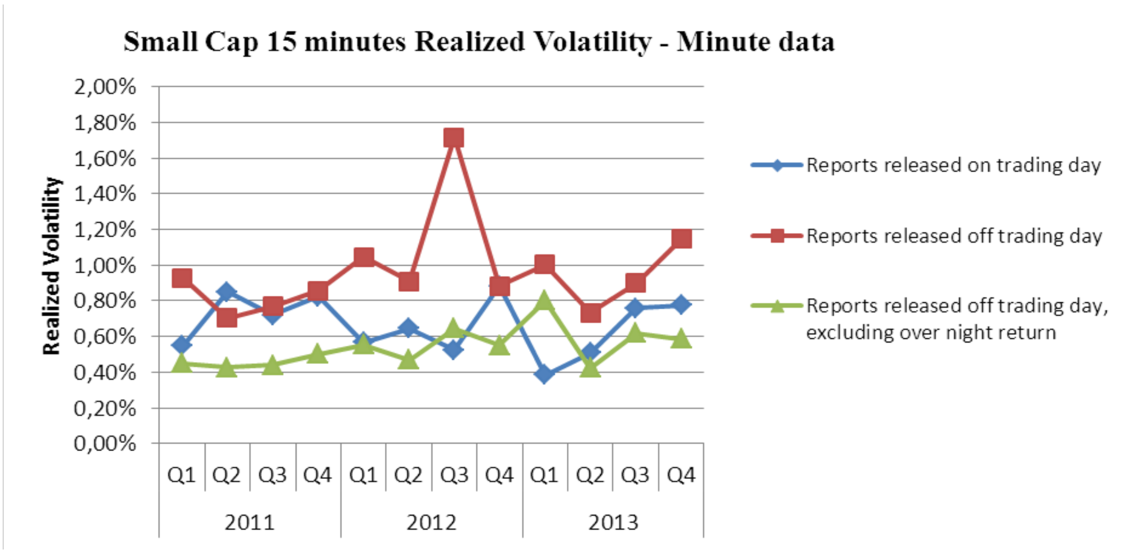



**Figure 4.6** Small Cap: Fifteen minutes return volatility for on trading, off trading and off trading excluding overnight return for based on Minute data

Graph 4.6 presents the results regarding Realized Volatility for 15 minute return data for the companies listed on Small Cap. Equivalent to the results regarding Large and Mid Cap, the return volatility for companies releasing their reports during off trading hours appears to be higher than for companies disclosing their financial reports during trading hours when including the overnight return. If excluding the overnight return from the calculations, the result changes and results in an overall higher Realized Volatility for companies releasing their reports during trading hours compared to companies releasing their reports when the market is closed. This is the case for all quarterly estimates except for Q3 2012 and Q1 2013 where the average realized volatility is lower for the companies releasing their reports during off trading hours compared to companies reporting on trading hours. From the calculations the Realized Volatility for on trading is in the range 0,39% (Q1 2013) to 0,88% (Q4 2012) and the Realized Volatility for off trading is in the range 0,70%(Q2 2011) to 1,15% (Q2 2012) (see Appendix 2 table 2.2). When excluding the overnight return from the estimate when calculating the Realized Volatility for companies releasing their reports during off trading hours the results changes and the Realized Volatility is overall higher for on trading than for off trading. Excluding overnight return when estimating off day realized return results in estimates in the range 0,42%(Q2 2013) to 0,80% (Q1 2013).

## 4.3 The impact of Overnight Return

As can be seen from the study by Ahoniemi and Lanne (2013) the overnight return is of importance when estimating the Realized Volatility for the companies that release their reports when the market is closed. This as a consequence of that the information that is released when the market is closed will be reflected in the opening price the next trading day. Therefor the price change and the overnight return might be large, depending on the information, and as a result having a large impact on the total daily return. Hence it is of importance to address the impact of the overnight return. In this study, for companies releasing their financial reports when the market place is closed, we estimate realized volatility from the close price of the previous day up until 15 minutes on the next trading day (09:15), indicating that the overnight return is included in this estimate. In the above section we showed that if excluding overnight return when estimating off day realized volatility, the realized volatility decreased significantly by approximately 0,40 percentage points on average, indicating that the overnight return that occurs due to the release of financial reports affect the final result on realized volatility significantly.

In order to show what impact the overnight return has on the realized volatility and how the trading appears within the 15 minute timeframe for the reports that are published off trading hours versus on trading hours, we calculate the average standard deviation of the returns for every minute within the 15 minute time period. Applying this method we get a picture of how the trading on average occurs every minute after a report is released. These calculations for Large Cap Mid Cap and Small Cap are presented in the following section.

Figure 4.7 presents the average return standard deviation for all companies listed on Large Cap that are included in the study for all quarters, Q1-Q4, for the period 2011-2013.

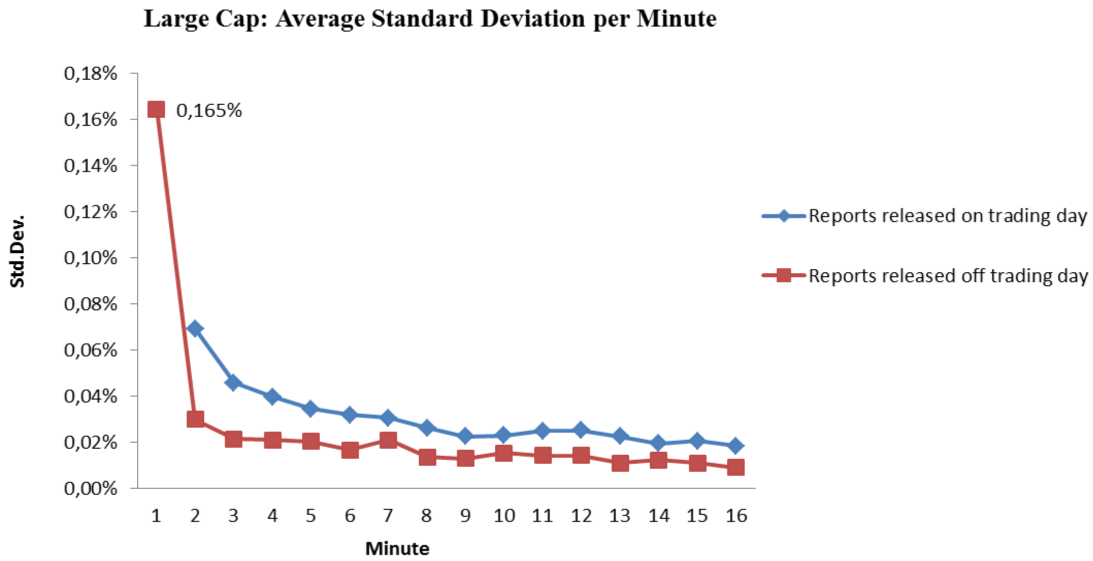
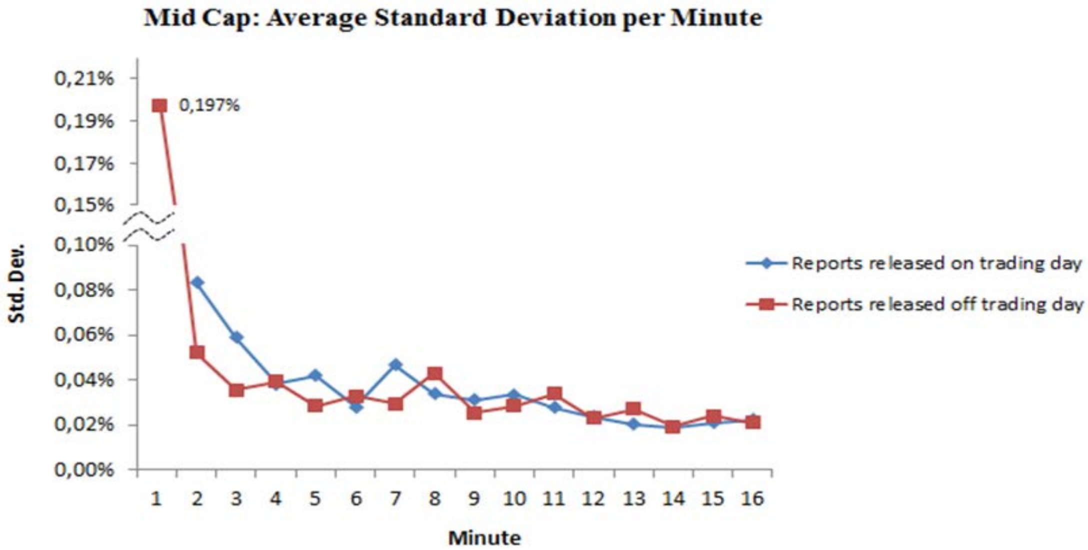



**Figure 4.7** Average Standard Deviation over the period 2011-2013 for the companies listed on Large Cap for each minute in the 15-minute period.

The graph shows that the first data point (1; 0,165%), which is the estimate of the average overnight return standard deviation for the companies releasing their reports off trading hours, is significantly higher than the other data points which all have estimates in the range 0,0089% to 0,0300 % . Hence, if excluding the effect of overnight return on Realized Volatility the average return volatilities for companies releasing their reports during non-trading hours fall into this range, resulting in a much lower total Realized Volatility. This indicates that the impact that the overnight return has on the intraday return and hence the Realized Volatility is high for companies that release their financial reports during non-trading hours, and if excluded, the Realized Volatility falls significantly.

Figure 4.8 presents the average return standard deviation for all companies listed on Mid Cap that are included in the study for all quarters over the period 2011-2013.

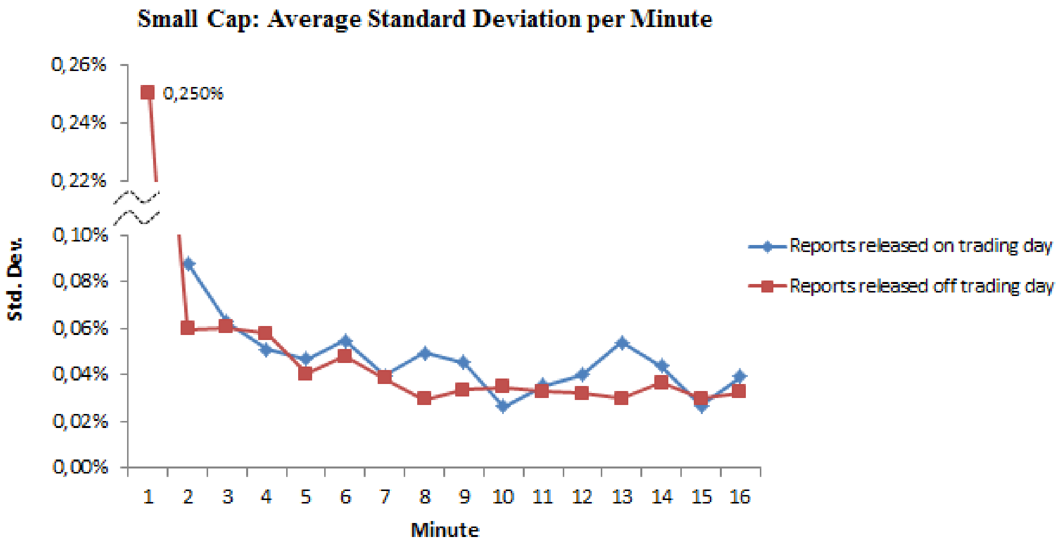



***(Note: The y-axis breaks at Std. Dev. = 0,10% and continues at Std. Dev. =0,15%)***

**Figure 4.8** Average Standard Deviation over the period 2011-2013 for the companies listed on Mid Cap for each minute in the 15-minute period.

Equivalent to the results for Large Cap, the first data point for Mid Cap in the graph (1;0,197%) shows the standard deviation for the overnight return. Apparent is that it has a value considerably larger than the other data points, (minute 2-16 which constitute the time frame 09:00-09:15) for the companies reporting off trading hours, which are in the range 0,0191% to 0,0522%. Also here this significantly higher value will have a large impact on the estimate of Realized Volatility for companies releasing their reports during non-trading hours. Comparing the data points of the curve, it appears that the highest standard deviation for companies releasing their reports during on trading hours is 0,0834% (data point 2;0,0834%), significantly smaller than the highest data point (1:0,197%) for companies reporting off trading hours.

Figure 4.9 presents the average standard deviation for all companies listed on Small Cap that are included in the study for all quarters for the period 2011-2013.




*(Note: The y-axis breaks at Std. Dev. = 0,10% and continues at Std. Dev. =0,22%)*

**Figure 4.9** Average Overnight Return Volatility over the period 2011-2013 for the companies listed on Small Cap for each minute in the 15-minute period.

Studying the results in the graph above which shows the average standard deviation of return for the companies listed on Small Cap over the period 2011-2013, we can see that the first data point (1;0,25%), is significantly higher than the other data points, which are in the range 0,0296% to 0,0606%. The high value of the overnight return will therefore have a large effect on the total Realized Volatility for the companies that release their financial reports during off trading hours, resulting in a high estimate for Realized Volatility. Comparing the curve for the companies releasing their reports during off trading hours to companies releasing their reports during on trading hours it appears that the highest standard deviation for companies releasing their reports during trading hours is 0, 088% (data point 2;0,088%).

## 4.4 Market Microstructure and Statistical Distribution

Since most of the theory suggests that high frequent intraday returns exhibit serial correlation, which most importantly arises from the market microstructure noise, the distributions of the dataset constituted by minute data are presented in the following. In the study from 2001, Andersen et.al found the data to be non-normally distributed with fatter tails than in a normal distribution and skewed to the right; this in essence means that the returns were serially correlated. As such, this paper follows a similar approach as Andersen et.al, by first showing the distribution of the variances in trades and then the distribution of the logarithmic standard deviations. The illustration of the distribution of the logarithmic standard deviation is essentially in order to see how much of the market microstructure that is corrected by taking the logarithmic standard deviations.

In order to be able to show the distributions of the data and how it vary within the fifteen minutes of trading, we calculate the mean, standard deviation, skewness and kurtosis of the squared returns for all the reports in this study separately. By dividing these distributions into the groups of which index the report belong to and if the report are released during trading time or when the market was closed, enables us to also see if the data is distributed differently in any of the scenarios. The results of these calculations for the Large Cap stocks are listed in table 4.10 below and are divided into percentiles, since the number of reports in all categories are high.

| **Distribution of Variance: Off trading** | | | | | **Distribution of Variance: On trading** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Number of reports: 467** | **LargeCap** | | | | **Number of reports: 206** | **LargeCap** | | | |
| | Mean. | Std.Dev. | Skew. | Kurt. | | Mean. | Std.Dev. | Skew. | Kurt. |
| Minimum | 0 | 0 | 0,74 | -1,21 | Minimum | 0 | 0 | 0,22 | -2,09 |
| 0,10 | 0,000001 | 0,000003 | 1,76 | 2,36 | 0,10 | 0,0000002 | 0,0000004 | 0,87 | -0,56 |
| 0,25 | 0,000006 | 0,000015 | 2,82 | 8,08 | 0,25 | 0,0000011 | 0,0000024 | 1,48 | 1,16 |
| 0,50 | 0,000020 | 0,000074 | 3,80 | 14,76 | 0,50 | 0,0000149 | 0,0000231 | 2,47 | 6,39 |
| 0,75 | 0,000061 | 0,000332 | 3,99 | 15,94 | 0,75 | 0,0000429 | 0,0000760 | 3,52 | 12,91 |
| 0,90 | 0,000280 | 0,001393 | 4,00 | 16,00 | 0,90 | 0,0000782 | 0,0001740 | 3,80 | 14,54 |
| Maximum | 0,002234 | 0,008327 | 4,00 | 16,00 | Maximum | 0,0001930 | 0,0004240 | 3,87 | 14,95 |
| **Mean Total** | 0,000092 | 0,000325 | 3,53 | 13,00 | **Mean Total** | 0,0000222 | 0,0000403 | 2,43 | 6,56 |

**Table 4.10** Distributions of Variances in trading during the 15 minute time window for all reports and all companies on Large Cap.

The above table show the Large Cap stocks and the distribution of the squared returns show that the data is non-normally distributed with high skewness (3,53 and 2,43 respectively on average) and high kurtosis (13 and 6,56 respectively, on average). Interesting to note is that the skewness and kurtosis are distinct higher for the companies that release their report off trading day, i.e. in the left column of the table relative to companies that released their report on trading day.

In order to adjust for the market microstructure in the above data, the logarithmic standard deviations is computed, this in a similar manner as before. The distributions of this approach for the stocks listed on Large Cap are shown in table 4.11 below.

| Distribution of Standard Deviation: Off trading | | | | | Distribution of Standard Deviation: On trading | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Number of reports: 467 | Large Cap | | | | Number of reports: 206 | Large Cap | | | |
| | Mean. | Std.Dev. | Skew. | Kurt. | | Mean. | Std.Dev | Skew. | Kurt. |
| Minimum | 0 | 0 | 0,08 | -1,52 | Minimum | 0 | 0 | -0,40 | -2,09 |
| 0,10 | 0,0005 | 0,0009 | 0,97 | 0,02 | 0,10 | 0,0002 | 0,0004 | 0,19 | -1,29 |
| 0,25 | 0,0014 | 0,0020 | 1,93 | 3,50 | 0,25 | 0,0005 | 0,0009 | 0,70 | -0,56 |
| 0,50 | 0,0027 | 0,0043 | 2,96 | 9,70 | 0,50 | 0,0027 | 0,0025 | 1,48 | 1,93 |
| 0,75 | 0,0047 | 0,0096 | 3,73 | 14,40 | 0,75 | 0,0047 | 0,0046 | 2,43 | 6,45 |
| 0,90 | 0,0086 | 0,0197 | 3,95 | 15,64 | 0,90 | 0,0065 | 0,0068 | 3,22 | 10,64 |
| Maximum | 0,0196 | 0,0444 | 4 | 15,90 | Maximum | 0,0091 | 0,0108 | 3,87 | 12,82 |
| **Mean Total** | 0,0035 | 0,0067 | 2,93 | 9,77 | **Mean Total** | 0,0028 | 0,0028 | 1,52 | 2,68 |

**Table 4.11** Distributions of logarithmic standard deviations in trading during the 15 minute time window for all reports and all companies on Large Cap.

The table shows improvements from the initial table, with lower skewness and kurtosis for both categories, where the distribution of the daytime reports still seem to be distinct closer to a normal distribution than the trading in off trade reports. This gap has also been improved for the on trading reports, but still the data is positively skewed for almost all the stocks in this study in both categories and even if the distribution of the on trading day reports are closer to a normal distribution, the data is non-normally distributed for both categories.

The paper proceeds with showing the distribution tables for Mid Cap and Small Cap respectively. The same approach as for Large Cap is used and also here all the reports in the sample are included as shown in table 4.12 below.

| Distribution of Variance: Off trading | | | | | Distribution of Variance: On trading | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Number of reports: 437 | Mid Cap | | | | Number of reports: 188 | Mid Cap | | | |
| | Mean. | Std.Dev. | Skew. | Kurt. | | Mean. | Std.Dev. | Skew. | Kurt. |
| Minimum | 0,000000 | 0,000000 | 0,76 | -1,46 | Minimum | 0 | 0 | 0,75 | -1,62 |
| 0,10 | 0,000001 | 0,000003 | 1,84 | 2,46 | 0,10 | 0 | 0 | 1,24 | -0,08 |
| 0,25 | 0,000008 | 0,000021 | 2,60 | 6,34 | 0,25 | 0 | 0 | 1,86 | 2,69 |
| 0,50 | 0,000058 | 0,000160 | 3,71 | 14,14 | 0,50 | 0,000015 | 0,000034 | 2,85 | 8,35 |
| 0,75 | 0,000240 | 0,000780 | 4,00 | 15,98 | 0,75 | 0,000052 | 0,000115 | 3,78 | 14,48 |
| 0,90 | 0,000830 | 0,002700 | 4,00 | 16,00 | 0,90 | 0,000164 | 0,000425 | 3,87 | 14,96 |
| Maximum | 0,002900 | 0,011000 | 4,00 | 16,00 | Maximum | 0,000733 | 0,001707 | 3,87 | 15,00 |
| **Mean Total** | 0,000150 | 0,000470 | 3,41 | 12,12 | **Mean Total** | 0,000029 | 0,000069 | 2,80 | 8,32 |

**Table 4.12** Distributions of Variances in trading during the 15 minute time window for all reports and all companies on Mid Cap.

In the above table the distributions of the variances are summarized for the Mid Cap stocks. The calculations show that the data is positively skewed and with high kurtosis, implying that the data is not normally distributed. As was the case with the distributions of Large Cap, the reports that are released during trading time i.e. the right column show to have lower skewness and kurtosis (2,80 and 8,32) on average compared to those companies that release their reports outside trading time (3,42 and 12,12).

Trying to adjust for market microstructure, the logarithmic standard deviations for Mid Cap are calculated. The calculations and distributions are shown in table 4.13 below.

| **Distribution of Standard Deviation: Off trading** | | | | | **Distribution of Standard Deviation: On trading** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Number of reports: 437** | **Mid Cap** | | | | **Number of reports: 188** | **Mid Cap** | | | |
| | Mean. | Std.Dev. | Skew. | Kurt. | | Mean. | Std.Dev | Skew. | Kurt. |
| Minimum | 0 | 0 | 0,35 | -1,76 | Minimum | 0 | 0 | -0,04 | -1,62 |
| 0,10 | 0,00020 | 0,00080 | 1,15 | 0,21 | 0,10 | 0 | 0 | 0,59 | -0,95 |
| 0,25 | 0,00100 | 0,00250 | 1,88 | 2,82 | 0,25 | 0,000008 | 0,000033 | 1,12 | 0,22 |
| 0,50 | 0,00320 | 0,00640 | 2,89 | 8,98 | 0,50 | 0,001597 | 0,002892 | 2,02 | 3,77 |
| 0,75 | 0,00700 | 0,01390 | 3,84 | 15,07 | 0,75 | 0,003767 | 0,005822 | 3,36 | 10,85 |
| 0,90 | 0,01240 | 0,02510 | 3,99 | 15,92 | 0,90 | 0,007061 | 0,010239 | 3,87 | 14,87 |
| Maximum | 0,02050 | 0,05160 | 4,00 | 16,00 | Maximum | 0,017925 | 0,020993 | 3,87 | 15,00 |
| **Mean Total** | 0,00410 | 0,00830 | 2,79 | 8,59 | **Mean Total** | 0,001969 | 0,003177 | 2,12 | 5,03 |

**Table 4.13** Distributions of logarithmic standard deviations in trading during the 15 minute time window for all reports and all companies on Mid Cap.

The results in the above table follows the same trend as was the case for the stocks listed on Large Cap and the data is also here positively skewed and with high kurtosis. This implies, as before, that the data is not normally distributed. Furthermore, the distribution of daytime reports has on average distinct lower skewness and kurtosis (2,12 and 5,03) relative to the average skewness and kurtosis for companies releasing their reports off trading hours (2,79 and 8,59). The same findings as for Large Cap which is interesting to note.

The table 4.14 below summarizes the distributions of the variances of the Small Cap stocks, with the same approach as for Large and Midcap.

| **Distribution of Variance: Off trading** | | | | | **Distribution of Variance: On trading** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Number of reports: 735** | **Small Cap** | | | | **Number of reports: 364** | **Small Cap** | | | |
| | Mean. | Std.Dev. | Skew. | Kurt. | | Mean. | Std.Dev. | Skew. | Kurt. |
| Minimum | 0 | 0 | 0,57 | -1,93 | Minimum | 0 | 0 | 0,79 | -1,60 |
| 0,10 | 0 | 0 | 1,74 | 1,84 | 0,10 | 0 | 0 | 1,31 | 0,28 |
| 0,25 | 0,000005 | 0,000016 | 2,57 | 6,08 | 0,25 | 0 | 0 | 2,10 | 3,57 |
| 0,50 | 0,000109 | 0,000316 | 3,71 | 14,15 | 0,50 | 0,000031 | 0,000084 | 3,47 | 12,33 |
| 0,75 | 0,000454 | 0,001416 | 4,00 | 16,00 | 0,75 | 0,000151 | 0,000412 | 3,87 | 15,00 |
| 0,90 | 0,002805 | 0,009429 | 4,00 | 16,00 | 0,90 | 0,000512 | 0,001272 | 3,87 | 15,00 |
| Maximum | 0,039281 | 0,155310 | 4,00 | 16,00 | Maximum | 0,001539 | 0,004047 | 3,87 | 15,00 |
| **Mean Total** | 0,000406 | 0,001321 | 3,42 | 12,20 | **Mean Total** | 0,000090 | 0,000230 | 3,09 | 10,10 |

**Table 4.14** Distributions of Variances in trading during the 15 minute time window for all reports and all companies on Small Cap.

In line with the results for Large and Midcap, the above table shows that also the Small Cap stocks are positively skewed and with a high kurtosis. Equal to Large and Mid Cap, also Small Cap companies exhibit to have a lower skewness and kurtosis for companies reporting on trading hours (3,09 and 10,10) compared to companies reporting off trading hours (3,42 and 12,20). However the large values imply that the distributions of the variances are not normally distributed. Therefore the distributions of the logarithmic standard deviations are estimated, this in order to potentially adjust for market microstructure.

The table 4.15 below shows the distribution of the logarithmic standard deviations for the Small Cap companies' reports.

| **Distribution of Standard Deviation: Off trading** | | | | | **Distribution of Standard Deviation: On trading** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Number of reports: 735** | **Small Cap** | | | | **Number of reports: 364** | **Small Cap** | | | |
| | Mean. | Std.Dev. | Skew. | Kurt. | | Mean. | Std.Dev | Skew. | Kurt. |
| Minimum | 0 | 0 | 0,23 | -1,93 | Minimum | 0 | 0 | 0,29 | -1,69 |
| 0,10 | 0 | 0 | 1,17 | 0,23 | 0,10 | 0 | 0 | 0,68 | -0,92 |
| 0,25 | 0,00046 | 0,00162 | 1,94 | 2,97 | 0,25 | 0 | 0 | 1,51 | 1,15 |
| 0,50 | 0,00385 | 0,00900 | 3,04 | 9,69 | 0,50 | 0,00168 | 0,00439 | 2,83 | 8,19 |
| 0,75 | 0,00895 | 0,01965 | 3,97 | 15,83 | 0,75 | 0,00535 | 0,01105 | 3,86 | 14,90 |
| 0,90 | 0,01977 | 0,04135 | 4,00 | 16,00 | 0,90 | 0,01206 | 0,01887 | 3,87 | 15,00 |
| Maximum | 0,07086 | 0,19639 | 4,00 | 16,00 | Maximum | 0,02362 | 0,03394 | 3,87 | 15,00 |
| **Mean Total** | 0,00535 | 0,01190 | 2,93 | 9,32 | **Mean Total** | 0,00283 | 0,00573 | 2,68 | 7,95 |

**Table 4.15** Distributions of logarithmic standard deviations in trading during the 15 minute time window for all reports and all companies on Small Cap.

The table above shows that, as was the case for both Large and Mid Cap, the skewness and kurtosis are lowered, and more so for the group of companies that release their report during trading day, which is in line with the results from Large and Mid Cap. Still the data is positively skewed and has high kurtosis, so that the data is not normally distributed.

In order to simplify the reading, a summary of the average distributions of the logarithmic standard deviations for all the companies and all reports, distinguished between indexes and if the company releases their report during trading time or when the market is closed is conducted and presented below in table 4.16.

| **Mean Total Distribution of Standard Deviation: Off trading** | | | | |
|---|---|---|---|---|
| | Mean | Std.Dev. | Skew. | Kurt. |
| LargeCap | 0,003 | 0,007 | 2,93 | 9,77 |
| MidCap | 0,004 | 0,008 | 2,79 | 8,59 |
| SmallCap | 0,005 | 0,012 | 2,93 | 9,32 |

| **Mean Total Distribution of Standard Deviation: On trading** | | | | |
|---|---|---|---|---|
| | Mean | Std.Dev. | Skew. | Kurt. |
| LargeCap | 0,003 | 0,003 | 1,52 | 2,68 |
| MidCap | 0,002 | 0,003 | 2,12 | 5,03 |
| SmallCap | 0,003 | 0,006 | 2,68 | 7,95 |

**Table 4.16** Mean distribution of logarithmic standard deviations in trading during the 15 minute time window, for all reports and all companies, divided in lists and between On/Off trading time reports.

Since a normal distribution has zero skewness and kurtosis of three, we can see that this data is not normally distributed. Interesting to note, however, is that the numbers is lower for companies releasing their reports at daytime relative to off-trading throughout this study.

# 5. Analysis

The purpose of this study is to estimate the return volatility after the disclosure of earnings announcements and further investigate if there exists any differences in volatility for companies releasing their reports on trading hours relative to off trading hours. The return volatility depends on how much the price fluctuates over a given time period and the price in turn is given by supply and demand from the investors' beliefs of the value of the firm. Since the valuation of a firm to a large extent is based on earnings announcements, the arrival of new information is of large importance. Consequently, if the information surprises the market the price will jump and affect the return volatility to a larger extent. In this study we draw attention to the immediate period (fifteen minutes) after the release of a company's earnings announcement. As Patell and Wolfson points out the speed of adjustment towards the efficient market price is most effective during the first 15 minutes after information is released. From the results (section four figure 4.7-4.9 ) where we outline every fifteen minute we can observe that overall the curves are decreasing for each minute. Also observable is that the standard deviation decreases at a diminishing rate for each minute, which further could indicate that the market adjust to the fair price.  We believe that how quickly it takes for the market to clear due to new information can be reflected in how volatile the stock return is in the immediate period after the release of financial reports, however it takes some short time period for the market to clear as traders are pushing the price to the fair value.

Considering the tick time dataset (over the period Q3-Q4 2013) the calculations show that the return volatility is higher for companies announcing their reports when the marketplace is open (09:00-17:29) compared to the return volatilities for companies releasing their reports when the marketplace is closed (17:30-08:59). This result is consistent for the companies listed on Large and Mid Cap and is in line with our assumption. We observe that the return volatility is approximately 0,1 to 0,2 percentage points higher for the companies reporting on trading day relative to companies reporting off day.

If excluding the effect of the overnight return from the estimate of Realized Volatility for companies releasing off trading hours the discrepancy between the volatilities increases even more. We suggest that this discrepancy might be due to overnight trading were the market have time to anticipate the new information and as a result when the market re-opens on the next trading day, the stock prices have already adjusted to the new information, indicating a lower intraday volatility for companies reporting off trading hours. We propose that when reports are released when the market is closed, overnight trading occurs in the sense that investors have time to evaluate the new information during night and in the morning, when the market re-opens; the company are traded closer to its fair value. An explanation to this phenomenon may be that since the valuation methods of stocks have similar patterns for many investors, the availability of the same information which is used as inputs in these models will create more homogeneous valuations, hence; a higher degree of agreement when they have more time to evaluate the new information before they start to trade.

Considering the results again when applying tick data in this study our estimations of the Realized Volatility for Large Cap and Mid Cap supports the assumption that return volatilities are higher for companies that release their financial reports when the stock market is open compared to companies that release their reports when the marketplace is closed. This reasoning can also be related to the efficient market hypothesis, EMH, which suggests that stock prices adjust quickly but not instantaneously to new information. For Small Cap, the results differ and our estimations show that the Realized Volatility is higher for companies releasing their reports when the stock market is closed, a result different to what was shown for Large and Mid Cap. However when excluding the effect of the overnight return, which has a large impact on the Realized Volatility measure, the return volatility is now higher for companies releasing their reports during on-trading hours for Q3 but for Q4 the final outcome remains unchanged.

The second sampling scheme applied in the study is Minute data. The Minute data of this study covers the period Q1-Q4 for each year 2011-2013, a considerably longer period than the Tick data. Considering the results, both regarding the companies listed on Large Cap as well as the companies listed on Mid Cap and Small Cap, we observe that the estimated Realized Volatility for companies releasing their reports on trading hours are lower than the return volatility for the companies releasing their reports during off trading hours, the opposite result to what was shown when using Tick data. Also here the overnight return serves for approximately half of the return volatility when measuring the Realized Volatility for the companies releasing their reports during non-trading hours. When excluding overnight returns the result changes and the return volatility is now overall higher for companies releasing their reports during daytime. The same reasoning as was made concerning tick data how the market anticipate new information and agrees upon the stock price can be made here.

In this study we calculate the return for companies releasing their reports during off trading hours in two ways; including overnight return and excluding overnight return. Distinguishing between these two measures it is apparent that the overnight return serves for approximately half of the total return volatility for companies releasing their reports during off trading hours; both when applying tick data as well as minute data. As a result the overnight return will have a significant and large effect on the final Realized Volatility for companies releasing their reports during off trading hours. In order to get a clearer picture of how big the impact of the overnight return is we outline the aggregate average standard deviation of the return for all companies on each separate list over the period 2011-2013 for each minute (see section 4.3 figure 4.7-4.9), where the calculations are based on minute data (however the same reasoning can be made for tick data, since if tick data is aggregated into minutes it will result in the same outcome). From the results it is observable that the estimated values of overnight return (minute 1) deviates from the other data points (minute 2-15) which all have much lower standard deviations. From the curve representing reports released off trading day it appears that the Realized Volatility decreases significantly (minute 2-15) in comparison to the overnight return (minute 1) when the market re-opens the next trading day, the Realized Volatility smoothens out and the price is moving toward the fair market price.

Since the overnight return constitute a part of the total daily return, the effect of overnight return need to be included in the estimate in order to picture the overnight trading that occurs. However, we believe that the high return that arises during off trading hours might not just be a cause of the reaction to new information but also it might be a reaction to other market activities going on. As Clark and Kelly (2011) points out, the high return from the close to the open might be a result of that active traders usually hold undiversified portfolios and that they fear negative, stock-specific news during night and as a result a large number of traders liquidate their portfolios at the end of the day and then restore their positions in the morning; hence these trades increase the close to open returns. Further we refer to the concept of liquidity premium as another explanation to the high overnight return. The concept of liquidity premium is a thoroughly discussed subject (see for example Amihud and Mendelson (1986), Amihud (2002) and Datar, Naik and Radcliffe (1998)) and the reasoning behind a liquidity premium is that the return increases with illiquidity, hence the more illiquid a stock is the higher return is demanded by investors. Amihud and Mendelson(1986) points out that a measure for illiquidity is the bid and the ask spread and how quickly the asset can be converted into cash. As such, during night, as there is an increased uncertainty, investors face the risk that a certain stock might become more illiquid the next trading day. As a consequence of fearing a less liquid stock the next trading day, the closing price of that stock might decrease. Thus, if there is a large discrepancy between the close and open price there will be a large overnight return which might work as compensation to investors holding stocks overnight. As such we think that the concept of a liquidity premium might be one of the factors that cause the high overnight return. Another study which gives support to that not too much focus should be paid to the impact on volatility by overnight return in this study is a study performed by Cliff et al. (2008). In the study they find a large discrepancy between night and day returns and that the overnight returns constitute the major part of the US Equity premium, however they do not find that the arrival of new information is the major contribution to this return and that it is instead due to other factors. This could give support to that the overnight return generally creates high volatility even in the absence of new company specific information. An additional reason to the large overnight return might be a result of that the financial markets are becoming more and more globalized. As a result of the increased globalization there arises new information constantly on the global market, all around the clock, even when the Swedish stock market is closed. As a consequence this new information will be anticipated in the stock price the new trading day. This information is not necessarily stock specific and might instead concern other macroeconomic events. This indicates that there are other market activities going on which affect the overnight return and as a result the Realized Volatility. Therefore we are of the opinion that in this study not too much attention should be paid to the impact of the overnight return on the Realized Volatility, this since the high overnight return is not just a consequence of the release of earning announcements but also a result of other market activities going on. Instead it is of interest in this particular study to see how the market reacts in the immediate 15 minutes after the release of reports, when the market is open; the intraday returns. We stress the fact that when comparing the Realized Volatility based on just the intraday returns it is shown that the Realized Volatility is overall higher for companies releasing their reports during on trading hours compared to companies releasing their reports during off trading hours which also support our assumption.

In this study we estimate the realized volatilities for the stocks on Large, Mid and Small Cap. We do this in order to explore if any differences regarding volatility after financial reports, between indices can be found. Since Realized Volatility is a model free approach we can just rely on the numerical results found in Appendix 2 table 2.1-2.2. However, from these tables it seems to be a clear trend that stocks listed on Small Cap have a higher Realized Volatility on average than those listed on Large and Mid Cap. Also to note, is that the average effect from the overnight return on the total Realized Volatility in off-trading reports seems to be of less importance for the Small Cap stocks relative to what impact the overnight return has on the results for Large and Mid Cap. The impact of the overnight return on total Realized Volatility, seem to be of most importance for the Large Cap stocks. One way of explaining this may be that the Large Cap stocks are the most actively traded and analyzed companies in Sweden, which in accordance with our results justifies this list as the most information efficient list. Further, when investors trust that the available price for a stock incorporates all available information they are more likely to trade that stock, in line with the finding from Warren et al (2003) from the implementation of REG FD in the US. When the number of investors trading is high, an efficient price is more likely to be present which implies lower volatility in expectation. As a result, the trading that occurs, when excluding the overnight return, results in a lower volatility for the Large Cap stocks relative to what is the case for the Mid and Small Cap lists. Also, as mentioned earlier, that many investors use similar valuation methods when valuing stocks may give an explanation to the smaller impact on overnight returns for Small Cap stocks relative to Large and Mid Cap. This, since these stocks are less analyzed on average, indicating that the information from the earning announcement continues to improve the price efficiency during the intraday trading to a higher extent than what is the case for the more liquid Large Cap stocks.

Due to the fact that we have two different data sets for a period of time in this study, we are observing that the results differ with respect to what data frequency that is used when estimating the Realized Volatility. From our results in Appendix 2 table 2.1-2.2, it seem to be a clear difference in volatility between data sets and especially so for the reports that are released on trading. The results estimated using tick time data relative to minute data yields clearly higher volatility for reports released during on trading hours, whereas the difference between reports that are released off trading hours is less distinctive. Reasons for why the tick time data set gives higher volatility in the reports that are released during trading can be several and among them is the market microstructure problem. But if we take a look at table 2.4 where the trades per company are showed, it is clear that the trading activity was very high during our fifteen minutes time windows with an average of more than 800 trades per company for Large Cap companies and approximately 100 and 40/80 trades per company for the Mid Cap and Small Cap lists respectively. What is interesting from this table is that the rate of price changing trades to total trades is about the same for all three indices but clearly higher for companies releasing their reports on trading day relative to off trading day. This might indicate that trading on reports that are released on trading are more information driven than the trading on reports that are released off trading. All else equal, more information driven trading could imply less impact from market microstructure and more efficient price moves.

Comparing our results with the study from Oomen and Griffin, who had about 10% rate of price-changing trades in their trading data, our data show also properties of being more information driven, maybe not surprising since we are estimating the activity after financial reports as opposed to them. However, since there are a lot of market activity going on within every minute after a report are released, our opinion is that the tick time data better catches the Realized Volatility conditioned on that the trading frequency is sufficiently high. As outlined in the theory section, $RV_t$ will theoretically, be unbiased and consistent as $n \rightarrow \infty$. Since we are only estimating the volatility during times when the market activity is abnormally high as well as that our data show properties of being more information driven than data from a random time period. Our believes is that tick time data may be favorable for the purpose of this study when estimating high information trading during short time periods. However, due to the fact that we have a limited amount of tick data, the comparison between sampling schemes becomes less accurate; hence, we content ourselves by showing what results respective sampling scheme yields and leave a comparison for future research in short term volatility estimations.

In order to get a picture of the market microstructure noise in our data, we outline the distributions of our minute data in table 4.10 - 4.16. In line with previous studies, (for example Andersen et, al. (2001)) on high frequent intraday stock returns, the data shows out to be dependent and autocorrelated. Even if the data are closer to a normal distribution after we adjusted it for logarithmic standard deviations, the data show properties of being positively skewed, with a high kurtosis. A skewed distribution with high kurtosis implies that the data are autocorrelated and this result is shown throughout in our study but where the distributions of outside trading day reports shows to be more so than on-trading day reports. One possible explanation to why the returns shows to deviate more from a normal distribution in off trading day reports relative to on trading day reports, may be that this data is more hurt by market microstructure noise. This since the trading probably is less information driven than it is when the report is released during trading-time. Some support for this statement can be found in table 2.4, where day-time reports seem to have a higher rate of price-changing transactions than off trading day reports. Another explanation to that the data is more skewed for the returns for companies releasing off trading hours might be that the data is hurt by outliers, particularly for reports released off trading hours is that the overnight return deviates from the intraday returns and as such might impact the distribution of the data.

From an efficient market perspective, market microstructure noise may be interpreted as sound signals because the investors then have the same information, and at the extreme, only market microstructure noise such as the bid-ask spread creates the intraday volatility. Since the distributions of the companies releasing their reports off-trading, are more skewed this may also give a hint about that there are more market microstructure in these reports relative to reports that are released during trading, implying more stable and price-efficient trading when a report are released when the stock market are closed.

Since the efficient market theory lies at the core of this study, it is interesting to further analyze our results from an efficient market perspective. Our results show that when excluding the overnight returns for off-trading day reports, the volatility seems to be higher in reports that are released when the stock market is open, throughout this study. This holds both under tick-time data and minute data, with just a few quarterly exceptions. When a report is released outside trading-time, the market participants have time to agree upon a price to trade that asset on until the market opens. Our study supports that this in general leads to a lower volatility under the opening hours of the stock market. If it is in the markets interest to minimize the possibilities of short term trading based on different information level, this may, taken in isolation, lead to that releasing a report when the market is closed is more efficient.

With different information level we do not mean that it necessarily is so that some market participants have more information available to them. What we instead mean is that trades may be made based on different information levels, due to that for example professional and algorithmic traders can utilize the available information with a faster pace than the average investor. By prohibiting companies to release their earnings announcements during the opening hours of the market, we claim that the short term trading based on different information level can be somewhat resolved. Further, for the market as a whole any benefits of releasing earning announcements during opening hours are from our point of view, hard to find. Theoretically it could be in order to minimize the risk of for example information leakage, meaning that a report should be publicly available immediately after it is produced and confirmed. However, since most of the companies that continuously, year after year, releases their reports during trading time do so at an already announced and pre-determined time (i.e. always at 11:00 or 13:00) this reasoning simply does not hold on average. Another approach could be to use so called trading halts, meaning that the stock could be halted for a specified time interval after the announcement were published, giving the investors some time to agree upon a price and evaluate the announcement before the trading halt are removed and trading reopened. Trading halts was investigated upon in a study by Brooks et.al (2003) who found benefits of such a restriction when the announcements were unanticipated, but since the release of earning announcements are anticipated we do not suggest such a regulation for the purpose of this study.

With this said, we do not claim that all price sensitive information that a company release should be released when the market is closed, since there is always a risk of for example information leakage as mentioned above, but as Wolfson and Patel (1984) states, that an earnings announcement in general includes much more information than for example a dividend announcement, we find it reasonable that for the sake of earnings announcements, they should, as far as it is possible be released when the stock market is closed.

# 6. Conclusion

The aim of this study is to measure the volatility of trading after the release of financial reports. Further, the focus is placed whether financial reports that are released during the opening hours of the market exhibit higher trading volatility than reports released when the market is closed. The model of use is the Realized Volatility model, which is estimated on two different data sets, namely a Tick Time data set and a Minute Time data set. For our Tick Time data set we find support for our assumption that reports released during the opening hours of the market, yields a higher trading volatility on average. For our Minute Time data set, the assumption is not supported when overnight returns are included. However, when excluding the overnight return in the volatility estimations, our assumption are supported throughout in this study, with just a few quarterly exceptions. Our results differ between what data sampling scheme that is used. Unfortunately we are not able to give any evidence to which sampling scheme that is superior for the purpose of this study due to the limited amount of historical Tick Time data. However, in common for both schemes is that when overnight returns are excluded, the Realized Volatility is higher for reports that are released during trading time. Hence; in order to minimize trading volatility and maximize the information level in trades our final suggestion is that financial reports should as far as it is possible be released when the stock market is closed.

In future research we would like to see a study which incorporates the importance that the overnight return brings to the results. As the overnight returns constitute a significant part of the volatility for companies releasing their reports during off trading hours, it would be of interest to see a research which investigates the overnight return for all companies and which isolate how much of the return that is caused by the release of financial reports and what is caused by other market activities. Also, as it is of interest to compare the different sampling schemes we would like to see a study which is based on the same time period for both tick data and minute data, a study which can resist the difficulties we met for the availability of tick data.

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# Appendices

## Appendix 1

**Figure 1.1** Number of companies releasing their reports on trading day vs. off trading day over the period 2011-2013, for all Large, Mid and Small Cap companies

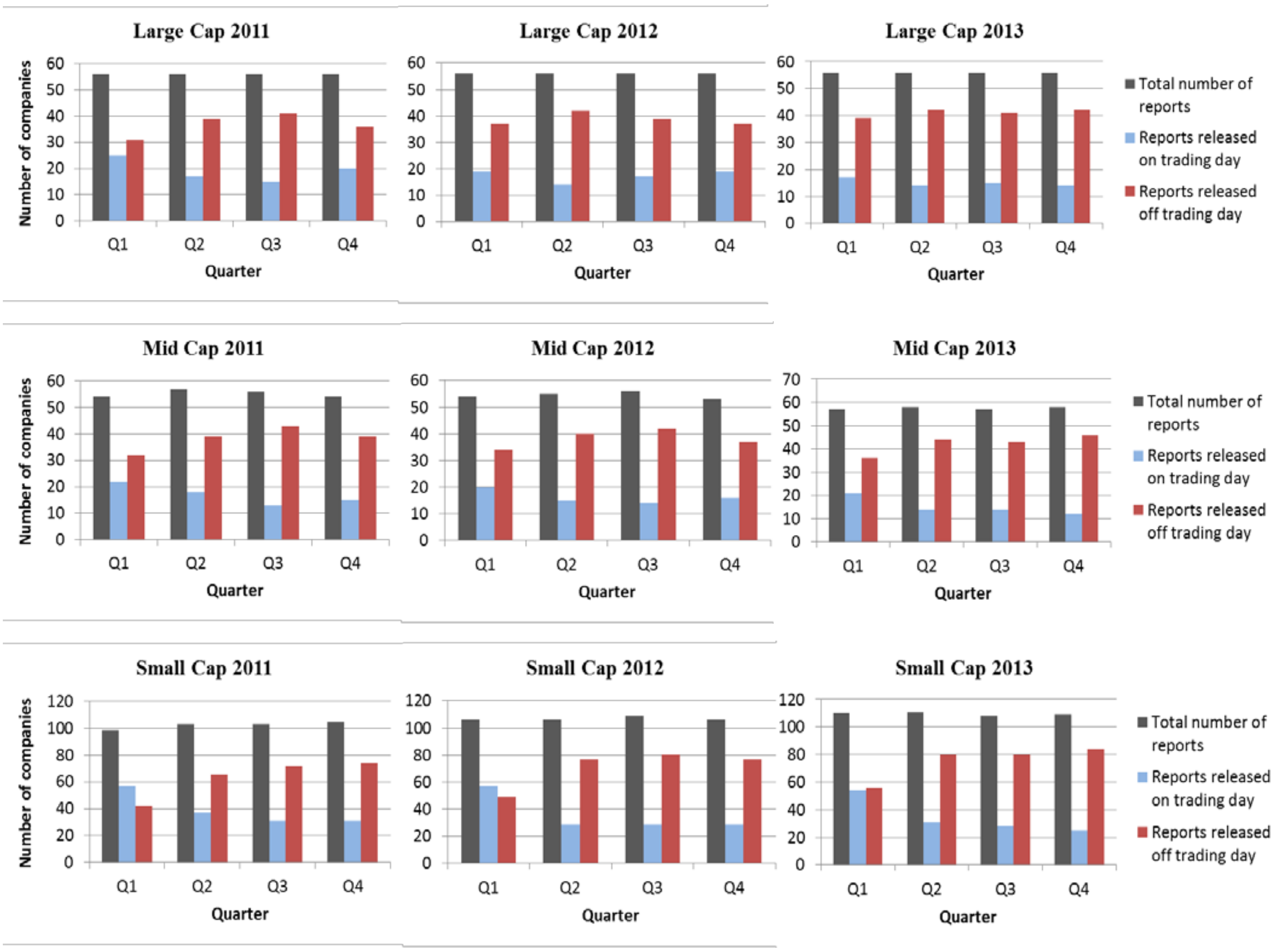

**Table 1.1** Example of trades and returns for the Large Cap stock Axfood. The left column shows transaction time sampling, the column in the middle shows Tick time sampling and the right column shows Minute data

| **AXFOOD** | **Transaction Data** | | |
|---|---|---|---|
| **Time** | **Price** | **Ln Return** | **Squared** |
| 00:00:00 | 316,6 | | |
| 09:00:03 | 323,6 | 0,0218690 | 0,0004783 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:03 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:07 | 323,6 | 0,0000000 | 0,0000000 |
| 09:00:10 | 325,4 | 0,0055470 | 0,0000308 |
| 09:00:10 | 325,4 | 0,0000000 | 0,0000000 |
| 09:01:03 | 325,4 | 0,0000000 | 0,0000000 |
| 09:01:03 | 325,4 | 0,0000000 | 0,0000000 |
| 09:01:05 | 323,9 | -0,0046204 | 0,0000213 |
| 09:01:11 | 325,3 | 0,0043130 | 0,0000186 |
| 09:01:11 | 325,3 | 0,0000000 | 0,0000000 |
| 09:01:12 | 325,4 | 0,0003074 | 0,0000001 |
| 09:02:00 | 324,4 | -0,0030779 | 0,0000095 |
| 09:02:00 | 324,3 | -0,0003083 | 0,0000001 |
| 09:02:06 | 325,4 | 0,0033862 | 0,0000115 |
| 09:04:17 | 327,0 | 0,0049050 | 0,0000241 |
| 09:04:17 | 327,0 | 0,0000000 | 0,0000000 |
| 09:04:27 | 327,0 | 0,0000000 | 0,0000000 |
| 09:04:27 | 327,0 | 0,0000000 | 0,0000000 |
| 09:08:35 | 328,7 | 0,0051853 | 0,0000269 |
| 09:08:35 | 328,7 | 0,0000000 | 0,0000000 |
| 09:08:35 | 328,7 | 0,0000000 | 0,0000000 |
| 09:08:35 | 328,0 | -0,0021319 | 0,0000045 |
| 09:09:17 | 328,7 | 0,0021319 | 0,0000045 |
| 09:09:29 | 328,6 | -0,0003043 | 0,0000001 |
| 09:11:47 | 331,5 | 0,0087866 | 0,0000772 |
| 09:11:47 | 331,5 | 0,0000000 | 0,0000000 |
| 09:12:09 | 332,5 | 0,0030121 | 0,0000091 |
| 09:12:09 | 332,4 | -0,0003008 | 0,0000001 |
| 09:12:09 | 332,4 | 0,0000000 | 0,0000000 |
| 09:12:09 | 332,5 | 0,0003008 | 0,0000001 |
| 09:12:09 | 332,4 | -0,0003008 | 0,0000001 |
| 09:12:09 | 332,4 | 0,0000000 | 0,0000000 |
| 09:12:10 | 332,4 | 0,0000000 | 0,0000000 |
| 09:12:10 | 332,4 | 0,0000000 | 0,0000000 |
| 09:12:17 | 331,5 | -0,0027113 | 0,0000074 |
| 09:12:26 | 332,5 | 0,0030121 | 0,0000091 |
| 09:12:57 | 332,4 | -0,0003008 | 0,0000001 |
| 09:12:57 | 332,0 | -0,0012041 | 0,0000014 |
| 09:12:57 | 332,0 | 0,0000000 | 0,0000000 |
| 09:12:57 | 332,0 | 0,0000000 | 0,0000000 |
| 09:12:58 | 332,0 | 0,0000000 | 0,0000000 |
| 09:13:43 | 334,0 | 0,0060060 | 0,0000361 |
| 09:13:52 | 334,0 | 0,0000000 | 0,0000000 |
| 09:13:53 | 333,9 | -0,0002994 | 0,0000001 |
| 09:14:56 | 332,4 | -0,0045025 | 0,0000203 |
| 09:14:56 | 332,4 | 0,0000000 | 0,0000000 |
| 09:15:00 | 331,5 | -0,0027113 | 0,0000074 |
| 09:15:00 | 331,5 | 0,0000000 | 0,0000000 |

| **AXFOOD Tick Data** | | | |
|---|---|---|---|
| **Time** | **Price** | **Ln Return** | **Squared** |
| 00:00:00 | 316,6 | | |
| 09:00:03 | 323,6 | 0,0218690 | 0,0004783 |
| 09:00:10 | 325,4 | 0,0055470 | 0,0000308 |
| 09:01:05 | 323,9 | -0,0046204 | 0,0000213 |
| 09:01:11 | 325,3 | 0,0043130 | 0,0000186 |
| 09:01:12 | 325,4 | 0,0003074 | 0,0000001 |
| 09:02:00 | 324,4 | -0,0030779 | 0,0000095 |
| 09:02:00 | 324,3 | -0,0003083 | 0,0000001 |
| 09:02:06 | 325,4 | 0,0033862 | 0,0000115 |
| 09:04:17 | 327 | 0,0049050 | 0,0000241 |
| 09:08:35 | 328,7 | 0,0051853 | 0,0000269 |
| 09:08:35 | 328 | -0,0021319 | 0,0000045 |
| 09:09:17 | 328,7 | 0,0021319 | 0,0000045 |
| 09:09:29 | 328,6 | -0,0003043 | 0,0000001 |
| 09:11:47 | 331,5 | 0,0087866 | 0,0000772 |
| 09:12:09 | 332,5 | 0,0030121 | 0,0000091 |
| 09:12:09 | 332,4 | -0,0003008 | 0,0000001 |
| 09:12:09 | 332,5 | 0,0003008 | 0,0000001 |
| 09:12:09 | 332,4 | -0,0003008 | 0,0000001 |
| 09:12:17 | 331,5 | -0,0027113 | 0,0000074 |
| 09:12:26 | 332,5 | 0,0030121 | 0,0000091 |
| 09:12:57 | 332,4 | -0,0003008 | 0,0000001 |
| 09:12:57 | 332 | -0,0012041 | 0,0000014 |
| 09:13:43 | 334 | 0,0060060 | 0,0000361 |
| 09:13:53 | 333,9 | -0,0002994 | 0,0000001 |
| 09:14:56 | 332,4 | -0,0045025 | 0,0000203 |
| 09:15:00 | 331,5 | -0,0027113 | 0,0000074 |

| **AXFOOD** | **Minute Data** | | |
|---|---|---|---|
| **Time** | **Price** | **Ln Return** | **Squared** |
| 00:00:00 | 316,6 | | |
| 09:00:00 | 325,4 | 0,0273853 | 0,0007500 |
| 09:01:00 | 324,3 | -0,0033554 | 0,0000113 |
| 09:02:00 | 325,4 | 0,0033554 | 0,0000113 |
| 09:03:00 | 325,4 | 0,0000000 | 0,0000000 |
| 09:04:00 | 327,0 | 0,0049357 | 0,0000244 |
| 09:05:00 | 327,0 | 0,0000000 | 0,0000000 |
| 09:06:00 | 327,0 | 0,0000000 | 0,0000000 |
| 09:07:00 | 327,0 | 0,0000000 | 0,0000000 |
| 09:08:00 | 328,0 | 0,0030534 | 0,0000093 |
| 09:09:00 | 328,6 | 0,0018276 | 0,0000033 |
| 09:10:00 | 328,6 | 0,0000000 | 0,0000000 |
| 09:11:00 | 331,5 | 0,0087866 | 0,0000772 |
| 09:12:00 | 332,0 | 0,0015072 | 0,0000023 |
| 09:13:00 | 333,9 | 0,0057066 | 0,0000326 |
| 09:14:00 | 331,5 | -0,0072137 | 0,0000520 |
| 09:15:00 | 331,4 | -0,0003017 | 0,0000001 |

## Appendix 2

**Table 2.1** Estimated Realized Volatility based on Tick data for on trading, off trading and off trading excluding over night return for Large, Mid and Small Cap.

| **LARGE CAP** | **15 minutes Realized Volatility** | | |
|---|---|---|---|
| TICK DATA | On trading | Off trading | Off trading, excluding over night return |
| 2013 | | | |
| Q3 | 0,0070 | 0,0064 | 0,0030 |
| Q4 | 0,0083 | 0,0062 | 0,0035 |

| **MID CAP** | **15 minutes Realized Volatility** | | |
|---|---|---|---|
| TICK DATA | On trading | Off trading | Off trading, excluding over night return |
| 2013 | | | |
| Q3 | 0,0126 | 0,0074 | 0,0047 |
| Q4 | 0,0089 | 0,0073 | 0,0046 |

| **SMALL CAP** | **15 minutes Realized Volatility** | | |
|---|---|---|---|
| TICK DATA | On trading | Off trading | Off trading, excluding over night return |
| 2013 | | | |
| Q3 | 0,0112 | 0,0120 | 0,0090 |
| Q4 | 0,0095 | 0,0149 | 0,0110 |

**Table 2.2** Estimated Realized Volatility based on Minute data for on trading, off trading and off trading excluding over night return for Large, Mid and Small Cap.

| **LARGE CAP** | **15 minutes Realized Volatility** | | |
|---|---|---|---|
| MINUTE DATA | On trading | Off trading | Off trading, excluding over night return |
| 2011 | | | |
| Q1 | 0,0037 | 0,0060 | 0,0020 |
| Q2 | 0,0050 | 0,0075 | 0,0032 |
| Q3 | 0,0065 | 0,0073 | 0,0027 |
| Q4 | 0,0042 | 0,0071 | 0,0022 |
| 2012 | | | |
| Q1 | 0,0034 | 0,0082 | 0,0024 |
| Q2 | 0,0050 | 0,0056 | 0,0021 |
| Q3 | 0,0058 | 0,0048 | 0,0020 |
| Q4 | 0,0039 | 0,0063 | 0,0023 |
| 2013 | | | |
| Q1 | 0,0038 | 0,0036 | 0,0026 |
| Q2 | 0,0049 | 0,0047 | 0,0016 |
| Q3 | 0,0053 | 0,0063 | 0,0022 |
| Q4 | 0,0050 | 0,0053 | 0,0020 |

| **MID CAP** | **15 minutes Realized Volatility** | | |
|---|---|---|---|
| MINUTE DATA | On trading | Off trading | Off trading, excluding over night return |
| 2011 | | | |
| Q1 | 0,0050 | 0,0066 | 0,0014 |
| Q2 | 0,0047 | 0,0122 | 0,0074 |
| Q3 | 0,0073 | 0,0090 | 0,0045 |
| Q4 | 0,0052 | 0,0078 | 0,0040 |
| 2012 | | | |
| Q1 | 0,0063 | 0,0082 | 0,0034 |
| Q2 | 0,0046 | 0,0080 | 0,0039 |
| Q3 | 0,0051 | 0,0076 | 0,0038 |
| Q4 | 0,0038 | 0,0078 | 0,0037 |
| 2013 | | | |
| Q1 | 0,0048 | 0,0047 | 0,0026 |
| Q2 | 0,0027 | 0,0065 | 0,0027 |
| Q3 | 0,0050 | 0,0079 | 0,0048 |
| Q4 | 0,0047 | 0,0071 | 0,0040 |

| **SMALL CAP** | **15 minutes Realized Volatility** | | |
|---|---|---|---|
| MINUTE DATA | On trading | Off trading | Off trading, excluding over night return |
| 2011 | | | |
| Q1 | 0,0055 | 0,0093 | 0,0045 |
| Q2 | 0,0085 | 0,0070 | 0,0043 |
| Q3 | 0,0072 | 0,0077 | 0,0044 |
| Q4 | 0,0082 | 0,0086 | 0,0050 |
| 2012 | | | |
| Q1 | 0,0057 | 0,0105 | 0,0055 |
| Q2 | 0,0065 | 0,0091 | 0,0047 |
| Q3 | 0,0052 | 0,0097 | 0,0065 |
| Q4 | 0,0088 | 0,0088 | 0,0055 |
| 2013 | | | |
| Q1 | 0,0039 | 0,0100 | 0,0080 |
| Q2 | 0,0051 | 0,0073 | 0,0042 |
| Q3 | 0,0076 | 0,0090 | 0,0062 |
| Q4 | 0,0077 | 0,0115 | 0,0059 |

**Figure 2.1** Distribution of Minute data for all reports Q1-Q4 2011-2013 divided into off trading and on trading for Large, Mid and Small Cap.