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High Frequency Trading and Its Impact on the Swedish Stock volatility

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Abstract

The existing studies have shown that the algorithmic trading has been playing an ever-increasing important role in both the U.S. and E.U. capital market. Many papers pay great attention on the high frequency trading, a special class of algorithmic trading, focusing on the impact that high-frequency activities have on the market quality. Investors engage in high frequency trading and interact with the market over millisecond horizons, resulting in a narrowed bid-ask spread, which, to some degree, abates the spurious volatility and autocorrelation in returns.

Brogaard (2012) have already made some research on the causal link between the high frequency trading and volatility before and after the 2008 short selling ban. We follow his methodology by applying the differernce-in-difference-in-difference (DDD) approach and try to make a study about the impact of the high frequency trading on the stock volatility during the normal market condition and uncertainty period in the 2008 crisis. Our conclusion is that the high frequency trading could reduce the stock specific volatility in Swedish stock market.

Key words: High frequency trading; market quality; realized volatility

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Contents

1. Introduction

1.1 Background

High frequency trading (HFT) is defined as a type of investment strategy by which stocks are bought and sold in a short period of time by a computer algorithm and held for a very short time, normally seconds or milliseconds. It is to make profit from those who take advantage of the extremely short-term changes in the market. Such transactions are so fast that many trading organizations put their “server farms” as close as to the computers in the Exchanges in order to catch the trading instructions via the speed of light.

Normally speaking, HFT has the following characteristics:

1. HFT is a program-driven trading finished by computers;
2. It has extremely high trading volume;
3. The rate of return is rather low but the return as a whole is stable;

Stocks are bought and sold many times within a trading day.

The popularity of high-speed computers has made the high-frequency transactions possible, and besides this, several changes of the regulatory legislation have also contributed to the evolution of high-frequency trading. In the year of 1998, the United States Securities and Exchange Commission have brought up the “Regulation Alternative Trading Systems as the introduction of competition, which has opened the front door for the competition between the electronic trading platform and major Exchange Markets. Two years later, almost every stock market in the US begins to offer the price which is the nearest to one cent of the unit rather than one sixteenth of a dollar for the unit, thus, resulting in further narrow the spread between the buying offer and sale offer. This kind of change has forced traders to make money by relying on these spread. Finally, the Securities and Exchange Commission has launched the Regulation National Market System in 2005, and according to its requirements, transaction instructions must be publicized in the whole country, rather than just within several stock markets or exchanges. When there is a tiny difference of a stock price between a Stock Exchange and the price in another Exchange, those who can take quick actions shall make money accordingly. Under this background, Chicago Federal Reserve Bank believes that high-frequency trading is beneficial to the market as it can increase the liquidity and decrease the volatility of the stock market.

In fact, there are already many discussions of the impact of the high-frequency trading between among the investing banks and other institutions in the investment banking institutions. Chicago Federal Reserve Bank report noted that about 70% of the total stock volume is completed by the high-frequency trading in the U.S. stock market, while only 2% of all the investing institutions are actually engaged in high frequency trading. The economic issues associated with high frequency trading in equity market are not new: the computerized trading became a significant tool to gain huge profit in the financial market since 1980s, while it also was blamed for exacerbating the crash in Oct. 19, 1987. In the following years, the computers involved have been rapidly improved and the algorithms that guide their trading have been steadily processed and become more sophisticated. See the New York Times (Oct. 10, 2011, High-Frequency Trading)

The significance of the speed for strategic reaction in the millisecond market could be much greater than that in the traditional market. Thus, one of the main concerns regarding HFT is that it exacerbates volatility and destabilized financial market. Suppose the daily volatility is generated from the 3% changes of value induced by random announcement information. This 3% changes might be captured by the high frequency traders who takes the strategic actions immediately. Is it fair to other traders who provide liquidity? The fast moving traders imposed costs on other traders, inducing the adverse selection cost which leads the market to failure. Most of the traditional traders in the stock markets have the restrictions to keep the markets stabilize, while high frequency traders have no such obligations. High frequency traders can take efficient actions to the information and exploit huge profit from the transactions, which could therefore drive the traditional liquidity traders out of the markets. As the result, at the stressful times, the high frequency traders can simply curtail their business, exacerbating the volatility and make the markets more fragile. The crash in 1987 and "flash crash" in 2010 demonstrate the possibility of market fragility when the fundamental liquidity providers step aside and high frequency traders eagerly to reduce their inventories. Moreover, we believe it is impossible to gain the fair chance to access the market information and transaction data. More and more attention has been paid on upgrading the trading systems both in the high frequency trading firms and securities exchanges in the recent years. By late 2011 regulators around the world, especially in U.S., were largerly cracking down on the computerized high speed trading, worried that these unfairly trading could make the market swing worse and be detrimental to the long-term investors.

And a small error in the program of high-frequency trading or any human negligence is likely to have a devastating impact on the whole market. For instance, most of the problem caused by high-frequency trading so far is resulted from incorrect instruction sent to the computer by human beings. Although the impact of this kind of error so far is still very limited, it has caused huge market volatility by many times.

Tokyo Stock Exchange announces that due to the failure of it trading system, the TOPIX Index (TOPIX) futures and other derivative products trading were all suspended from 9:22 on August 7th, 2012. This is the second system failure within 7 months and TSE is forced to stop due to a technical failure in a high frequency transactions. On February 2nd this year, the TSE announces a serious technical failure, which lasted nearly three and a half hours. There are 241 shares suspended from trading, including Sony, Tokyo Electric Power and other major Japanese stock.

Over the past years, HFT has progressively gained a foothold in financial markets, enabled and driven by interplay of execution venues and significant advances in information technology. It has been focusing on the high-frequency trading especially since May 6, 2010, when the later known ''flash crash'' drastically woke up the whole financial markets. The Dow Jones industrial average stock index plunges about 1,000 points in more than 20 minutes, a drop of 9 percent; the culprit of this event is the landmark in the history of high-frequency trading. A main concern regarding the recent development of HFT is its relationship with its impact on the market quality, especially the volatility.

During the past twenty years the rapid change of the technology has altered the financial markets. Instead of human traders, nowadays investing banks or security firms are employing computers to access the ever-changing information data, analyze the rapid electronic information and finally take the action to trade differently. Both the US and European Union have passed many a piece of legislation recently to regulate the securities markets. The milestones are the Markets in Financial Instruments Directive (MiFID) in the European Union and the Regulation National Market System (RegNMS) in the US. Meanwhile, substantial developments in information technology (IT) have spurred an electronic revolution.

1.2 Problem Discussion

There are many perceived benefits of HFT including liquidity provision, lower transaction coasts, and price discovery, but previous work has suggested that different types of investor could have a destabilizing effect on stock price for a variety of reasons (Chung, Choe, and Kho, 2009; Delong, shleifer, summers, and Waldmann,1990). While it appears that high frequency trading on the rise, it is unclear whether intense high frequency trading increases the price volatility in the stock market. Therefore it is crucial important to understand the relationship between HFT and the volatility. Additionally, current studies in this field mostly focuses on the stock market in the US, however, very few papers had researched about the European area, especially the Swedish stock market. Peter Norman, the Minister of Swedish financial market, has also expressed their expectation of examining the high frequency trading's influence on the Swedish stock market volatility, in order to determine whether they should take some measures to control the high frequency trading activities.

1.3 Aim and Purpose

This paper investigates the impact of high frequency trading on the volatility of stock returns in Swedish stock market. We applied the research bases on the data from a high-frequency trading database which consists of all trades for the main cash market instruments on the NAZDAQ OMX. The sample period occurs during 2006 and 2008. Sample period during 2006 featured the normal levels of volatility and the economic crisis of 2008 featured the elevated levels of volatility in the stock market. These data allow us to make researches on the activity and trading by high frequency traders over different economic environment and across different stocks. The price volatility can be linked with the timing of heavy and light HFT participation.

Some argue that high frequency traders destabilizing stock market by trading as a group and induce short-term imbalance. Others consider them as market stabilizers who enter the market and dampen the price volatility when it appears to overreact to some information. Thus, we are interested in answering the question: How does HFT influence price volatility? To address this question, we apply the difference-in-difference-in-difference (DDD) approach to study the activity and impact of trading by high frequency traders over time and across different types of stock.

1.4 Delimitation

The empirical research in the paper is limited to the sample size, only three liquid stocks and three less liquid stocks in the Swedish stocks market are investigated. Fortunately, the sampling stocks manifest the similar charteristics, enabling us to establish a general relationship between HFT activity and volatility. Additionally, driven by limited availability of transaction information we examine the overall high frequency trading activities' impact on the stock specific volatility based on an aggregate daily volatility and does not charteristic different types of HFT activities, such as liquidity demanding and liquidity supply.

In order to conduct in-depth analysis, the paper focuses on the impact of high frequency trading on the volatility, and does not study the influence of high frequency trading activities on other factors.

1.5 Structure of the paper

The rest of the paper is as follows. In order to provide the reader with a solid foundation for understanding later the first section introduces the basic information about the high frequency trading. Section 2 comes up with the theoretical background about high frequency trading and about the impact it has on the market quality, especially on the volatility. Section 3 is mainly the description about the data. Section 4 we describe a tool for measuring price volatility-a model-free estimator called realized volatility and the method we employed to mitigate the bias. Section 5 means to show the statistical and empirical results for the stock returns and realized volatility. Section 6, to study the impact of high frequency trading on stock-specific volatility, we use a DDD approach. Finally, we discuss our findings which are presented in the conclusion.

2. Theoretical Backgrounds

The high frequency trading has caught the eyeball of many researchers and a growing number of papers find that it may improve or degrade market characteristics. Like other traditional intermediaries, high frequency trading is central to the trading process, has short holding periods, and is trading traded very frequently.

Unlike traditional intermediaries, however, HFT do not grant privileged access to the market, which is not available to others. Without such privileges, there is no clear basis for imposing the traditional obligations of market makers (Panayides (2007)).The first theoretical model was built by Cvitanic and Kirilenko(2010), studying the effect of high frequency trading on transaction prices, trading volume and intertrade duration. They also construct the profits of high frequency trading respected to the properties of low frequency traders. Then other papers came into public analyzing how differently and to what kind of degree investment time horizons can impact the market quality.

Gsell and Gomber(2009) showed that algorithmic trading engines fundamentally differ from human traders in their order submission, modification and deletion behavior as they exploit the real-time market data and the latest market movements.

The algorithmic trading, which can be simply named as AT, it is defined as "the use of computer algorithms to automatically make trading decisions, submit orders, and manage those orders after submission" (Hendershott and Riordan, 2009). Hendershott, Jones and Menkveld (2008) build the first theoretical model to measure the causal effect of algorithmic trading on liquidity. According to their research, for large stocks in particular, algorithmic trading narrows spreads, reduces adverse selection, and reduces trade-related price discovery. The empirical results indicate that algorithmic trading improves liquidity. Hendershott and Riordan (2009), they build the empirical model based on the 30 DAX stocks on the Deutsche Boerse. According to their research results, the AT can react quickly to the changes of the market by closely monitoring the information and liquidity. In this case, AT contributes more efficiency in price discovery process than normal human trading. However, they also found that there is no causal relationship between AT behavior and volatility which is different from other conventional research findings.

Chaboud, Chiquoine, Hjalmarsson and Vega (2009) examined the AT's effects on the foreign exchange market. Their empirical results show that there is no evidence for the causal relationship between AT and Volatility, similar to Hendershott and Riordan (2009).

High frequency trading and AT are similar in that they both make transaction decisions though automatic trading system. HFT is a subset of algorithmic trading (AT). HFT can be treated as a "hyper-active algorithmic trading strategy where a trader moves in and out of stocks with extremely short holding intervals in an attempt to capture small profits per trade"(Brogaard, 2012).

Brogaard (2012) study the high frequency trading's effects on market quality using the dataset containing 26 high frequency traders in 120 stocks over two sample periods during the financial crisis from 2008 to 2009. By examining the interaction between the activities of high frequency traders and U.S equity markets, he finds that high frequency traders trade relatively more as volatility increases in the short run, but tend to decrease their frequency of trading in the long run.. The high frequency traders' activities contribute more to the price discovery than other normal investors and appear to help lower the market volatility. His research is a complement to our study in section 4. He finds that HFT activities Granger causes volatility and volatility Granger causes HFT activities, the increased stock specific volatility could lead HFT firms to decrease their trading. In this article, we only examine the impact of HFT activities on the stock specific volatility on Swedish stock market. Another difference between Brogaad's thesis and ours is that his sample period spans one week in February 2010, while our sample spans three months in 2008 after the financial crisis and provides insights in the changes of the stock transactions during heightened uncertainty period of time. We view the study in the stressful period is necessary and important in analyzing HFT activities' impact on the market environment in different aspects. In Brogaad's paper, he shows that HFT activities in the current financial markets reduce intraday volatility, which is testified in our papers through the contemporaneous graphical representation.

The HFT activities could negatively affect the market during stressful periods in a negative way. The joint CFTC/SEC report (Sep. 30, 2010) regarding the "flash crash" presents the detailed event occurred in May 6th, 2010. The report finds that the high frequency traders initially provide the liquidity by placing buy and sell orders without inventory positions. However, the high frequency traders chose to reduce, stop, or significantly curtail their positions to decrease their risk in the episode when the fundamental buyers withdraw from the market. Researches on the "flash crash" found that HFT activities is not the blasting fuse of the downfall, but they are likely to extent the severity of the crisis. Kirilenko, Kyle, Samadi, and Tuzun (2010) provided research on the activities of different traders during the "flash crash" in the futures markets. They concluded that, while these high frequency traders did not trigger the downfall in the flash crash, their activities exacerbated the market volatility.

Hasbrouck and Saar (2011) analyzed the HFT activities' impact on the market quality by using the TotalView-ITCH dataset over both the normal market conditions and a heightened economic uncertainty period in 2008. We also applied the similar sample period by choosing data samples in the year 2006 and 2008. In Hasbrouck and Saar (2007), they emphasized how technology improves the traders' dynamic trading strategies when they chase market prices or search for latent liquidity. As it described in Kaniel, Saar and Titman (2008), individual investors tend to buy the previously declined stocks and sell following price increases to reduce the risk. The traders, who are fast enough to take the action, could impose fundamental news on other traders and the market failure then could be induced due to higher adverse selection cost. Hendershott and Riordan (2011) provided further studies on the interaction between investors and market in the millisecond environment using algorithmic trading. They concluded that the HFT activities could improve the criterion for market quality, including liquidity and short-term volatility.

In order to study the impact of high frequency trading on stock volatility, first of all, we need to compute the volatility. Obviously, volatility for equities is inherently unobservable. As we know, most of the volatility has been estimated with economic models such as ARCH, GARCH and so on. Applying the standard deviation of the assets or equities' returns, or directly using the volatility indicators such as absolute returns, most of the volatilities could be captured.

In high frequency trading field, volatility modeling applied in forecast intraday return varying, the time range almost between 1 minters to 240 minters so that the assets return estimation can be more accurate and efficiency. Current research diversify the volatility model as linear and non-linear, and the most popular and widely use is the generalized autoregressive conditional heteroskedasticity (GARCH, Bollerslev(1986)) model. Pagan and Schwert were among the first to apply GARCH model in estimate financial asset return volatility, and they estimated stock return volatility by GARCH and E-GARCH model (Nelson (1991)). Franses and Van Dijk (1996) proposed to estimate stock return volatility of Germany, Holland, Spain, and Italy and Sweden stock exchange by non-linear GARCH models, and their research results proposed that non-linear GARCH model can significantly improve the linear GARCH model efficiency in volatility forecasting. Anderson and Bollerslev (1998) used their research to confirm that GARCH series is more accurate as a volatility estimation model. On the other hand, Admati and Pfleiderer (1988) have studied the price and volume using intraday patterns; it is an earlier intraday price volatility forecast theory. Engle, Ito and Lin (1990) researched intraday volatility in the foreign currency market. Bessembinder and Seguin (1993) studied the intraday price, volume and market depth applying high frequency data. Furthermore, compared with these complicated economics models to derive the latent volatility, a large number have found that applying much simpler techniques could also lead to the same results.

If we go back, the earlier related literature has also steadily progressed by using the higher-frequency data in the millisecond markets. For instance, Officer (1973) estimated the annual volatility from monthly returns moving series based on the New York stock exchange data. Whereas Merton (1980) employed the monthly data created by the average squares of monthly logarithmic returns to construct the variance estimator over 1926-1978, and he also applied the daily returns to estimate monthly variance covering a shorter sample of 1962-1978. Moreover, Schert (1998) estimated the daily NYSE stock market standard deviation based on the 15-minutes returns. Finally, Andersen, Bollerslev, Diebold and Labys (1999) constructed the model-free estimates of daily exchange rate volatility by exploiting 5-minute returns. However, there are not any explicit yardsticks for the approach of volatility. From the view of standard modeling evaluation criteria, models based on the squared or absolute returns provide seemingly poor volatility estimates. However, contrary to this traditional judgment, the empirical results in resent papers demonstrate that these models could actually produce accurate estimates.

Concurrent with the ascending use of high frequency trading data, recent studies have clarified different comparative volatility estimators. The newly mentioned theory on this topic is so called realized volatility estimator. Andersen and Bollerslev (1998) showed the empirical evidence that the realized volatility computed from the high frequency intraday returns is an effectively and meaningful error-free volatility measure.

This paper adds to the literature in three ways. Firstly, we apply the analysis based on the unique dataset of Sweden stock market. By having the NASDAQ-OMX dataset, the item for each stock transaction has been clarified, such as the trading time, volume, and transaction price. In addition, we collect data from two sample periods, which represents extraction of different economic environment, so that the interpretation of the findings could be further analyzed. Secondly, motivated by the drawbacks of the popular methods and models, we applied the model-free estimator realized volatility extract from the high frequency intraday returns. The mechanics of our methods are simple: we computed the daily volatility by aggregating the high-frequency intraday squared returns. In order to mitigate the microstructure effects, we turned to the tool called “volatility signal plot” which has been first used in Fang (1996) and then named by Andersen and Bollerslevdiebold and Labys (2010). Last but not least, by applying the difference-in-difference approach, the study tries to analyze the changes of stock specific daily volatility as the exogenous shock reduce HFT activities.

3. Data and Sample

Data in this paper comes from the unique high-frequency trading database. It contains all trades for the main cash market instruments on the NAZDAQ OMX.

Brogaard(2012) uses the similar dataset to study the HFT activities. Data in the paper includes all trades occurred on the Nasdaq and BATS exchange during regular trading hours in 2008, 2009 and 2010. He has applied the CBOE S&P 500 Volatility Index （VIX）to capture the market-wide volatility. In Brogaad (2012), he separated the stocks into three categories, Small, Medium and Large, basis on their stock market capitalization. The Small stocks range from \$0.02 to \$0.5 billon, the Medium stocks from \$1.1 to \$3.7 billion, and the Large stocks from \$11.7 to \$176 billion. In order to making striking comparison in the DDD approach, we selected the samples from the

Large and Small categories. We have three Small stocks, Rorvik Timber AB ($0.02billion), Aspiro ($0.05billion), Beijer alma AB($0.5billion), and three Large stocks, ABB $42.86billion), Ericsson ($33.98billion), Volvo ($30.14billion) in our samples. These are listed in Table 1 as well as some statistic description.

[Insert Table 1 here]

In order to make it parallelism comparable, we choose transaction data from two sample periods. Our first sample period is from October to December in 2006 (63 trading days) which represents the normal market condition. The Swedish stock market is relatively stable during this time period, with the OMX Stockholm 30 Index of 1,043.36 at the beginning and 1,147.21 at the end of December.

The second sample period is from October to December in 2008 (62 trading days). As is known to all, Bear Stearns was fire sold at $2 per share after it had closed at $30 on March 14, which is the starting point of the financial crisis among the U.S investing banks (Forbes, 03.17 2008). Lehman Brothers, filed for bankruptcy in September and Merrill Lynch was purchased by the Bank of America at the same day (Bloomberg October 13, 2008). The Super-Prime Mortgage crisis in U.S then leads to a downturn in the global economy which also affected the European counties. The instability stock market values then fell dramatically in both the US and Europe, with the Dow closes below 11,000 and OMX Stockholm 30 Index falling to 768.49 at the end of September 2008. The OMX Stockholm 30 Index continued to fall down to 662.33 at 30th Dec, 2008. After the crisis, SEC had taken temporary emergency action to prohibit short selling in financial companies. The short sale ban indirectly stopped some HFT traders from trading the banned stocks. It’s an exogenous shock to the European stock markets. As a result many countries in Europe implemented the similar short sales bans, removing substantial HFT activities from the stock markets. As is shown above, the second sample period we choose represents the period with high uncertainty in the market.

Finally, similar as Brogaard (2012), we use the VSTOXX to capture European market-wide volatility.

4. Realized Volatility Measurement

Stock market volatility is not a directly observable variable. Lots of researches have been made in this field to address this problem. The most popular statistical models approached to capture the volatility are the ARCH model and the Stochastic Volatility model. For example, Andersen &Bollerslev (1997)'s research has shown that ARCH and stochastic volatility models do provide good volatility forecasts. High frequency data have primarily been used for estimation of financial volatility and realized volatility is become a well known quantity that is constructed from high frequency intraday returns. Moreover, construction of daily realized volatility is model free and can be simply described as the sum of intraday high-frequency squared returns. Studies making use of this insight include French, Schwert, and Stambaugh (1987), who construct monthly return volatility as the sum of squared daily returns and Andersen and Bollerslev (1998), Hsieh (1991),Taylor and Xu (1997) who estimate daily return variance by summing squared intra-day returns. In our paper, realized volatility is measured by realized variance (RV), and besides, it is equal to the value of corrected RV.

4.1 Theory

The realized variance is a well-known quantity that can be traced back to Menton (1980). He has noticed that the variance of a time-invariant Gaussian diffusion process (over a fixed time-interval) can be estimated arbitrarily accurately as the sum of squared realizations, provided that the data are available at a sufficiently high sampling frequency. RV can be used as proxy for theoretical quantities such as the conditional variance (CV), the quadratic variation (QV) and the integrated variance (IV), see Barndorff-Nielsen &Shephard(2002a.2002b) and Andersen &Bollerslev (1998),Hansen (2003).

Hansen and Lunde (2003,2005,2006) have made a definition for the realized variance in their research， In this section, we decide to compute the stock-specific realized variance by using the similar method as Hansen and Lunde's did.

We let $\{p^*(t)\}_{t\in[0,\infty)}$ denote a latent log-price process in continuous time interval and use $\{\mathrm{p(t)}\}$ to denote the observed log-price process. The observed price process $\mathrm{p(t)}$ may differ from the efficient price process$p^*(t)$.

$$\mathrm{p} = p^* + \mu \tag{1}$$

The noise process, u, may be caused by market microstructure bias such as bid-ask bounces, however, the discrepancy between p and $p^*(t)$ can also be induced by the technique applied to construct p(t).

We shall assume that the price process satisfies the stochastic differential equation, $\mathrm{d}p^*(t) = \mu(t)dt - \sigma(t)d\omega(t)$, where ω(t) is a standard Brownian motion, $\sigma(t), \mu(t)$ is a "smooth" time-varying (random) function that is independent of ω(t) and $\sigma^2(t)$ is Lipschitz. This allows us to define the integrated variance,

$$IV_{[a,b]} \equiv \int_a^b \sigma^2(t)dt \tag{2}$$

That is our object of interest. So we can treat $\{\sigma^2(t)\}$ as deterministic quantities although we view the volatility path as random above. The Lipschitz condition is a smoothness condition that requires$|\sigma^2(t) - \sigma^2(t+\delta)| < \varepsilon\delta$, for some ε, all t and δ. However the assumption that ω(t) and σ(t) are independent is not essential. The weaker assumptions, used in Zhang et al. (2005) and Zhang(2005), are sufficient in this framework.

The RV is an empirical estimate of the IV that is constructed from intraday returns. Given the times, $\mathrm{a} = t_0 < t_1 <\ldots t_i <\ldots< t_m < b$. We call $\in= \{t_{0,}t_{1,} \ldots, t_{m,}\}$ a partition of [a,b]. For the special case where intraday returns are equidistant in calendar time, such that $t_i = t_{i-1} + \delta$, for i=1,…,m, where $\delta \equiv (b-a)/m$. In this case, $\delta,$ the length of each subinterval$[t_i{-}\delta, t_i]$approaches to zero as *m* increases. The intraday returns are now defined by:

$$r^*_{i,m} = p^*(t_i) - p^*(t_i - \delta)\ i = 1, \ldots, m \tag{3}$$

Similarly, at which the price is observed, the intraday returns are defined by

$$r_{i,m} = p(t_i) - p(t_i - \delta)\ \ i = 1, \ldots, m \tag{4}$$

And

$$\varepsilon_{i,m} = \mu(t_i) - \mu(t_i - \delta), \ \mathrm{i} = 1, \dots, \mathrm{m} \tag{5}$$

The observed intraday return can be decomposed to $r_{i,m} = r^*_{i,m} + \varepsilon_{i,m}$, The integrated variance over each subinterval is defined as

$$\sigma^2_{i,m} = \int_{t_i-\delta}^{t_i} \sigma^2(s)ds \quad , \mathrm{i}=1,\dots,\mathrm{m} \tag{6}$$

And we note that Var($r^*_{i,m}$)= E($r^*_{i,m}$)= $\sigma^2_{i,m}$ (7)

The realized variance of $p^*(t)$ is defined by

$$\mathrm{RV}^{*\,\in}_{[a,b]} = \sum_{i=1}^{m} r^{*2}_{i,m} \tag{8}$$

and $\mathrm{RV}^{*\,\in}_{[a,b]}$ is consistent for the IV, as $\mathrm{m} \to \infty$, see e.g. Protter (2005).The realized variance of observed price process *p*, which is given by

$$RV^{\in}_{[a,b]} = \sum_{i=1}^{m} r^2_{i,m} \tag{9}$$

is observable but suffers from a well-known bias problem.

The equidistant price observations p(t) must typically be interpolated from transaction prices or quotations, such as the previous-tick and linear interpolation methods that were introduced by Wasserfallen& Zimmermann (1985) and Andersen &Bollerslev (1997). There is a discussion of these two methods in Dacorogna,Gencay, M ̈uller, Olsen &Pictet (2001, sec. 3.2.1) and a theoretical argument that favors previous-tick method in Hansen &Lunde (2003, 2006). Our empirical results are based on the previous-tick method.

4.2 Bias and Bias Correcting RV

The realized variance of high frequency trading is perfect in measuring the volatility if the transaction price can be observed continuously and without measurement error, as it mentioned in Merton (1980). It suggests that the calculation of realized variance should be based on the highest sampling frequency. However, the standard measure of RV, (9), suffers from a bias problem that is due to autocorrelation in the intraday returns. The autocorrelation is caused by market microstructure effects such as: bid-ask bounces, non-synchronous trading and misrecordings, for example, Andreou&Ghysels (2002), Bai, Russell &Tiao (2004), and Oomen (2002). The autocorrelation in intraday returns may become more of an issue as the sample frequency increase. In this case, lowering sampling frequencies is an efficient method to mitigate the autocorrelation bias. However, as we talked above, there may be a discrepancy between p and $p^*(t)$ induced by the technique applied to construct p(t) and it appears to be aggravated as sampling frequency decrease. An obvious drawback of sampling at low frequencies (to avoid the discrepancy) is that this approach discards information, such that the resulting estimator may be inefficient.

As it mentioned in Andersen et al. (2001), "…the organizational structure of the market …Such market microstructure features … can seriously distort the distributional properties of high frequency intra-day returns." In the research made by Barndorff-Nielsen &Shephard (2002), they have discussed about the frequency "...It is dangerous to make inference based on extremely large values of M (M is the number of observations) for the effect of model misspecification can swamp the effects we are trying to measure… it seems sensible to use moderate values of M …"

Hence, a tension arises: the optimal sampling frequency will likely not be the highest available, but rather some intermediate ones, ideally high enough to produce a volatility estimate with negligible sampling variation, yet low enough to avoid microstructure bias. Consequently, the choice of underlying sampling frequency is critical, and there are some literatures have already offered guidance for making the decision.

Bandi& Russell (2005) has developed a conditional mean-squared error (MSE) method for the contaminated valotility estimator. The optimal sampling can be determined at the minimum of conditional MSE. Andersen, Bollerslev, X.Diebold and Labys (1999), and Zhang, Mykland&Ait-Sahalia (2005) have introduced a model-free graphical diagnostic called "volatility signature plot" to determine the moderate frequency. In the "volatility signal plot" graphical, the average realized variance are plotted on the graph against the sampling frequency. Hansen &Lunde (2006) have introduced a link manifesting the relationship between the bias of the realized variance and the microstructure noise. Our motivation of applying "volatility signature plot" method is highly pragmatic, as we seek to determine the moderate underlying sampling frequency for calculating the realized variance. On the other hand, we attempt to characterize different market microstructures in terms of their volatility signatures. The volatility signature plots reveal the patterns of bias injected in realized variance as underlying returns are sampled progressively more frequently. It may therefore be useful in guiding the section of sampling frequency. Interestingly, the volatility signature is isomorphic to the variance function, which has been widely used in financial researches. .

[Insert Figure 1 here]

In Figure 1, there are six representative volatility signal plots where the average realized variance are plotted against sampling frequency. The integer k denotes the sampling interval. For instance, for k=1 we construct the realized variance base on 1minute sampling frequency intraday returns; for k=2 we construct the realized variance base on 2minutes sampling frequency intraday returns. The six graphs display the Large stocks included in OMX30 index. Figure 1 represent liquid Large stocks for which the largest average realized variance is estimated at the highest sampling frequency, corresponding to the smallest value of k. It can be explained by the negative autocorrelation in the intraday returns induced by the microstructure bias. While as the returns aggregates with the observing interval become larger and larger, the fluctuations in the intraday return series tend to decrease and the overall realized variance is lower. As it shows in Figure 1, the volatility signal plots stabilize at roughly k=20 where the sampling frequency is 20minutes. Although the microstructure effects will be even smaller for the sampling frequency larger than 20minutes, calculation of realized variance may suffer from higher sampling error caused by the ever-increasing large intraday return intervals. Therefore, for this special case, 20minutes sampling frequency is used to derive the credible realized variance which is a reasonable tradeoff between microstructure bias and sampling error.

[Insert Figure 2 here]

In Figure 2, it represents three less liquid small stocks, which volatility signal plots are different from the Large ones. The microstructure factors cause positive autocorrelation effects on the high frequencies, leading to lower estimate of realized variance. The volatility signal plots don’t stabilize until the sampling frequency reaches about k=20. In this case, the realized variance for Small stock is similarly constructed on 20minutes sampling frequency base. Consequently, the realized volatility of Large stocks and Small stocks can be both estimated at 20minutes sampling interval.

However, much remains to be done, including extensions of signature of plots to multivariate. Nevertheless, we feel confident that the high quality realized volatility can be constructed in high frequency trading and the potential for utilizing volatility signature plots in determining the underlying sampling frequency.

4.3 Empirical Result of Realized Volatility

4.3.1 Descriptive Statistic of the Return

In the first panel of table 2, it shows the frequency descriptive statistics of ABB in 2006. As regard as the statistical description, return series at seven different frequencies are approximately near to zero mean. However, the 1-minute unit data has the highest value of standard deviation than other units, indicating the 1-minute sampling frequency has significantly different from the mean value and the distribution is more discrete.

In the second panel of table 2, it shows the same content for Aspiro Company in 2006. We find that the 1-minute unit data also has the largest standard deviation than others. In this case, other companies are supposed to have the similar statistic distributions.

[Insert Table 2 here]

Figure 3 shows the distributions of the daily return series for the three Large stocks in twenty-minutes sampling frequency during in the sample periods. For instance, though the stock return of ABB Company varies in each observing days in 2006, it displays substantial stability and fluctuated around the mean level. The distributions are similar for another two companies.

[Insert Figure 3 here]

Figure 4 shows the same content for the other three Small stocks. The daily returns of Small stocks display the similar statistic characteristic with the Large ones.

It can be easily found that the intraday returns cluster in every 20 minutes frequency samples. Otherwise, in case of the large-sized observations, the clustering phenomenon is not clearly analyzed here.

[Insert Figure 4 here]

4.3.2 Descriptive Statistic of Realized Volatility

Table 3 shows the distribution of daily realized volatility for ABB at different sampling frequencies in 2006. The 1-minute unit data has the largest mean. And all the realized volatility are severely right-skewed and leptokurtic as it illustrates in Table 3.

[Insert Table 3 here]

Since the daily realized volatility is the sum of the squared intraday return, it is always positive. Observed stock return is constructed in a very short interval, so most of the values are around zero. The swelling ones maybe caused by sampling errors in constructing the intraday returns or unusually transactions among the sample period.

[Insert Figure 5 here]

5. The Influence of High Frequency Trading on Volatility

Stock traders who engage in the high frequency trading and interact with the market in millisecond intervals are at one extreme side of the market participants' continuum. Most of the stock traders are not able to choose or choose not to make transactions in this high speed market, but these investors' activities are still playing an important part in measuring the market quality. Moreover, the turbulent market may drive the traditional liquidity traders out of the markets, exacerbating the price volatility in the market. As a result, many people may have the following question, how do high frequency traders use the algorithms to interact with the stock market in milliseconds related to the range of price observed over seconds, minutes or hours? And whether the algorithm has a destabilizing effect on stock price?

In this article, in order to evaluate whether the high frequency traders' activities cause the volatility to increase or decrease, we analyze how volatility changes when an exogenous shock alters the level of HFT activities. In this case, an exogenous shock occurs in 2008 and a differences-in-difference-in-differences approach is implemented to determine how stock volatility change as the HFT activities decrease. The result shows that the stock volatility increases while high frequency activities are removed from the current market. In order to verify this result in our research, an instrument variable so called VSTOXX index is implemented.

5.2 A Natural Experiment around the Short-sale Ban

After the 2008 financial crisis, SEC had taken temporary emergency action to prohibit short selling in financial companies. The short sale ban implemented in September 19, 2008 on the publicly traded securities of 799 financial companies, which indirectly stopped some HFT traders from trading the banned stocks. It's an exogenous shock to the European stock markets and as a result many countries in Europe implemented the similar short sales bans. For instance, U.K. has applied the ban in September 19, 2008, Norway is in October 8, 2008 and Germany is in September 20, 2008. Beber and Pagano (2011) have made empirical researches about the effects of the short sale ban in 30 countries (most are European markets and some developed non-European markets). According to their study, 31.5 percent of the stocks in their sample were affected by the ban on the short sales by October 1st, 2008 when most bans were operative. In this case, the Short Sale Bans heavily decreased the level of HFT activities. However, not all the HFT firms were prohibited from short trading and HFT firms which registered as market makers were able to continue their transactions. As a result, while the HFT activities largely dropped, it still remains well above zero.

In this section, a twice differences-in-differences (DDD) approach based on both the period before and after the ban, the stocks affected and unaffected, is applied to determine how the realized volatility changed after the reduction of the HFT activities. We use this approach to study the impact on volatility due to the changes in HFT activities after the 2008 Short Sale Ban. In addition, the approach taken here uses six different stocks to represent the affected and unaffected stocks. It is applied to control the time-varying HFT activities which are not related to the exogenous shocks.

The VSTOXX Indices are designed to reflect the market expectations of volatility by measuring the square root of the implied variance across all options of a given time to expiration, based on the EURO STOXX 50 live-timing options prices[1].

The ratio in the stock realized volatilities to VSTOXX is defined as the volatility factor in this paper. We are interested in the differences of volatility ratios computed before and after the implementation of Short Sale Ban, for affects and unaffected stocks. The large stocks of ABB, Ericson and Volve, are liquid equities which are included in the 30 most actively traded stocks on the Stockholm stock Exchange. The empirical studies in Brogaard (2012) shows that while the intraday HFT-activities matters at different time scales, their participation in small stocks are less affected by volatility movements. We assume that the HFT activities are more common in actively traded stocks, so the transactions of these large stocks are severely affected by the high frequency trading. The small stocks of Aspiro, Beijer Alma AB and Rorvikt, are less liquid equities, and they are turned out to be almost unaffected by the high frequency trading. As different to the normal DDD approach, the differences between the stocks with more or less HFT change is not a dummy variable, but a continuous one. Instead a having three variables, the approach taking here use two variables and the third one is applied to measure a particular pairs.

The first DDD approach is implemented between affected and unaffected stocks. The differences of average volatility ratios for the affected and unaffected stock are what we are interested. This controls for time-varying HFT activities and it is not related to the exogenous shock in 2008. The second DDD approach is implemented between the different sample periods. We graph the differences of the average volatility ratios

[1]The definition of VSTOXX is posted on the homepage of STOXX.

before and after the implementation of 2008 short-sale ban separately for the affected and unaffected stock to study how the dampened HFT activates influence stock volatility. This approach does not measure the impact of the exogenous shock on the volatility itself since the designed variable of interest is the variation captured among the affected stock or the unaffected stock. We control the time-series variation that may provide the relationship between HFT and volatility by capture the interested difference between affected and unaffected stock based on the level of HFT participation in 2006 and 2008. I control for the stock specific less-HFT related influences by including stock specific effects.

More specifically, we make a further analysis by taking the next following two steps. Firstly, we compute the volatility ratio by matching the stock realized volatilities with VSTOXX index at each transaction date during the two sample periods. Secondly, we calculate the Dvs_t variation, the difference between the average volatility ratios for the affected Large stocks and the unaffected Small stocks:

$$\mathrm{Dvs}_{\mathrm{t},\ 2006} = \frac{1}{3}\sum_{\mathrm{i}=1}^{3}\left[\frac{\mathrm{RV}_{\mathrm{i,t}}}{\mathrm{VSTOXX}_{\mathrm{t}}}\right]_{\mathrm{Affected}} - \frac{1}{3}\sum_{\mathrm{j}=1}^{3}\left[\frac{\mathrm{RV}_{\mathrm{j,t}}}{\mathrm{VSTOXX}_{\mathrm{t}}}\right]_{\mathrm{unaffected}} \quad (10)$$

$$Dvs_{t,\ 2008} = \frac{1}{3}\sum_{i=1}^{3}\left[\frac{RV_{i,t}}{VSTOXX_t}\right]_{\mathrm{Affected}} - \frac{1}{3}\sum_{j=1}^{3}\left[\frac{RV_{j,t}}{VSTOXX_t}\right]_{\mathrm{unaffected}} \quad (11)$$

$RV_{i,t}$ is the Large stock i's realized volatility at day t, $RV_{j,t}$ is the small stock j's realized volatility at day t. The first term on the right side is the average volatility ratio of affected stocks at day t.

[Insert Figure 6 here]

As it shows in the Figure 6, most of the plots either on the difference curve Dvs_{2006} or Dvs_{2008} are smaller than zero. Besides, the volatilities of large stocks are lower than those of small stocks in the common economic environment (2006). It is more likely that the active participation of high frequency traders decrease the stock volatility of Large stocks, which is consistent with HFT decrease volatility. However, many more plots on difference curve Dvs_{2008} are above the abscissa axis. It may be due to the changing and uncertain stock market environment or the company specific business alterations in 2008. As we mentioned previously, the high frequency traders have no obligations to make the market stable. They may tend to curtail their actively trading and reduce their inventories in the stressful times, which could exacerbate the volatility and cause markets fragile. However, it is not sufficient to verify our assumption, since the fractions of the high frequency trading among the total transactions are not clear for the Large stocks and Small stocks.

Thus, we continue to calculate Dvt_i, which is the difference between the stock specific average volatility ratios in 2006 and 2008. The first terms at the right side is the average expressed as follow:

$$Dvt_i = \frac{1}{T_1}\sum_{t=1}^{T_1}\left[\frac{RV_{i,t}}{VSTOXX_t}\right]_{2006} - \frac{1}{T_2}\sum_{t=1}^{T_2}\left[\frac{RV_{i,t}}{VSTOXX_t}\right]_{2008} \quad (12)$$

The first term, on the right side of the function, is the stocks' average volatility ratio at sample period in 2006, $RV_{i,t}$ is stock i's daily realized volatility at day t, T_1 is equal to 63 and T_2 is equal to 62. As we mentioned above, the high frequency trading activities is at the normal level at 2006, while it decreased after the 2008 Short Sale Ban.

[Insert Figure 7 here]

As it shows in Figure 7, except for Aspiro, the values of Dvt_i are all smaller than zero. For ABB, Erricson and Volve, the Dvt_ivalues are severe smaller than zero. However, for Beijer Alma AB and Rorvikt, the values have much less distance to zero. Figure 7 presents strong result concerning the impact of high frequency trading on stock's volatility, it could be that the volatility for large stocks are severely increased after the high frequency trading removed from the stock market after the short sale ban. While the small stock' volatility displays little differences between the normal periods and stressful periods, due to the light participation of high frequency traders. This is consistent with HFT decreasing intraday volatility.

Andersen, Bollerslev(2000) examines the casual link between high frequency trading and volatility, based on the U.S. stock market. The method employed in our paper is similar with theirs, measuring the price volatility by constructing realized volatility and examining the relationship between HFT and volatility through the contemporaneous graphical representation. Andersen, Bollerslev(2000) find that HFT decreases intraday volatility, which we are also interested in. We also found that the volatility will be execrated in the financial crisis. They have studied the impact of volatility on the HFT activities. In the short run high frequency traders trade relatively more as volatility rise, while in the long run high frequency traders curtail their trading as volatility rises. Due to the limited available data, we can only examine the high frequency trading's influence on the price volatility. Their findings can be treated as a supplement of our studies.

6. Conclusion

This paper studies the impact of HFT activities on the stock specific volatility in Swedish stock market. Considering the significant role of the high frequency traders, it is important to clarify the interaction between market participants and potential for new regulation in the millisecond transactions. One the concern is that the HFT activities may destabilizes financial markets and exacerbates the price movement in the stock market. In this case, understanding how the HFT influences stock volatility can provide insight into controlling high frequency traders' activities.

The analysis of the impact of HFT on the stock volatility in this paper is twofold: how to measure the price volatility? How do HFT activities affect volatilities? We use the model-free estimator realized volatility to capture the stock-specific volatility based on their intraday returns. Volatility signature plot reveals a negative noise-price correlation and is proposed for choosing the optimal sampling frequency in our paper. That is, the highest available sampling frequency for which the autocovariance bias term is negligible. It is helpful in lowering the bias occurs during the construction of RV, trading off between the microstructure noise induced autocorrelation bias and deviation from efficient price caused by technique used to construct the observed price. In the empirical experiment, we find that the HFT is traded at an extreme low profit in one transaction-stock return fluctuates around zero, and the stock-specific intraday volatility increases with sampling frequency, which is consistent with volatility signal plot.

Finally, we analyze whether HFT increases or decreases the stock volatility in the Swedish stock market. Using the DDD approach between the affected and unaffected stocks, we find that, after controlling for time-series variation, HFT in the common market environment reduces the intraday volatility. Though the experiment implemented before and after the exogenous shock in 2008, we found that the removal of HFT activities in the stock market increases the stock volatility for the liquid stocks.

Another approach, due to limited data in the current dataset, we can explore in future research, is to find out how the volatility affects high frequency traders' activities. Understanding how the volatility impacts HFT activity can provide insight into knowing how to expect the level of HFT activities and the related benefits and costs.

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Apendix

Table 1: **Dataset Stocks**

Company	Main Business	Market Cap. (Stockholm Exchange, MSEK)	Enterprise Value (MSEK)
ABB	power and automation	278,695.06	308,237.09
Errison	telecommunications equipment and data communication systems	222,412	189,023.49
Volve	transportation related products and services	185,990.75	295,069.93
Aspiro	music streaming and TV and video streaming services	343.8	286.3
Beijer alma AB	industrialized springs and cables	3,495.21	3,420.01
Rorvik Timber AB	wood processing operations	179.48	1,081.48

Table 2: **Statistic Description of Intraday Return for ABB and Aspiro Intraday Return at Each Sampling Frequency**

ABB Company 2006

Time Frequency	1min	5mins	10mins	15mins	20mins	30mins	60mins
Mean	1.48E-05	4.39E-05	8.07E-05	1.20E-04	1.58E-04	2.34E-04	4.57E-04
Minimum	-0.2032	-0.1832	-0.1405	-0.1642	-0.1405	-0.1642	-0.1383
Maximum	0.1592	0.1524	0.1434	0.1455	0.1457	0.1476	0.1756
Std Dev.	0.0054	0.0088	0.0104	0.0135	0.0146	0.0172	0.0279
Skewness	-1.4888	-1.4792	0.6838	-0.4731	0.6358	0.1416	-0.1530
Kurtosis	1240.7280	529.3488	408.5752	230.6785	208.7151	158.2155	57.4401

ABB Company 2008

Time Frequency	1min	5mins	10mins	15mins	20mins	30mins	60mins
Mean	-4.99E-06	-2.22E-05	-4.35E-05	-6.48E-05	-8.67E-05	-1.28E-04	-2.49E-04
Minimum	-0.6178	-0.6170	-0.6233	-0.6350	-0.6306	-0.6188	-0.6157
Maximum	0.6123	0.5880	0.5858	0.5858	0.6123	0.5858	0.6129
Std Dev.	0.0156	0.0285	0.0391	0.0458	0.0542	0.0566	0.0979
Skewness	1.5355	1.2011	0.1519	0.2837	-0.0955	0.3170	0.0927
Kurtosis	1272.9350	362.8275	191.5894	144.4393	109.5176	98.7760	35.7255

Aspiro Company 2006

Time Frequency	1min	5mins	10mins	15mins	20mins	30mins	60mins
Mean	-1.99E-05	-3.34E-05	-4.49E-05	-5.73E-05	-6.41E-05	-8.75E-05	-1.20E-04
Minimum	-0.0851	-0.0808	-0.0803	-0.0773	-0.0741	-0.0760	-0.0688
Maximum	0.0968	0.0939	0.0939	0.0939	0.0822	0.0699	0.0910
Std Dev.	0.0072	0.0092	0.0104	0.0116	0.0121	0.0133	0.0153
Skewness	0.4435	0.4885	0.5117	0.4799	0.3385	-0.0922	0.2008
Kurtosis	52.4517	36.6032	28.2005	23.2344	21.7978	16.1500	13.4149

Aspiro Company 2008

Time Frequency	1min	5mins	10mins	15mins	20mins	30mins	60mins
Mean	-2.18E-04	-3.01E-04	-3.41E-04	-4.45E-04	-4.63E-04	-5.03E-04	-4.69E-04
Minimum	-0.1508	-0.1442	-0.1398	-0.1133	-0.1252	-0.1222	-0.1054
Maximum	0.1652	0.1564	0.1506	0.1570	0.1398	0.1133	0.1133
Std Dev.	0.0268	0.0461	0.0340	0.0323	0.0324	0.0332	0.0318
Skewness	-0.1332	0.3636	0.6727	0.8619	-0.2149	-1.1355	-0.1114
Kurtosis	9.4125	15.7002	12.7605	12.4221	11.5261	14.8631	7.4368

Intraday Return at 20 minutes Sampling Frequency

	ABB 2006	ABB 2008	Erricson 2006	Erricson 2008	Volve 2006	Volve 2008
Mean	0.0002	-0.0001	0.0001	-0.0001	0.0000	-0.0002
Std Dev.	0.0146	0.0542	0.0117	0.0513	0.0080	0.0806
Skewness	0.6358	-0.0955	-0.0785	0.8615	0.3602	-0.0361
Kurtosis	208.7151	109.5176	224.1489	131.9180	207.7788	67.5106
Minimum	-0.1405	-0.6306	-0.2266	-0.7339	-0.1430	-0.8073
Maximum	0.145669	0.6122952	0.2384937	0.6842976	0.1537118	0.8190055

	Aspiro 2006	Aspiro 2008	Beijer Alma AB 2006	Beijer Alma AB 2008	Rorvikt 2006	Rorvikt 2008
Mean	-0.0001	-0.0005	0.0003	-0.0006	0.0008	-0.0017
Std Dev.	0.0121	0.0324	0.0063	0.0217	0.0145	0.0414
Skewness	0.3385	-0.2149	0.0969	-0.2229	-5.2964	0.4221
Kurtosis	21.7978	11.5261	10.0959	6.4933	85.1287	5.0888
Minimum	-0.0741	-0.1252	-0.0379	-0.1087	-0.2162	-0.1241
Maximum	0.0822381	0.1397619	0.0430174	0.097455	0.0763223	0.1767504

Table 3: **Statistic Description of Daily Volatility for ABB and Aspiro**

Daily Volatility at Each Sampling Frequency

ABB 2006

Time Frequency	1min	5mins	10mins	15mins	20mins	30mins	60mins
Observations	63	63	63	63	63	63	63
Mean	0.0066	0.0067	0.0051	0.0058	0.0052	0.0049	0.0045
Std Dev.	0.0160	0.0232	0.0209	0.0217	0.0209	0.0213	0.0235
Skewness	2.9345	4.9618	6.3070	5.6827	6.2544	6.1507	4.9318
Kurtosis	11.7491	30.1164	45.3615	38.3389	44.7677	42.8804	29.4261

ABB 2008

Time Frequency	1min	5mins	10mins	15mins	20mins	30mins	60mins
Observations	62	62	62	62	62	62	62
Mean	0.1014	0.0773	0.0743	0.0685	0.0724	0.0535	0.0837
Std Dev.	0.2352	0.2022	0.1994	0.1959	0.2077	0.1804	0.2259
Skewness	2.6008	3.2715	3.5204	3.6998	3.4429	4.3728	3.0796
Kurtosis	9.2679	14.2340	16.4277	17.5260	14.6597	22.8235	12.2832

Aspiro 2006

Time Frequency	1min	5mins	10mins	15mins	20mins	30mins	60mins
Observations	63	63	63	63	63	63	63
Mean	0.0033	0.0032	0.0031	0.0031	0.0029	0.0027	0.0026
Std Dev.	0.0047	0.0048	0.0046	0.0045	0.0043	0.0037	0.0041
Skewness	2.4025	2.4861	2.4607	2.3158	2.4076	2.2842	2.3332
Kurtosis	8.6752	8.7525	8.5125	7.8435	8.4766	8.6308	7.8644

Aspiro 2008

Time Frequency	1min	5mins	10mins	15mins	20mins	30mins	60mins
Observations	62	62	62	62	62	62	62
Mean	0.0112	0.0224	0.0109	0.0088	0.0082	0.0074	0.0070
Std Dev.	0.0174	0.0455	0.0211	0.0160	0.0137	0.0139	0.0099
Skewness	3.4858	4.8094	3.3584	3.3582	3.1933	5.7086	3.2429
Kurtosis	14.9325	30.5477	12.9245	14.2791	12.8994	39.3627	14.1102

Daily Volatility at 20 minutes Sampling Frequency

	ABB 2006	ABB 2008	Erricson 2006	Erricson 2008	Volve 2006	Volve 2008
Observations	63	62	63	62	63	62
Mean	0.0052	0.0724	0.0036	0.0655	0.0016	0.1660
Std Dev.	0.0209	0.2077	0.0144	0.2072	0.0065	0.3460
Skewness	6.2544	3.4429	6.3720	3.3403	5.2801	1.9490
Kurtosis	44.7677	14.6597	45.8369	13.0354	32.6976	5.4649

	Aspiro 2006	Aspiro 2008	Beijer Alma AB 2006	Beijer Alma AB 2008	Rorvikt 2006	Rorvikt 2008
Observations	63	62	63	62	63	62
Mean	0.0029	0.0082	0.0005	0.0034	0.0021	0.0126
Std Dev.	0.0043	0.0137	0.0007	0.0036	0.0070	0.0117
Skewness	2.4076	3.1933	2.7794	1.8154	7.2707	1.2632
Kurtosis	8.4766	12.8994	11.4502	5.7921	56.0057	4.0442

Figure 1

Volatility Signal Plot of Large Stocks

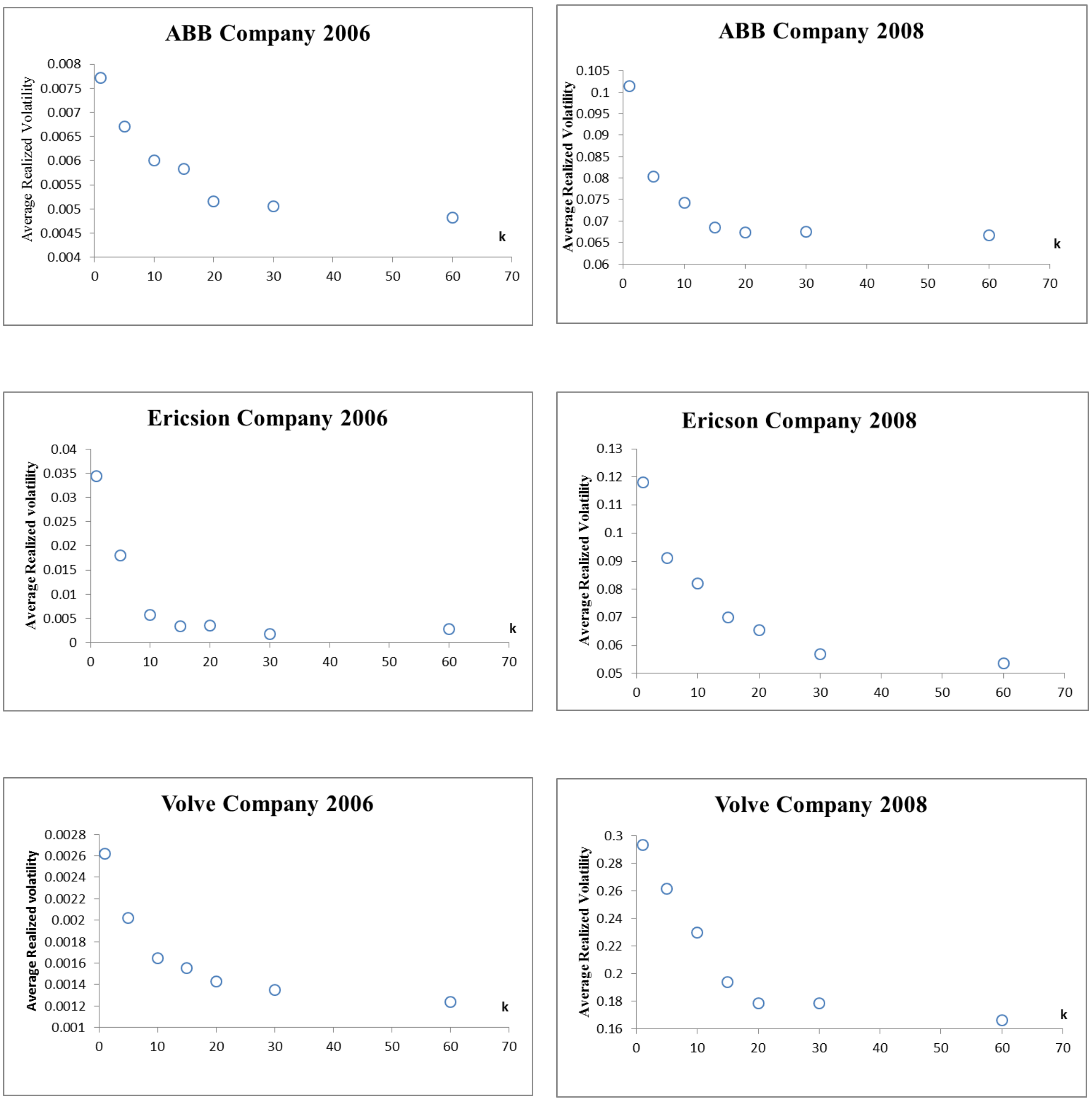
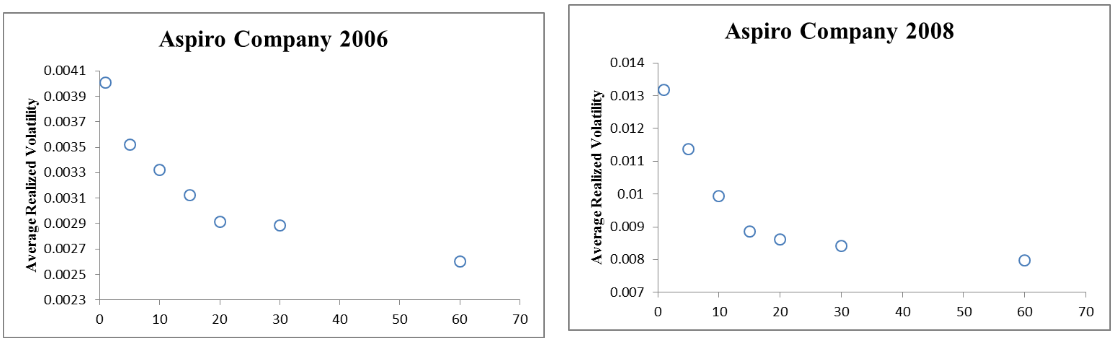


Figure 2

Volatility Signal Plot of Small stocks



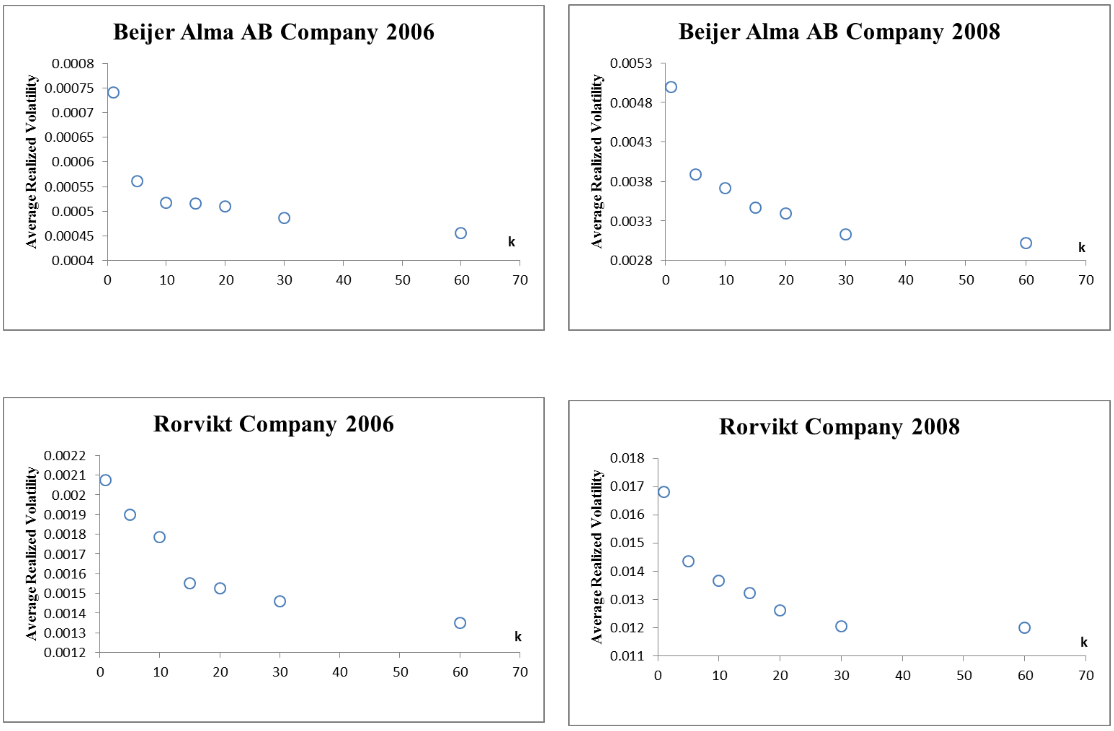
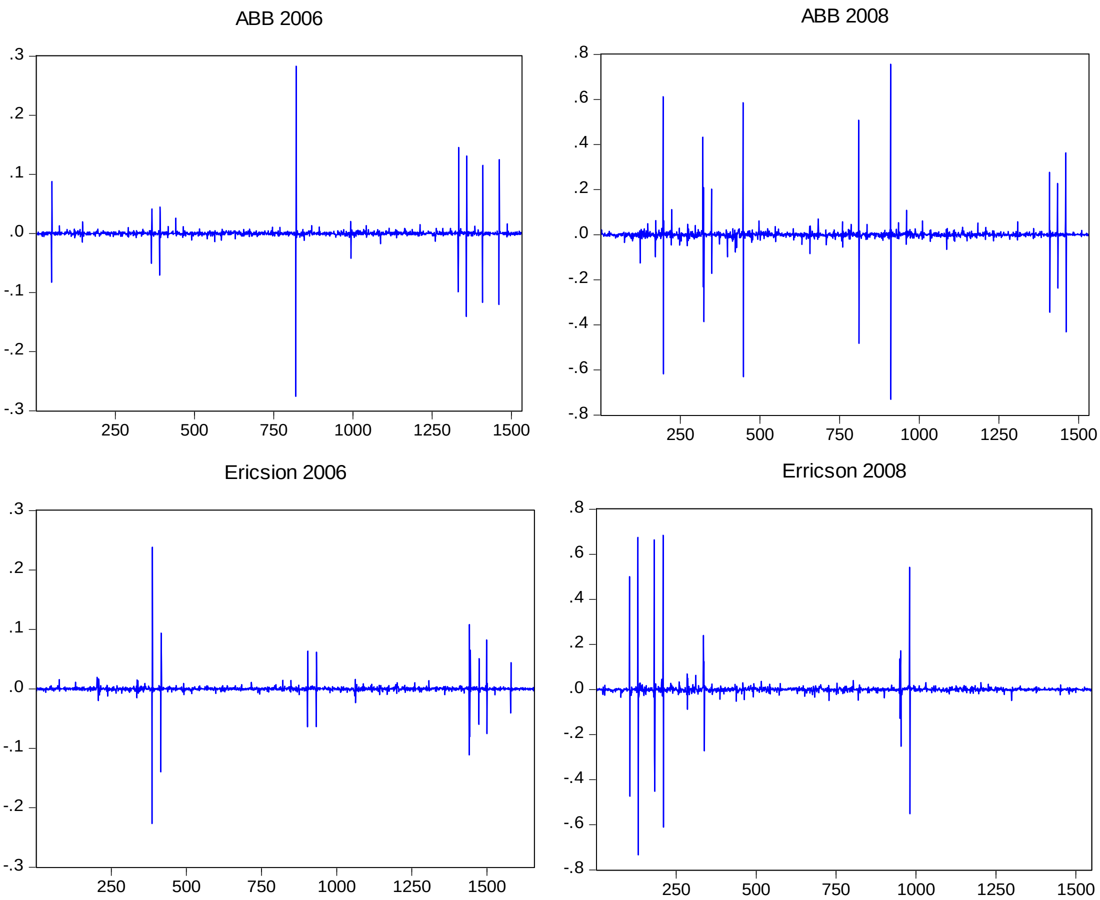


Figure 3

Large Stocks Intraday Returns at 20 minutes Sampling Frequency



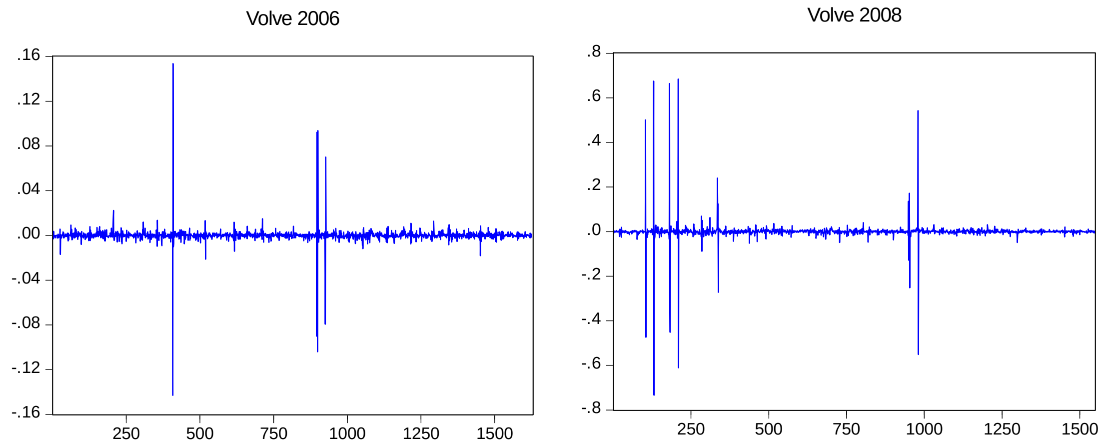
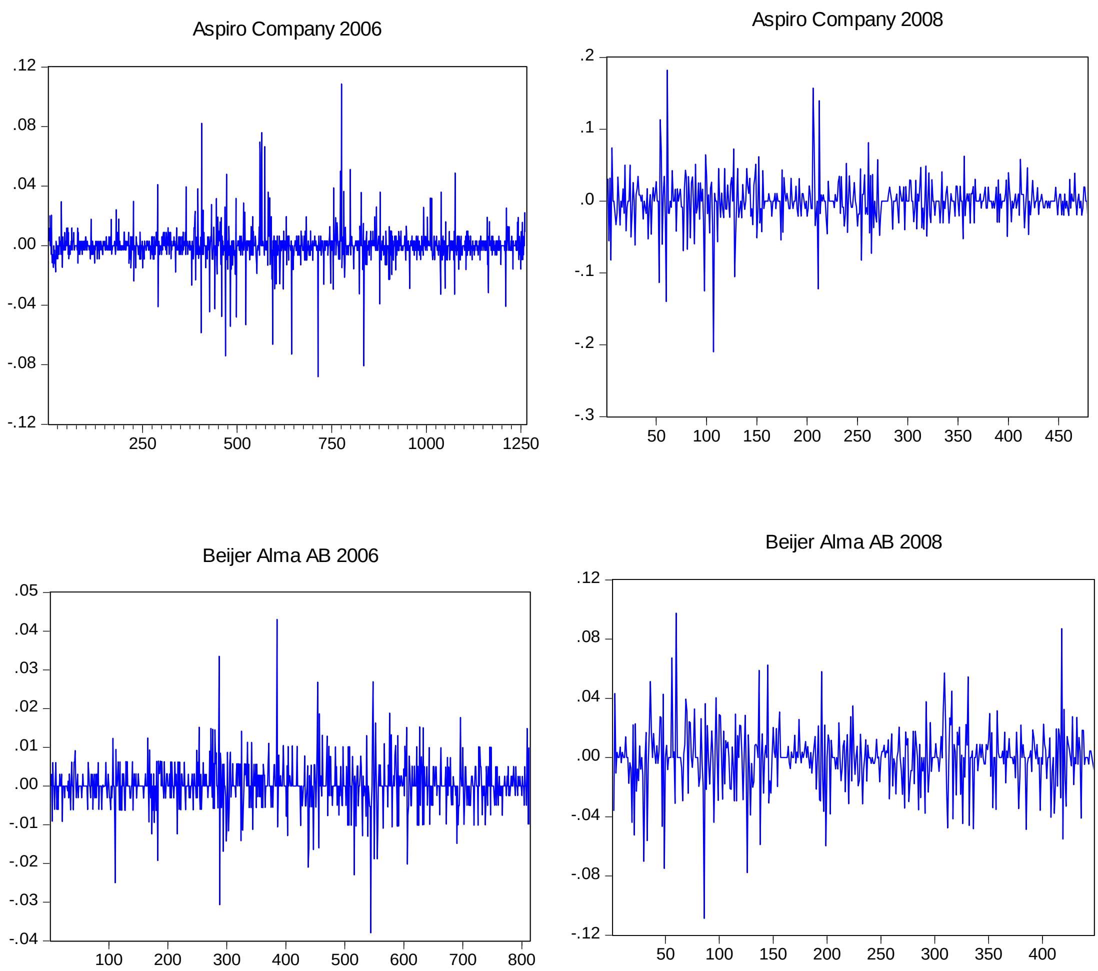


Figure 4

Small Stocks Intraday Returns at 20 minutes Sampling Frequency



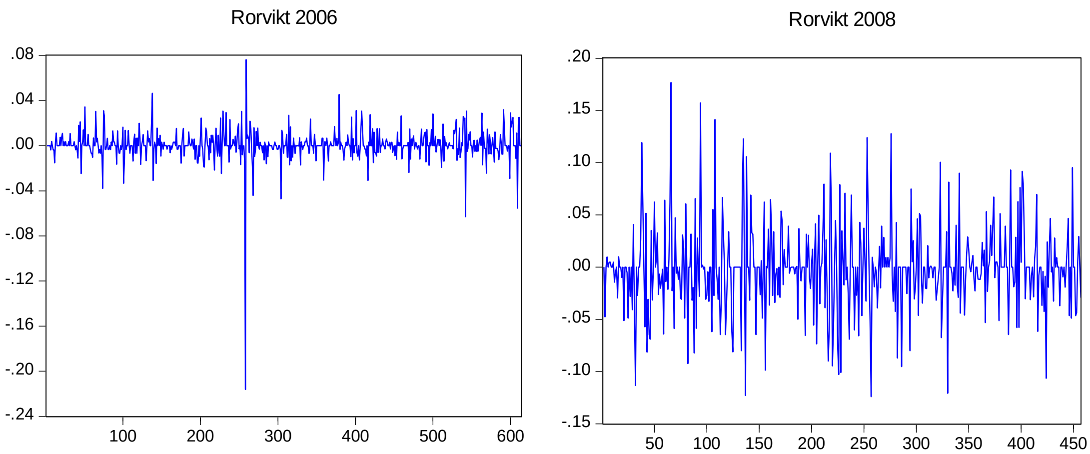
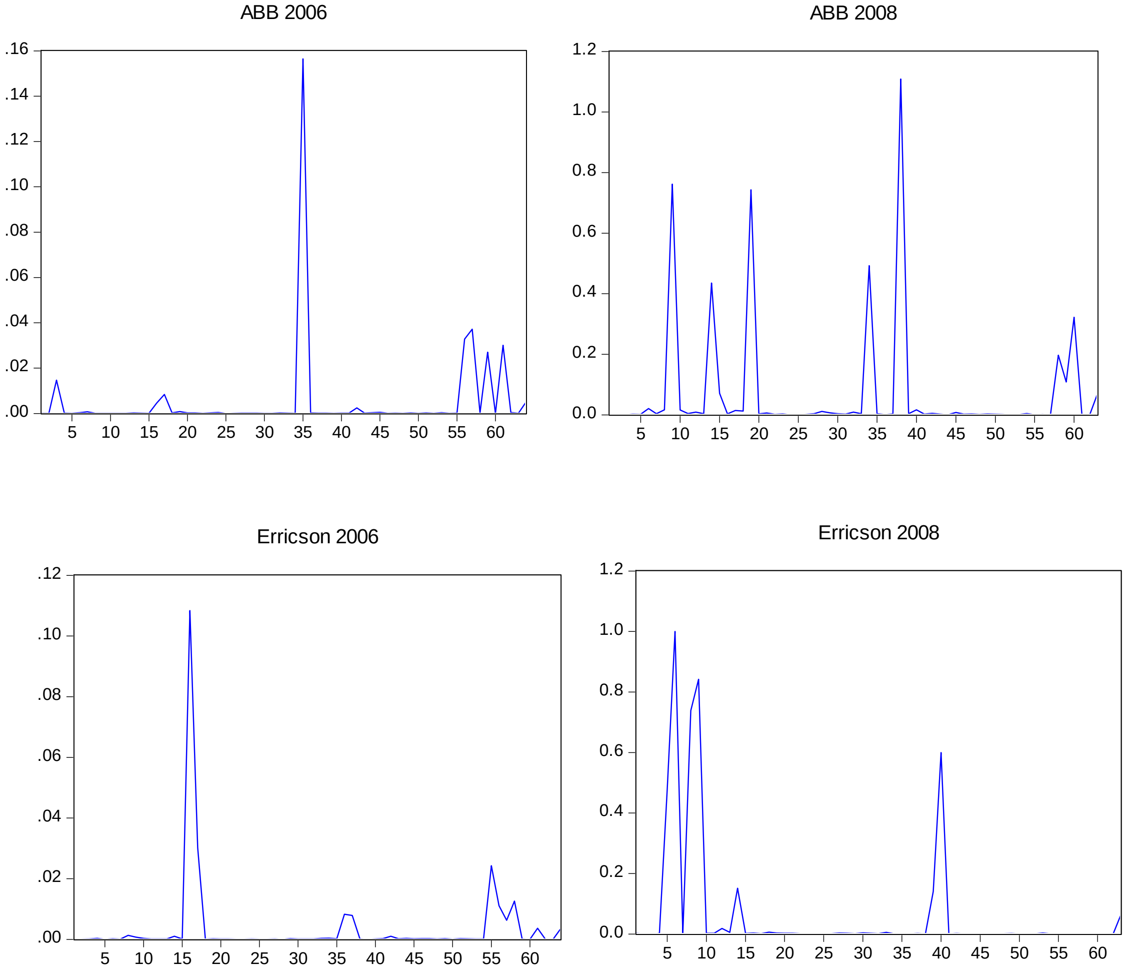
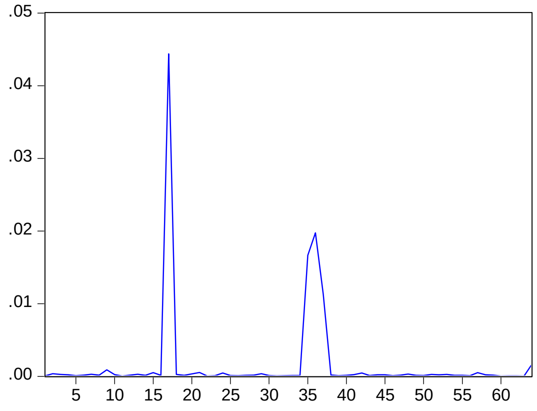


Figure 5

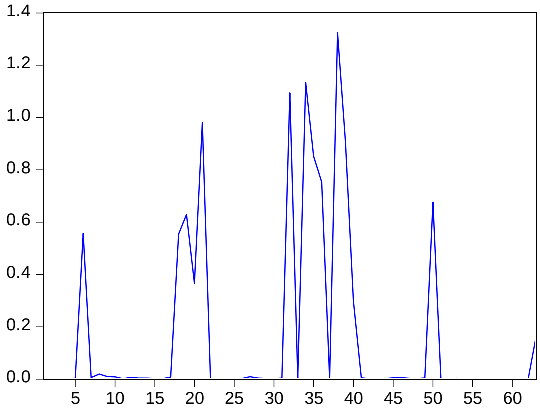
Daily Volatility at 20 minutes Sampling Frequency



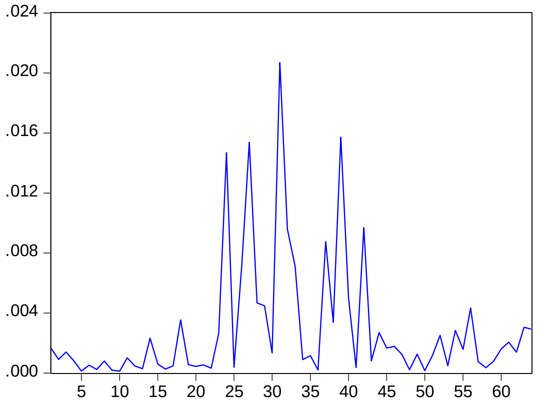
Volve 2006



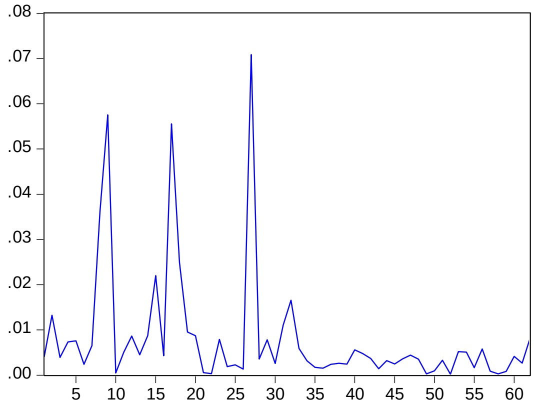
Volve 2008



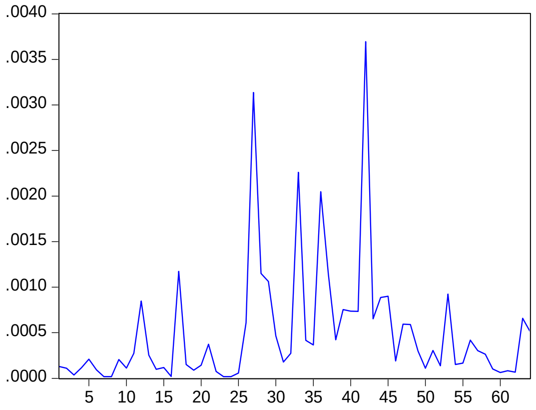
Aspiro 2006



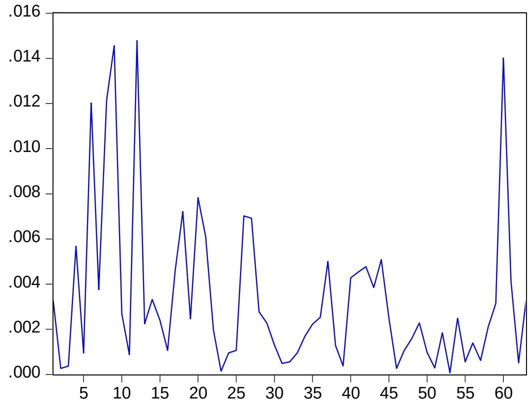
Aspiro 2008

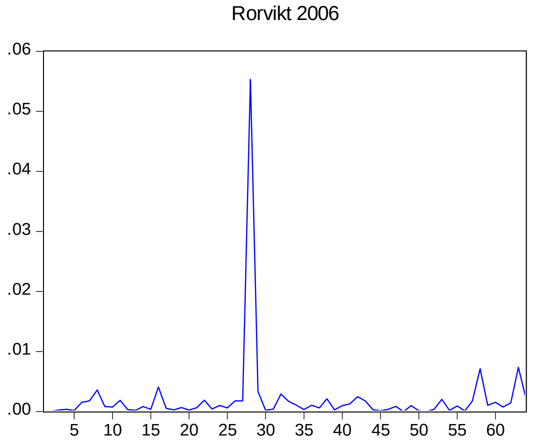


Beijer Alma AB 2006



Beijer Alma AB 2008





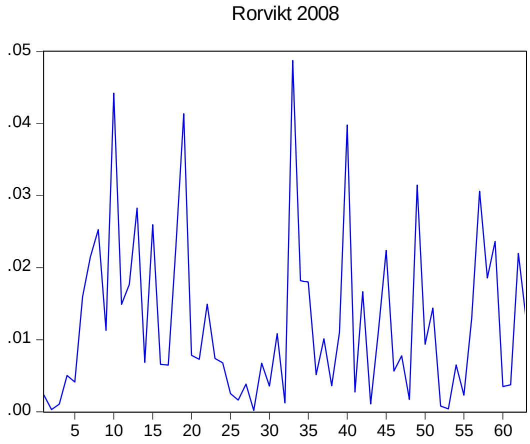
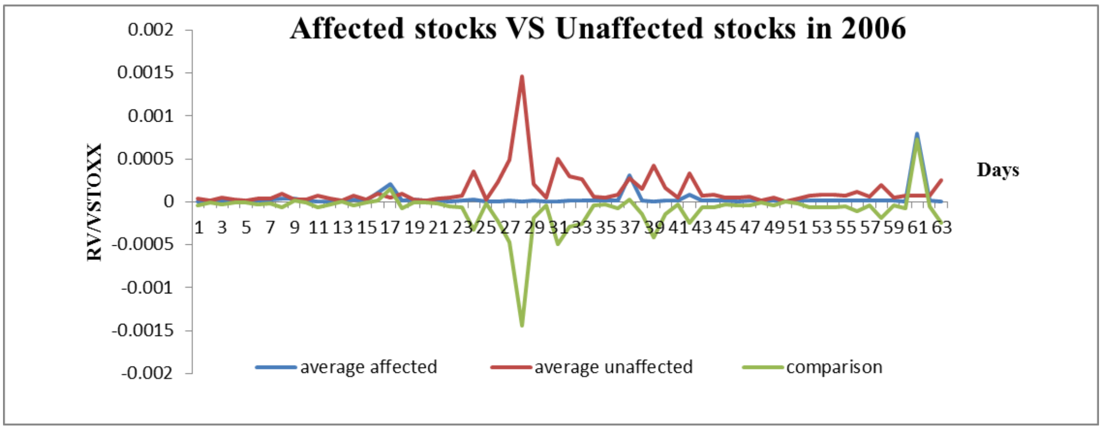


Figure 6

Daily Dvs_t Ratio Comparisons between Affected Stocks and Unaffected Stocks



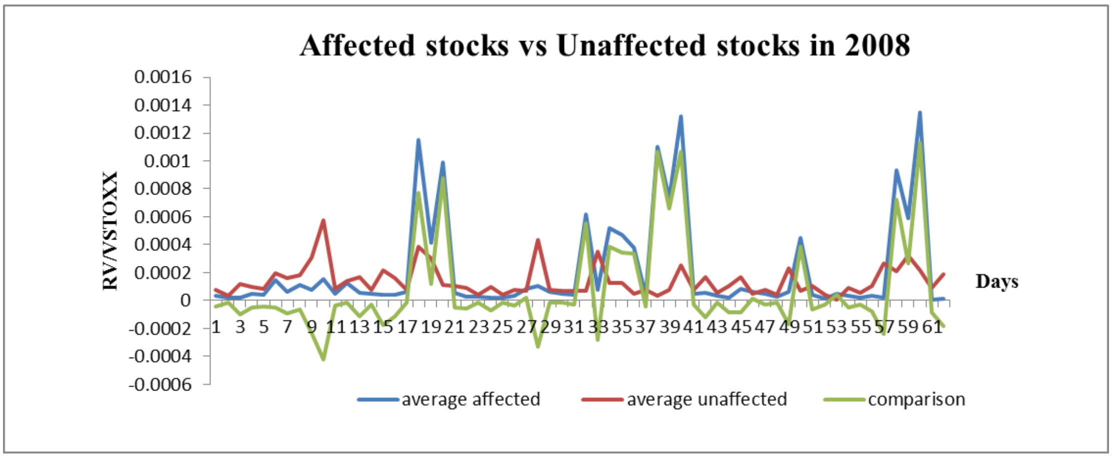


Figure 7

Stock-specific Dvt_i Ratio Comparison between 2006 and 2008