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Volatility Interruptions, idiosyncratic risk, and stock return

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Dedication

To my Mother for her unconditional love, patience, and nurturing
In loving memory of my Father who guided and believed in me
To my brother, Abdullah, for the special bond we share
To my sisters, Maha and Ghaida, for their care and respect
To my dear wife, Rhada, for her continued support
To the joy of my life, my sons, Abdulaziz and Mazen
To my best friend, Abdulrahman
I dedicate this dissertation

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ABSTRACT

The objective of this paper is to examine the impact of implementing the static and dynamic volatility interruption rule on idiosyncratic volatility and stock returns in Nasdaq Stockholm. Using EGARCH and GARCH models to estimate the conditional idiosyncratic volatility, we find that the conditional idiosyncratic volatility and stock returns increase as stock prices hit the upper static or dynamic volatility interruption limits. Conversely, we find that the conditional idiosyncratic volatility and stock returns decrease as stock prices hit the lower static or dynamic volatility interruption limit. We also find that the conditional idiosyncratic volatility is higher when stock prices reach the upper dynamic limit than when they reach the upper static limit. Furthermore, we compare the conditional idiosyncratic volatility and stock returns on the limit hit days to the day before and after the limit hit events and find that the conditional idiosyncratic volatility and stock returns are more volatile on the limits hit days. To test the volatility spill-over hypothesis, we set a range of a two-day window after limit hit events and find no evidence for volatility spill-over one or two days after the limit hit event, indicating that the static and dynamic volatility interruption rule is effective in curbing the volatility. Finally, we sort stocks by their size and find that small market cap stocks gain higher returns than larger market cap stocks upon reaching the upper limits, both static and dynamic.

JEL Classification: G1, G2, F3.

Keywords: Circuit breakers, price limits, static and dynamic volatility interruption, limit hit events, trading halts, conditional idiosyncratic volatility, volatility spill-over, market capitalization, stock return.

CHAPTER 1

The Impact of Static and Dynamic Interruptions Mechanism on Idiosyncratic Volatility in NASDAQ Stockholm

1. Introduction:

1.1. Background:

The goal of market regulators and policymakers is to enhance the efficiency of financial markets while preventing markets from a sudden meltdown due to bad news, high frequency trading, manipulations, or market panic. For this, regulators continuously impose new rules and regulations on financial markets. Following the market crash of October 19, 1987 and in light of the Black Monday, a growing number of regulatory reports and academic papers discussed the event of the 1987 crash and whether regulations around that time were effective in absorbing the shock. They also proposed different trading mechanisms to help market regulators improve financial markets.

Circuit breakers were first proposed by former United Stated Treasury Secretary, Nicholas Brady, after the 1987 market crash. They were first imposed on the New York Stock Exchange in 1987 after the Dow Jones Industrial Average (DJIA) plunged by 22.6%. The Brady Commission (1988) suggests implementing market wide circuit breakers. The report also suggests that trading halts should not be triggered frequently, suggesting setting high bounds for circuit breakers. Moreover, The Chicago Mercantile Exchange (CME), known as the Miller Report, reports that any implementation of price limits should be carefully evaluated to help ameliorate issues related to the first hours of trading[1]. However, in 1988, the U.S. Securities and Exchange Commission, SEC, issued a report that was not in favor of any trading halts or price limits mechanisms imposed

[1] For more information see: (1) Commodity Futures Trading Commission (CFTC). "Final Report on Stock Index Futures and Cash Market Activity during October 1987 to the U.S. Commodity Futures Trading Commission." The Division of Economic Analysis and the Division of the Trading and Markets, January 1988. (2) U.S. General Accounting Office. "Financial Markets: Preliminary Observations on the October 1987 Crash." Report to the Congressional Requesters, January 1988. (3) Brown, S. and Warner, J. "Using Daily Stock Returns."/our/ia/ of Financial Economics 14 (1985), 3-31. Chicago Board of Trade. "The Report of the Chicago Board of Trade to the Presidential Task Force on Market Mechanisms." December 1987.

on stock markets. They claim that mechanisms such as different time openings for different financial markets are more effective in facing market swings.

Lehmann (1989) defines circuit breakers as "devices for halting or limiting trading when prices move too much." In general, circuit breakers halts are imposed when a financial asset reaches a certain threshold, +/-10% for example, depending on the rules of that specific market. Once a halt is triggered, the index or stock in this case cannot be traded for a certain period of time that could amount to minutes, hours, or even an entire day depending on market regulations to allow for the volatility of the halted asset to drop. Thus, circuit breakers can be thought of as some temporary pauses on trading a specific financial asset once they reach a certain threshold. Overall, circuit breakers temporarily put the market on hold due to a sudden surge or downfall to allow for the market to adjust and prevent massive collapses from occurring. Countries such as Japan, France, China, South Korea, and many more followed the United States in imposing circuit breakers in their financial markets.

1.2. <u>Development of Circuit Breakers:</u>

Moser (1990) identifies three types of circuit breakers: order-imbalance circuit breakers, volume-induced circuit breakers, and price-change circuit breakers. Moser explains that "Order-imbalance circuit breakers are intended to protect the interests of market makers in specialist markets. Volume-induced circuit breakers are intended to protect the viability of back-office operations. Price change circuit breakers are intended to bring excessive volatility under control."

The 2010 Flash Crash Market questioned the effectiveness of market-wide circuit breakers and encouraged regulators to re-engineer circuit breakers to fit specific market characteristics. Hence, modified versions of circuit breakers have been introduced in many international financial markets.

Abad and Pascual (2013) point out two main types of circuit breakers: price limits and trading halts. They distinguish between two types of price limits, daily price limits and intraday price limits. Daily price limits, also known as the order rejection model, are a volatility stabilizer mechanism that puts some upper and lower bounds on trading, curbing the day-to-day volatility. To explain, regulators set a daily percentage range of trading that is based on previous day's closing price. Thus, stock prices cannot neither exceed nor go below the price limit bounds, allowing the market to stabilize. Once the daily price limits are triggered, trades beyond price limits cannot be executed. The intraday price limits, known as volatility interruption (VI hereafter), are more sophisticated models of the daily price limits. The VI mechanism combines (1) an intraday price limits, known as the dynamic VI, that are based around the last traded orderbook price, and (2) daily price limits, known as the static VI, that are based around the last auction price, which may have been the price traded in VI from earlier that day, the opening auction, or in case there was no trade for either of these, then the official closing price of the previous day. The dynamic VI is triggered when the difference between a stock's most recent execution price and potential execution price exceeds a specified price range, while the static VI is triggered when the difference between the price at the previous call auction and the potential execution price exceeds specified price range. Therefore, it is logical for the range of the static VI to be wider than the dynamic one. It is important to note that some markets adopt dynamic VI exclusively.

Abad and Pascual (2013) also distinguish between two types of trading halts, asset-specific trading halts and market-wide trading halts. The market-wide trading halt is a discretionary model and trading halts are activated under specific circumstances determined by market regulators such as recessions or market turmoil. Unlike the asset-specific trading halts model, trading halts in a market-wide model may include all financial instruments or certain securities.

The objective of this paper is to examine the impact of implementing the static and dynamic VI on idiosyncratic volatility in Nasdaq Stockholm. Static and dynamic VI were adopted around the same time. To the best of our knowledge, this is the first paper to study the impact of static and dynamic VI on idiosyncratic volatility and the volatility spill-over. In fact, this is the first paper to ever study the relationship between idiosyncratic volatility and any type of circuit breakers around the world, not only static and dynamic VI, including price limits and trading halts. Previous studies have examined the impact of VI on price discovery, information asymmetry, adverse selection and market quality, but none deal with idiosyncratic volatility.

As far as contribution is concerned, this paper contributes to the body of literature in many ways. First, this paper enriches the literature on Market Microstructure by providing new evidence from NASDAQ OMX Nordic on the impact of the newly introduced static and dynamic VI mechanism on the market. The mainstream of papers discussing VI in the market microstructure literature focus on their impact on price discovery, market quality, and information asymmetry; hence, this paper expands the VI literature by looking at different angles, such as the idiosyncratic volatility and the volatility spill-over hypothesis. Second, it also adds value to the price limits and circuit breakers literature since VI is one form of price limits discussed by Abad and Pascual (2013). Third, we believe this paper is a great addition to the asset pricing literature. There are two opposing views on the relationship between idiosyncratic volatility and the cross sectional of stock returns. Ang, Hodrick, Xing, and Zhang (2006) show that there is a negative correlation between lagged realized idiosyncratic risk and returns, while Fu (2009) shows a positive correlation between conditional idiosyncratic volatility estimated using (EGARCH) models and expected stock returns. This paper sheds the light on the effect of VI on idiosyncratic volatility while providing supporting evidence to the literature. Finally, this paper contributes to the portfolio management literature by providing insights to portfolio manager on the level of risk, measured by idiosyncratic volatility, that can be expected from stocks that frequently hit the upper or lower limits.

The remainder of this paper is organized as follows. Sections 2 reviews relevant literature review, motivation, and hypotheses development. Sections 3 describes the data and methodology used in our analyses. Section 4 presents and interprets the results. Section 5 summarizes the findings and concludes.

2. Literature Review, Motivation, and Hypotheses Development:

2.1 Literature Review:

2.1.1 Literature Review Related to Circuit Breaker and Price Limits:

The literature in price limits identifies two opposing views. Some claim that price limits improve financial markets quality and others claim otherwise. Lehmann (1989) argues that in markets where price limits are imposed, the imbalance of supply and demand in daily trading causes the prices to reach the limits. Hence, volatility increases in longer horizons, causing liquidity to drop. Subrahmanyam (1994) investigates the impact of circuit breakers on market volatility. The results show that the implementation of circuit breakers causes market volatility to surge and therefore, market liquidity to drop. Moreover, Diacogiannis, Patsalis, Tsangarakis, and Tsiritakis (2005) examine the impact of imposing price limits on overreactions in Athens Stock Exchange and find evidence of short-term overreaction during periods of one day upper limit hit, two days upper limit hits, three days upper limit hits, and one day lower limit hit.

George and Hwang (1995) select a sample of stocks from the Tokyo stocks exchange to examine the volatility of the daily returns based on the opening and closing prices and its relation to price limits. They find that for highly traded stocks in Tokyo stocks exchange, volatility is higher for opening price compared to closing price. This indicates that close-to-close returns are higher, because of lower volatility, than open-to-open returns. This finding contradicts with the goal of price limit rule, concluding that price limit rule increases volatility.

Kim and Rhee (1997) study the price limit performance in Tokyo Stock Exchange. They begin by examining the claims of support and opposition of the price limit rule. They state that advocates of the price limits rule believe that such mechanism helps mitigate stock price volatility; does not affect trading movement; and reduces overreaction. On the other side, opponents of this rule claim that price limit causes higher volatility in the long-run (volatility spillover), negatively affecting (delaying) the price discovery process. Since price limits restrict trading, opponents argue that trading activity will get affected accordingly. The paper examines both sides of the argument and concludes that price limits do not curb volatility for stocks that reach price limits more frequently as fast as stocks that do not normally hit the price limit. This is in line with the findings of Lehmann (1989) and George and Hwang (1995). They also show that stocks that reach price limits tend to delay price discovery, compared to stocks that do not reach price limits. This is consistent with Fama (1989) who shows that circuit breakers delay price discovery and increase volatility.

Cho, Russell, Tiao, and Tsay (2002) use high frequency data in their empirical work to investigate the magnet effect of price limits in Taiwan Stock Exchange. The magnet effect of price limit is the tendency for a stock price to accelerate towards the upper limit as the stock price gets close to the upper bound. However, the opposite does not hold true. As a matter of fact, stock prices tend to move solely toward the lower limit as they get closer to the lower bound. The empirical results confirm the existence of the magnet effect, which is caused by the illiquidity risk and investors behavior in Taiwan Stock Exchange. To confirm the accuracy of their model in capturing the magnet effect, they apply their model on the S&P 500 where the price limit rule is not applicable. The results show no evidence of the magnet effect.

Tooma (2011) investigates the existence of the magnet effect of price limits in the Egyptian stock exchange for the period from 1997 to 2002, where a 5 percent price limit was imposed. The paper uses pooled time series data for two sub-groups of firms; one for the period when price limit was imposed and another for when it was not in place in order to apply a logit model of probability of hitting the 5 percent limit. Results show that the change in the coefficient between periods, when price limits were not imposed compared to the period when they were imposed, is consistent with the magnet effect hypothesis. The coefficient indicates that the magnet effect is higher in the period when the price limit was imposed compared to the period when price limit rule was not in effect. In other words, the probability of reaching the price limit has increased after imposing the price limit rule, consistent with Cho et al (2002).

Advocates of the price limit rule, on the other hand, regard price limits positively, claiming that price limits reduce price volatility. They argue that setting daily upper and lower bounds for stock prices to move within helps manage price volatility and gives room for market participants to cool off. This prevents investors from initiating a market panic and avoid overreaction, thus, allowing volatility to drop.

Yang Chu, Ko, and Lee (2018) study the effect of price limits on continuing overreaction and momentum in Taiwan Stock Exchange and find that imposing price limits reduces investors overreaction. Kim and Yang (2003) investigate whether price limits can play a role in reducing overreaction in Taiwan Stock market under two hypotheses: the cooling-off hypothesis and the magnet hypothesis. They find that overreaction increases as prices are approaching price limits and decreases as prices sequentially hit the price limits.

Deb, Kalev, and Marisetty (2017) apply the propensity score matching techniques to narrow the sample selection bias in Kim and Rhee (1997). They show that price limits are effective in reducing the transitory volatility in days after price limits are hit. Moreover, they did not find any evidence of the volatility spill-over. These finding contradict with the finding of Kim and Rhee (1997).

Ma, Rao, and Sears (1989) investigate the effectiveness of price limits in the U.S. future market for four commodities: corn, silver, treasury bonds, and soybeans. The results indicate that price limits can be used as a device to monitor price movement and volatility in volatile markets. Ma et al (1989) point out three benefits for imposing price limits. First of all, price limits can be used to attenuate credit risk. Second, price limits can serve as a tool to prevent the market from overreacting as a result to news. Third, price limits can be used to prove that markets are not as liquid.

Kim and Park (2010) introduce a manipulation-based model to test reasons behind the adoption of price limits in stock markets. Their model shows that imposing the price limit rule discourages market manipulation. They also argue that based on their model, a possible reason for market regulators to impose price limit rules is that the level of manipulation is high. They go on to modify their model to estimate price limits levels and conclude that markets with high levels of corruption and low public enforcement tend to have high price limits.

Deb, Kalev, and Marisetty (2010) investigate whether or not price limits are bad for equity markets. They notice the growing literature criticizing price limits and decide to test it themselves. To do so, they gathered a sample of 58 stock markets, which represents about 80% of the world's equity markets. Surprisingly, about 71 percent, 41 equity markets, out of the sample imposes the price limits rule. They find that markets that impose price limits are characterized by low legal and technical development, low levels of transparency, higher corruption levels, and low business disclosure. These finding are consistent with their hypothesis even after robust.

2.1.2 Literature Review Related to Volatility Interruptions:

Due to the novelty of the VI, four papers have discussed the new mechanism. Kwon, Eom, La, and Park (2018) examine the effect of introducing the static and dynamic VI to the pre-existing price limits in the Korean Stock Market. They find that the static VI has a weak impact in stabilizing price discovery, while the dynamic VI has a positive effect in stabilizing price discovery. They also find that static IV has limited effect as it provides similar results as the existing price limits system.

Brugler and Linton (2014) study the role of static VI on market quality in London Stock Exchange. They argue that market quality become worse after a long suspension from lower static VI events. Nevertheless, they document that lower static VI helps in interrupting poor market quality to other stocks in times when the market is at distress. Finally, they show that upper static VI causes excessive trading spill-overs.

Zimmermann (2013) examine the impact of VI on price discovery in Deutsche Börse Xetra. The study shows that "volatility interruptions contribute to about 36 percent of pre-interruption price uncertainty revelation." The paper also claims that when VIs offers an accurate direction of price discovery, subsequent volatility drops. Lastly, the paper documents although market quality improve after an VI is triggered, market traders continue to be alert and watchful.

Abad and Pascual (2010) observe the impact of the static VI on the Spanish Stock Exchange. They document a surge in information asymmetry risk prior to a VI halt, hypothesizing that informed traders anticipate their trading strategies arounds VI halts; they conclude that VI increases information asymmetry. Finally, the authors conclude that high levels of volatility, illiquidity and trading activities will remain in the market even after the introduction of the static VI mechanism.

2.2. Motivation and Hypotheses Development

After the 2010 flash crash, many European exchanges announced the introduction of a new trading mechanism aiming to reduce market volatility. On June 14, 2010, about one month after the flash crash, the Euronext introduced the Static VI, in addition to the pre-existing dynamic VI, to all its exchanges in Amsterdam, London, Paris, Lisbon, Brussels, and Dublin. Three months later, on September 30, 2010, NASDAQ OMX Nordic introduces an updated VI to its Nordic markets to protect investors and listed companies form excess volatility. Nordic markets include Stockholm, Helsinki, Copenhagen, and Iceland exchanges.

Similar to European exchanges, Asian exchanges follow suit. On September 1, 2014, The Korean Stock Exchange introduced the dynamic VI and on June 15, 2015, they announced the introduction of the static VI.

In this paper, we only focus on one type of circuit breaker, the VI mechanism, both static and dynamic. We examine the impact of VI on idiosyncratic volatility in Stockholm stock exchange. We chose Stockholm stock exchange for two main reasons. First, Stockholm stock exchange is the largest market in Nasdaq OMX Nordic and due to the fact that it is managed by Nasdaq, its level of efficiency is much higher compared to those locally managed in other European markets. Second, it adopts the VI mechanisms, both static and dynamic. To the best of our knowledge, this is the first paper to study the impact of VI on the idiosyncratic volatility and volatility spill-over.

The main purpose of implementing the VI rule is to protect investors form excess volatility by mitigating day to day volatility. Nevertheless, the direction of stock prices, whether up or down, significantly impacts stock volatility. That is when prices are rising, which is approaching the upper static or dynamic limits, investors receive this as good news and rush to buy the share to make a profit. Investors' overreaction to jumps in stock prices increases volatility. In fact, Diacogiannis et al (2005) provide evidence that overreaction is present when reaching the upper limits. Thus, we expect idiosyncratic volatility to increase as stock prices approach upper static and dynamic limits:

H_1: Idiosyncratic volatility increases when a stock hits the upper static limit.
H_2: Idiosyncratic volatility increases when a stock hits the upper dynamic limit.

On the other hand, in the case of bad news, investors underreact to falling stock prices because they do not wish to sell their shares at lower prices, waiting for share prices to bounce back. Therefore, investors' underreaction lowers volatility. This leads us to investigate the following hypotheses:

H_3: Idiosyncratic volatility decreases when a stock hits the lower static limits.
H_4: Idiosyncratic volatility decreases when a stock hits the lower dynamic limits.

Furthermore, because dynamic VI has lower range than static VI, we should observe more frequent dynamic hits than static hits. In fact, it has been documented in this study that we have more dynamic limit occurrences than static limit occurrences. We will be discussing this in more details in the descriptive statistics section. This leads us to hypothesize that investors will be more concerned with the dynamic hits than with the static hits due to their frequent limit hits, which may create some panic among investor and increases stock volatility as a result. Hence, we wish to test the following hypotheses:

H_5: Stocks that reach the upper dynamic limits witness higher idiosyncratic volatility than stocks that reach the upper static limits.

To further investigate hypotheses 1 and 2 by looking at the idiosyncratic volatility one day before and day after the limit hit day for both upper static and dynamic. We expect our earlier hypotheses to hold. That is, idiosyncratic volatility is higher on the upper limit hit day compared to the day before and the day after the limit hit. We test the following hypotheses:

H_6: Idiosyncratic volatility is higher on days when the static upper limit is reached compared to the day before and the day after.

H_7: Idiosyncratic volatility is higher on days when the dynamic upper limit is reached compared to the day before and the day after.

Similarly, we further investigate hypotheses 3 and 4 and test the following hypotheses:

H_8: Idiosyncratic volatility is lower on days when the static lower limit is reached compared to the day before and the day after.

H_9: Idiosyncratic volatility is lower on days when the dynamic lower limit is reached compared to the day before and the days after.

The literature proposes two opposing views on whether or not trading mechanisms cause volatility spill-over after the limits are reached (i.e. Kim and Rhee (1997) and Deb, Kalev, and Marisetty (2017)). This motivates us to investigate the spill-over hypothesis within the scope of the static and dynamic VI mechanisms. Hence, we wish to test the following hypotheses:

H_{10}: Idiosyncratic volatility starts to decline one day after a stock reaches the static upper limits and continues to decline during the second day.

H_{11}: Idiosyncratic volatility starts to decline one day after a stock reaches the dynamic upper limits and continues to decline during the second day.

H_{12}: Idiosyncratic volatility starts to augment one day after a stock reaches the static lower limits and declines during the second day.

H_{13}: Idiosyncratic volatility starts to augment one day after a stock reaches the dynamic lower limits and declines during the second day.

3. Data and Methodology:

We obtain daily stock prices and related financial data from DATASTREAM. We obtain data on Swedish 3 months Treasury Bill from Sweden central bank (Riksbank). Fama and French factors are obtained from Kenneth French's website. Data for Stockholm spans from September 30, 2010 to December 29, 2017. We chose September 30, 2010 to be the starting date for our sample because this is the date when static and dynamic VI was first put into effect. There are 378 stocks traded in Stockholm Stock Exchange. We drop stocks that were listed after December 29, 2017 or have observations less than one week. The final sample consists of 344 firms. The table below summarizes the static and dynamic VI range in Nasdaq Stockholm:

Exchange	Static Limit (stock)	Static Limit (Index)	Dynamic Limit (stock)	Dynamic Limit (Index)	Suspension time for static	Suspension time for dynamic
Stockholm	+/- 15% from opening	+/- 10% from opening	+/- 5% from the last traded price	+/- 3% from the last traded price	3 minutes	1 minute

To identify static and dynamic limit hit occurrences, we follow the following steps. We assume upper static limits are reached when any of the following conditions occur:

$$H_t \geq O_t + \textit{Static limit (15\%)} \tag{1a}$$

$$C_t \geq O_t + \textit{Static limit (15\%)} \tag{1b}$$

where H_t and C_t represent Day t's high and close price, respectively, and O_t represents Day t's open price.

We assume Lower static limits are reached when any of the following conditions occur:

$$C_t \leq O_t - \textit{Static limit (15\%)} \tag{2a}$$

$$L_t \leq O_t - \textit{Static limit (15\%)} \tag{2b}$$

where L_t represent Day t's low and price

Similarly, we assume upper dynamic limits are reached when any of the following conditions are met:

$$H_t \geq O_t + \textit{Dynamic limit (5\%)} \tag{3a}$$

$$C_t \geq O_t + \textit{Dynamic limit (5\%)} \tag{3b}$$

$$C_t \geq H_t + \textit{Dynamic limit (5\%)} \tag{3c}$$

And Lower dynamic limits are reached when any of the following conditions are met:

$$L_t \leq O_t - \textit{Dynamic limit (5\%)} \tag{4a}$$

$$C_t \leq O_t - \textit{Dynamic limit (5\%)} \tag{4b}$$

$$C_t \leq L_t - \textit{Dynamic limit (5\%)} \tag{4c}$$

Once we determine the number of upper and lower hits from static and dynamic VI, we estimate the idiosyncratic volatility. Fu (2009) and Spiegel and Wang (2005) use the EGARCH model to estimate the idiosyncratic volatility, whereas Bali and Cakici (2008) GARCH and EGARCH to estimate the conditional idiosyncratic volatility. We employ two conditional time-varying measures[2] to estimate the idiosyncratic volatility: The exponential generalized autoregressive conditional heteroskedastic model (EGARCH) and the generalized autoregressive conditional heteroskedastic model (GARCH). To estimate the idiosyncratic volatility, we assume Fama and French (1993) three-factors model, Carhart (1997) four-factor model, and Fama and French (2015) five-factors model. We estimate Fama and French (1993) three-factors model as follows:

$$R_{i,t} - R_{f,t} = \beta_{i,t}\left(R_{m,t} - R_{f,t}\right) + s_{i,t}\, SMB + h_{i,t} HML + \varepsilon_{i,t} \qquad (5)$$

where $R_{i,t}$ is the return on stock i, $R_{m,t}$ is the market return, $R_{f,t}$ is the risk-free rate, SMB is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML is the difference between the returns on diversified portfolios of high and low B/M stocks, and $\varepsilon_{i,t}$ is a zero-mean residual.

We estimate Carhart (1997) four-factor model as follows:

$$R_{i,t} - R_{f,t} = \beta_{i,t}\left(R_{m,t} - R_{f,t}\right) + s_{i,t}\, SMB + h_{i,t} HML + u_{i,t} UMD + \varepsilon_{i,t} \qquad (6)$$

Where the momentum factor, UMD, is calculated as the equal-weight average of the returns of small and big winners minus losers.

We estimate Fama and French (2015) five-factors model as follows:

$$R_{i,t} - R_{f,t} = \beta_{i,t}\left(R_{m,t} - R_{f,t}\right) + s_{i,t}\, SMB + h_{i,t} HML + r_{i,t} RMW + C_{i,t} CMA + \varepsilon_{i,t} \quad (7)$$

where RMW is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and CMA is the difference between the returns on diversified portfolios of low (conservative) and high (aggressive) investment stocks.

We use $\varepsilon_{i,t}$ from each model, the FF three-factor model, Carhart four-factors model and FF five-factor model, to estimate the conditional idiosyncratic volatility. We use $\varepsilon_{i,t}$ as input in both

[2] Fu(2009) and Spiegel and Wang (2005) confirm that estimating the idiosyncratic volatility using a conditional time-varying measures are superior to OLS based measure such as the methodology proposed by Ang et al (2006).

EGARCH and GARCH models. The first measure of conditional idiosyncratic volatility is the EGARCH model of Nelson (1991):

$$\ln(h_t) = \alpha_0 + \alpha_1 \left(\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}\right) + \lambda_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}\right| + \beta_1 \ln(h_{t-1}) \tag{8}$$

Unlike other ARCH family models that use the value of ε_{t-1}^2, the EGARCH model employs ε_{t-1} as the level of standardized value. One of the unique functions of the EGARCH model is that it captures the leverage effect. When $\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}$ is positive, the positive shocks indicate good news which causes less volatility. The impact of the positive shocks on the log conditional variance is then $\alpha_1 + \lambda_1$. When $\frac{\varepsilon_{t-1}}{h_{t-1}^{0.5}}$ is negative however, the negative shocks indicate bad news which creates more volatility. The impact of the negative shocks on the log conditional variance is then $-\alpha_1 + \lambda_1$.

The Second measure of conditional idiosyncratic volatility is the GARCH model of Bollerslev (1986):

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i} \tag{9}$$

Where $p \geq 0$, $q \geq 0$

$\alpha_0 \geq 0$, $\alpha_i \geq 0$ i= 1, …., q,

$\beta_i \geq 0$ i= 1, …., p

Following the literature, we use EGARCH (1, 1) process and GARCH (1, 1) process. The residuals from these processes are our conditional idiosyncratic volatility.

In an attempt to reduce the effect of heteroskedasticity in our results, we take the natural logarithm of the idiosyncratic volatility measures following Panousi and Papanikolaou (2012), Change and Dong (2004), Malkiel and Xu (2003), and Sias (1996).

4. Results and Interpretations:

4.1. Descriptive Statistics:

Table 1 shows the summary statistics of 344 stocks in Nasdaq Stockholm during the period from September 30, 2010 to December 29, 2017. The minimum stock return is -2.28% and the maximum is 2.32% with an average of -0.0016% stock return. We do not observe high spikes in stock return and this is due to the VI mechanism that restricts stocks from increasing or decreasing above or below certain range. Stocks liquidity is relatively high in Nasdaq Stockholm as indicated by the Amihud (2002) measure with a mean of -12.40. Moreover, stock volatility is considerably low with an average of 0.02%. As far as stock profitability is concerned, the average return on equity is 9.37% and the median is 11.67% indicating that stocks in Nasdaq Stockholm are profitable. The average firm leverage ratio and book to market ratio is 22.29% and 61.52%, respectively. Hence, stocks in Nasdaq Stockholm are characterized by being profitable, liquid, and possessing low levels of volatility for the period following the imposition of the VI mechanism in September 30, 2010 to December 29, 2017.

The literature in asset pricing suggests that idiosyncratic volatility measures must be positively correlated. Ang et al (2009) show that the three idiosyncratic volatility measures used in his paper are highly positively correlated. Fu (2009) finds a positive, but moderate 0.46 correlation between the conditional idiosyncratic volatility and idiosyncratic volatility constructed following Ang et al (2006). Following the literature, we use Paerson's correlation matrix. Table 2 shows Paerson's correlation matrix between the six conditional idiosyncratic volatility used in this study. The correlations between the idiosyncratic volatility measures in this study are highly positively, ranging from 0.82 to 0.99, and statically significant at 1%.

Table 3 shows the VI occurrences for both static and dynamic limits sorted by year, market capitalization, and market sector. In total, 59,445 times the VI were triggered from September 30, 2010 to December 29, 2017. Static limits were reached 3,618 times (2,252 static upper hits and 1,366 static lower hits) compared with 55,827 for dynamic limits (27,259 and 28,568 limits hit for dynamic upper and lower limits, respectively). It is not surprising to observe greater dynamic VI occurrences than static because of the limit range. It is common to observe a stock reaching 5% from opening price but not common to observe a stock reaching 15% from yesterday's closing price, and this explains why we have more dynamic occurrences compared with their static counterparts.

The year following the implementation of the VI rules, 2011, witnessed the highest VI occurrences with a total of 10,501 limit reaches. Out of the 10,501 hits, 288 static upper hits, 228 static lower hits, 4,234 dynamic upper hits, and 5,751 dynamic lower hits. Moreover, small market cap stocks witnessed the highest VI occurrences with 30,882 compared with 8,173 and 20,390 for large and medium market cap stocks, respectively. It can be observed here that small market cap stocks are more volatile compared to large and medium market cap stocks. Moreover, medium market cap stocks are more volatile large market cap stocks. This is consistent with the literature that small size firms tend to be more volatile compared to their larger counterparts. Fu (2008) shows that "Small firms tend to have higher idiosyncratic volatilities than large firms."[3] Furthermore, we sort stocks by their market sectors. Nasdaq Stockholm is divided into ten main sectors: Basic Materials, Consumer Goods, Consumer Services, Financials, Health Care, Industrials, Oil and Gas, Technology, Telecommunications, and Utilities. Industrials and Health care sectors observed the highest VI occurrences with 13,549 and 13,371 limit hits, respectively. Conversely, Utilities and Telecommunications sectors witnessed the lowest VI occurrences with 533 and 639 limit hits, respectively.

4.2. Volatility Interruptions and Idiosyncratic Volatility:

Now that we have estimated the conditional idiosyncratic volatility, we test our hypotheses. To test for the effect of VI on idiosyncratic volatility, we create four dummy variables: static upper, static lower, dynamic upper and dynamic lower hit events. Following Ferreira and Laux (2007), we estimate the following fixed effect regression model:

$$\Psi_{i,t} = a_0 + b_0\, LimitDUM_{i,t} + b_1\, Size_{i,t} + b_2 \left(\frac{M}{B}\right)_{i,t} + b_3\, ROE_{i,t} + b_4\, Leverage_{i,t} + b_5\, VROE_{i,t} + Time\ Dummies + Firm\ Fixed\ Effects + \varepsilon_{i,t} \tag{10}$$

[3] See also Duffee (1995) for more information.

Table 1: Summary Statistics

This table shows summary statistics for 344 stocks listed in Nasdaq Stockholm during the period from September 30, 2010 to December 29, 2017. "**Size**" is the market capitalization "in millions of Swedish Krona" calculated as the stock closing price times the number of shares outstanding, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Leverage**" Total liabilities to total assets ratio, "**ROE**" Net income over the difference between total assets and total liabilities, "**ILLIQ**" Amihud's (2002) illiquidity calculated the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity, "**Closing price**" stock daily closing price, "**Daily returns**" stock daily return, "**Return volatility**" daily return simple volatility.

	Descriptive Statistics				
	Mean	**Median**	**Std. Dev.**	**Min**	**Max**
Closing price	79.28	52.05	94.20	0.02	1,767.17
Daily returns	- 0.0016%	0.00%	1.38%	-2.28%	2.32%
Volatility	0.02%	0.01%	0.2%	0.0%	0.05%
Leverage	22.29%	19.75%	18.35%	0.0%	56.15%
ROE	9.37%	11.67%	13.24%	-18.63%	26.50%
ILLIQ	-12.402	-12.19	3.09	-22.58	2.21
B/M	61.52%	50.44%	40.35%	14.04%	138.45%
Size	690	67.80	1,200	1.27	3,680

Table 2 "Paerson's Correlation Matrix": This table shows the Paerson's correlation matrix among the different idiosyncratic volatility used in this study. Significance level is reported below each correlation.

	EIVOL5	GIVOL5	EIVOL4	GIVOL4	EIVOL3	GIVOL3
EIVOL5	1.0000					
GIVOL5	0.9985	1.0000				
	0.0000					
EIVOL4	0.9555	0.9646	1.0000			
	0.0000	0.0000				
GIVOL4	0.9554	0.9641	0.9983	1.0000		
	0.0000	0.0000	0.0000			
EIVOL3	0.8272	0.8347	0.8416	0.8403	1.0000	
	0.0000	0.0000	0.0000	0.0000		
GIVOL3	0.8259	0.8334	0.8403	0.8392	0.9984	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0000	

Table 3 "Volatility Interruptions Occurrences": This table shows the volatility interruptions occurrences categorized by Static and Dynamic hits for 344 stocks listed in Nasdaq Stockholm during the period from September 30, 2010 to December 29, 2017.

Panel A: *VI occurrences by year*

Year	Static Upper	Static Lower	Dynamic Upper	Dynamic Lower	Occurrences Per Year
2010	64	52	718	670	**1,504**
2011	288	228	4,234	5,751	**10,501**
2012	314	215	3,369	3,972	**7,870**
2013	361	169	3,305	3,145	**6,980**
2014	295	193	3,255	3,380	**7,123**
2015	330	194	4,479	4,204	**9,207**
2016	335	177	4,519	4,527	**9,558**
2017	265	138	3,380	2,919	**6,702**
Total No. of Occurrences	**2,252**	**1,366**	**27,259**	**28,568**	**59,445**

Panel B: *VI occurrences by Market Capitalization:*

Size	Static Upper	Static Lower	Dynamic Upper	Dynamic Lower	Occurrences MC
Large Cap	118	82	3,987	3,986	**8,173**
Medium Cap	641	325	9,987	9,437	**20,390**
Small Cap	1,493	959	13,285	15,145	**30,882**
Total No. of Occurrences	**2,252**	**1,366**	**27,259**	**28,568**	**59,445**

Panel C: *VI occurrences by Sectors:*

Sector	Static Upper	Static Lower	Dynamic Upper	Dynamic Lower	Occurrences Sector
Basic Materials	114	56	1,915	1,787	**3,872**
Consumer Goods	133	75	2,271	2,342	**4,821**
Consumer Services	163	95	2,560	2,515	**5,333**
Financials	227	130	3,024	3,374	**6,755**
Health Care	602	310	5,985	6,474	**13,371**
Industrials	387	248	6,288	6,626	**13,549**
Oil & Gas	30	16	620	530	**1,196**
Technology	558	423	4,058	4,334	**9,373**
Telecommunications	8	5	274	352	**639**
Utilities	30	8	264	234	**533**
Total No. of Occurrences	**2,252**	**1,366**	**27,259**	**28,568**	**59,445**

Where $\Psi_{i,t}$ is the log conditional idiosyncratic volatility computed form either model (8) or (9), $LimitDUM_{i,t}$ is the VI dummy associated with conditions (1) to (4). $Size_{i,t}$ is the firm's market capitalization, $\left(\frac{M}{B}\right)_{i,t}$ is the firm book-to-market ratio, $ROE_{i,t}$ is the firm return on equity ratio, $Leverage_{i,t}$ is the firm debt to asset ratio, and $VROE_{i,t}$ is volatility on ROE. It is important to point out that panel data settings might suffer from inflated t-statistics which could possibly lead to inaccurate inferences and conclusions. For this, we follow Rogers' (1983, 1993) method to correct for heteroscedasticity, serial correlation, or contemporaneous cross-sectional correlations of error terms by adjusting standard errors for clustering at the firm level. In addition to clustering the standard error, we include a year fixed effect dummy for each year in the sample to control for any economic changes as suggested by and Lins et al (2017). We expect a positive relationship between the idiosyncratic volatility and $\text{LimitDUM}_{\text{StaticUpper}}$ and $\text{LimitDUM}_{\text{DynamicUpper}}$. We also expect a negative relationship between the idiosyncratic and $\text{LimitDUM}_{\text{StaticLower}}$ and $\text{LimitDUM}_{\text{DynamicLower}}$. Moreover, following Ferreira and Laux (2007), we expect a negative correlation between idiosyncratic volatility and B/M, size, and VROE, and a positive correlation between idiosyncratic volatility and ROE and Leverage.

Table 4 presents the results of equation (10) using 6 different conditional idiosyncratic volatility measures. The main independent variable we wish to test is Static Upper, which is a limit dummy that takes the value of 1 if any of the conditions in (1a) or (1b) is met and zero otherwise. The dependent variable in column (1) is the conditional idiosyncratic volatility estimated from an EGARCH model in equation (8) based on the the FF 3-factors model in equation (5), while dependent variable in column (2) is the conditional idiosyncratic volatility estimated from a GARCH model in equation (9) based on the FF 3-factors model in equation (5). Similarly, the dependent variable in column (3) is the conditional idiosyncratic volatility estimated from an EGARCH model in equation (8) constructed from the Carhart 4-factors model in equation (6) and the dependent variable in column (4) is the conditional idiosyncratic volatility estimated from a GARCH model in equation (9) and constructed from the Carhart 4-factors model in equation (6). The dependent variables in columns (5) and (6) is the conditional idiosyncratic volatility estimated from an EGARCH and GARCH models in equations (8) and (9), respectively, and based on the FF 5-factors model in equation (7).

As we expected, the coefficients of Static Upper are positive and statically significant at 1% level of significance through all six models 0.84, 0.85, 0.88, 0.88, 0.88, and 0.86 respectively. The results of Table 4 indicate that when stocks reach the static upper limit, idiosyncratic volatility increases by an average of 84% to 88%, compared to stocks that did not hit the static upper limit. This evidence provides support to our first hypothesis that idiosyncratic volatility increases when stocks hit the static upper limit. Moreover, the signs of the control variables are as expected and consistent with Ferreira and Laux (2007), positive for ROE and Leverage and negative for Size, B/M, and VROE.

Furthermore, the main independent variable in Table 5 is the dynamic upper limit. The coefficient of dynamic upper limit in all different models are positive and statically significant at 1% significant level. These results indicate that when stocks reach the dynamic upper limit, the conditional idiosyncratic volatility increases by an average of 94% to 98% compared to stocks that did not hit the dynamic upper limit. This result provides support to our second hypothesis that idiosyncratic volatility increases when stocks hit the dynamic upper limit. The signs of the control variables are as expected as well.

Comparing the results from Tables 4 and 5, we observe that idiosyncratic volatility increases by 94% to 98% when stocks reach the dynamic upper limits and 84% to 88% when they reach the upper static limit, a difference of about 10%. Thus, we conclude that stocks reaching the upper dynamic limits witness higher conditional idiosyncratic volatility and are more volatile than stocks reaching the upper static limits. Put differently, although the conditional idiosyncratic volatility increases as stocks reach static or dynamic upper limit, it is even higher when stocks reach the dynamic upper limit by an average of 10%. This lends support to hypothesis 5.

Table 6 presents the results of the impact of stocks reaching the static lower limit on the conditional idiosyncratic volatility. Through all different models, the coefficients of the independent variable static lower are negative and statistically significant. This indicates that when stocks reach the static lower limit, the conditional idiosyncratic volatility decreases by an

__Table 4__ reports the results of estimating equation (10). The dependent variable is firm's conditional idiosyncratic volatility measured using EGARCH and GARCH model from estimating the FF 3-factors model, Carhart 4-factors model and FF 5-factors model. The independent variables are "**Static Upper**" which is a dummy variable that equals one if any of the conditions in (1a) or (1b) is met and zero otherwise, "**ROE**" firm return on equity, "**Size**" is market capitalization, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price , "**Leverage**" is firm debt to asset ratio and "**VROE**" is ROE volatility. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Expected Sign	FF 3 Factors		Carhart 4 Factors		FF 5 Factors	
		E-IVOL (1)	G-IVOL (2)	E-IVOL (3)	G-IVOL (4)	E-IVOL (5)	G-IVOL (6)
Static Upper	+	**0.84** [a]	**0.85** [a]	**0.88** [a]	**0.88** [a]	**0.88** [a]	**0.86** [a]
		(42.70)	(42.94)	(40.60)	(40.67)	(39.89)	(41.09)
ROE	+	**0.20** [a]	**0.21** [a]	**0.22** [a]	**0.23** [a]	**0.21** [a]	**0.22** [a]
		(3.39)	(3.51)	(3.80)	(3.88)	(3.74)	(3.96)
Size	-	**-9.88e-11**	**-1.00e-10** [a]	**-1.19e-10** [a]	**-1.21e-10** [a]	**-1.12e-10** [a]	**-1.09e-10** [a]
		(-5.48)	(-5.51)	(-6.89)	(-6.99)	(-6.54)	(-6.37)
B/M	-	**- 0.011** [c]	**- 0.011** [c]	**- 0.0092**	**- 0.0094** [c]	**- 0.0131** [b]	**- 0.0127** [b]
		(-1.82)	(-1.84)	(-1.63)	(-1.71)	(-2.30)	(-2.33)
Leverage	+	**0.0021** [a]	**0.00120** [a]	**0.003** [a]	**0.003** [a]	**0.004** [a]	**0.003** [a]
		(5.81)	(5.93)	(5.03)	(5.04)	(6.12)	(5.47)
VROE	-	**-2.60e-06** [b]	**-2.64e-06** [b]	**- 0.00008** [a]	**- 0.00008** [a]	**- 0.00007** [a]	**-0.00008** [a]
		(-2.11)	(-2.15)	(-2.90)	(-2.86)	(-3.32)	(-3.28)
Firm fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by		**Firm**	**Firm**	**Firm**	**Firm**	**Firm**	**Firm**
N		**255,414**	**255,127**	**258,710**	**258,402**	**258,732**	**258,992**
Adj R^2		**0.025**	**0.025**	**0.030**	**0.030**	**0.024**	**0.026**

(**a**) significant at 1% , (**b**) significant at 5% and (**c**) significant at 10%

average of -14% to -19% compared to stocks that did not hit the static lower limit. Such a finding is in line with hypothesis 3 that idiosyncratic volatility decreases when stocks hit the lower static limits.

Table 7 reports the results of the effect of stocks reaching the dynamic lower limit on the conditional idiosyncratic volatility. The coefficients of the independent variable dynamic lower through all the different models are negative and statistically significant at 1% level of significance. While this evidence provides support to hypothesis 4, it suggests that when stocks reach the dynamic lower limit, conditional idiosyncratic volatility decreases by an average of -8% to -13% compared to stocks that did not hit the dynamic lower limit. From Tables 6 and 7, we conclude that although conditional idiosyncratic volatility decreases as stocks reach static or dynamic lower limit, it is even lower when stocks reach the dynamic lower limit by an average of -6%.

To further examine our earlier hypotheses, we compare the limit hit events to the day before and after each event to ensure that the impact of limit hit on the idiosyncratic volatility is not due to an event from the day before or a continuation of a previous event. Following Ferreira and Laux (2007), we estimate the following fixed effect regression model:

$$\Psi_{i,t} = a_0 + b_0\, DayBeforeDUM_{i,t-1} + b_1\, LimitDUM_{i,t} + b_2\, DayafterDUM_{i,t+1} + b_3\, 2DaysafterDUM_{i,t+2} + b_4\, Size_{i,t} + b_5 \left(\frac{M}{B}\right)_{i,t} + b_3\, ROE_{i,t} + b_6\, Leverage_{i,t} + b_7\, VROE_{i,t} + Time\ Dummies + Firm\ Fixed\ Effects + \varepsilon_{i,t} \qquad (11)$$

Where $\Psi_{i,t}$ is the log conditional idiosyncratic volatility computed form either model (8) or (9), $DayBeforeDUM_{i,t-1}$ is a dummy variable for the day before the limit hit event, $LimitDUM_{i,t}$ is the VI dummy associated with conditions (1) to (4), $DayafterDUM_{i,t+1}$ is a dummy variable for the day after the limit hit event, $2DaysafterDUM_{i,t+2}$ is a dummy variable for two days after the limit hit event, $Size_{i,t}$ is the firm's market capitalization, $\left(\frac{M}{B}\right)_{i,t}$ is the firm book-to-market ratio, $ROE_{i,t}$ is the firm return on equity ratio, $Leverage_{i,t}$ is the firm debt to asset ratio, and $VROE_{i,t}$ is volatility on ROE.

Table 5 reports the results of estimating equation (10). The dependent variable is firm's conditional idiosyncratic volatility measured using EGARCH and GARCH model from estimating the FF 3-factors model, Carhart 4-factors model and FF 5-factors model. The independent variables are "**Dynamic Upper**" which is a dummy variable that equals one if any of the conditions in (3a), (3b), or (3c) is met and zero otherwise, "**ROE**" firm return on equity, "**Size**" is market capitalization, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Leverage**" is firm debt to asset ratio and "**VROE**" is ROE volatility In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Expected Sign	FF 3 Factors		Carhart 4 Factors		FF 5 Factors	
		E-IVOL (1)	G-IVOL (2)	E-IVOL (3)	G-IVOL (4)	E-IVOL (5)	G-IVOL (6)
Dynamic Upper	+	**0.94** [a]	**0.94** [a]	**0.98** [a]	**0.98** [a]	**0.98** [a]	**0.97** [a]
		(100.09)	(99.93)	(93.57)	(91.39)	(97.61)	(97.47)
ROE	+	**0.20** [a]	**0.21** [a]	**0.21** [a]	**0.21** [a]	**0.20** [a]	**0.20** [a]
		(4.01)	(4.14)	(4.24)	(4.35)	(4.24)	(4.55)
Size	-	**-8.03e-11** [a]	**-8.17e-11** [a]	**-9.48e-11** [a]	**-9.69e-11** [a]	**-8.77e-11** [a]	**-8.55e-11** [a]
		(-5.13)	(-5.13)	(-6.43)	(-6.58)	(-5.95)	(-5.78)
B/M	-	**- 0.012** [b]	**- 0.011** [b]	**- 0.009** [b]	**- 0.01** [b]	**- 0.0132** [a]	**- 0.0127** [a]
		(-2.12)	(-2.13)	(-202)	(-2.20)	(-2.91)	(-3.01)
Leverage	+	**0.001** [a]	**0.0009** [a]	**0.002** [a]	**0.002** [a]	**0.002** [a]	**0.002** [a]
		(4.17)	(4.06)	(5.51)	(5.55)	(7.58)	(6.40)
VROE	-	**-1.67e-06**	**-1.71e-06**	**- 0.00008** [b]	**- 0.00006** [a]	**- 0.00005** [b]	**-0.00006** [b]
		(-1.26)	(-1.30)	(-2.25)	(-2.22)	(-2.39)	(-2.44)
Firm fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by		**Firm**	**Firm**	**Firm**	**Firm**	**Firm**	**Firm**
No		**255,414**	**255,127**	**258,710**	**258,402**	**258,732**	**258,992**
Adj R^2		**0.08**	**0.08**	**0.087**	**0.087**	**0.082**	**0.085**

(**a)** significant at 1% , (**b)** significant at 5% and (**c)** significant at 10%

Table 6 reports the results of estimating equation (10). The dependent variable is firm's conditional idiosyncratic volatility measured using EGARCH and GARCH model from estimating the FF 3-factors model, Carhart 4-factors model and FF 5-factors model. The independent variables are "**Static Lower**" which is a dummy variable that equals one if any of the conditions in (2a) or (2b) is met and zero otherwise, "**ROE**" firm return on equity, "**Size**" is market capitalization, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price and "**VROE**" is ROE volatility. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Expected Sign	FF 3 Factors		Carhart 4 Factors		FF 5 Factors	
		E-IVOL (1)	G-IVOL (2)	E-IVOL (3)	G-IVOL (4)	E-IVOL (5)	G-IVOL (6)
Static Lower	-	**- 0.19** [c]	**- 0.19** [c]	**- 0.15** [b]	**- 0.16** [b]	**- 0.15** [b]	**- 0.14** [b]
		(-1.88)	(-1.92)	(-2.21)	(-2.28)	(-2.37)	(-1.96)
ROE	+	**0.19** [a]	**0.20** [a]	**0.21** [a]	**0.22** [a]	**0.14** [b]	**0.20** [a]
		(3.11)	(3.22)	(3.51)	(3.58)	(2.24)	(3.62)
Size	-	**-1.01e-10** [a]	**-1.02e-10** [a]	**-1.21e-10** [a]	**-1.24e-10** [a]	**-1.51e-09** [a]	**-1.11e-10** [a]
		(-5.42)	(-5.46)	(-6.88)	(-6.97)	(-5.02)	(-6.40)
B/M	-	**- 0.012** [c]	**- 0.012** [c]	**- 0.01**	**- 0.01** [c]	**- 0.01** [c]	**- 0.01** [b]
		(-1.80)	(-1.80)	(-1.62)	(-1.70)	(-1.89)	(-2.25)
Leverage	+	**0.002** [a]	**0.0019** [a]	**0.003** [a]	**0.003** [a]	**0.032** [a]	**0.003** [a]
		(5.36)	(5.45)	(4.80)	(4.81)	(5.13)	(5.23)
VROE	-	**-2.66e-06** [b]	**-2.70e-06** [b]	**- 0.00008** [a]	**- 0.00009** [a]	**- 0.00009** [a]	**- 0.00008** [a]
		(-2.18)	(-2.22)	(-2.95)	(-2.92)	(-3.43)	(-3.36)
Firm fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by		**Firm**	**Firm**	**Firm**	**Firm**	**Firm**	**Firm**
N		**255,414**	**255,127**	**258,710**	**258,402**	**258,732**	**258,992**
Adj R^2		**0.02**	**0.02**	**0.022**	**0.022**	**0.021**	**0.021**

(**a**) significant at 1% , (**b**) significant at 5% and (**c**) significant at 10%

Table 7 reports the results of estimating equation (14). The dependent variable is firm's conditional idiosyncratic volatility measured using EGARCH and GARCH model from estimating the FF 3-factors model, Carhart 4-factors model and FF 5-factors model. The independent variables are "**Dynamic Lower**" which is a dummy variable that equals one if any of the conditions in (4a), (4b), or (4c) is met and zero otherwise, "**ROE**" firm return on equity, "**Size**" is market capitalization, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Leverage**" is firm debt to asset ratio and "**VROE**" is ROE volatility In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Expected Sign	FF 3 Factors		Carhart 4 Factors		FF 5 Factors	
		E-IVOL (1)	G-IVOL (2)	E-IVOL (3)	G-IVOL (4)	E-IVOL (5)	G-IVOL (6)
Dynamic Lower	-	**- 0.13** [a]	**- 0.13** [a]	**- 0.09** [a]	**- 0.10** [a]	**- 0.08** [a]	**- 0.09** [a]
		(-5.29)	(-5.37)	(-3.28)	(-3.36)	(-2.95)	(-3.43)
ROE	+	**0.19** [a]	**0.20** [a]	**0.21** [a]	**0.21** [a]	**0.20** [a]	**0.20** [a]
		(3.06)	(3.17)	(3.47)	(3.55)	(3.38)	(3.58)
Size	-	**-1.01e-10** [a]	**-1.03e-10** [a]	**-1.21e-10** [a]	**-1.24e-10** [a]	**-1.14e-10** [a]	**-1.11e-10** [a]
		(-5.42)	(-5.46)	(-6.86)	(-6.96)	(-6.53)	(-6.39)
B/M	-	**- 0.012** [c]	**- 0.012** [c]	**- 0.01**	**- 0.01** [c]	**- 0.01** [b]	**- 0.01** [b]
		(-1.77)	(-1.79)	(-1.61)	(-1.69)	(-2.22)	(-2.24)
Leverage	+	**0.002** [a]	**0.002** [a]	**0.003** [a]	**0.003** [a]	**0.004** [a]	**0.003** [a]
		(5.47)	(5.57)	(4.83)	(4.84)	(5.89)	(5.26)
VROE	-	**-2.68e-06** [b]	**-2.72e-06** [b]	**- 0.00009** [a]	**- 0.00009** [a]	**- 0.00008** [a]	**- 0.00008** [a]
		(-2.19)	(-2.23)	(-2.96)	(-2.92)	(-3.43)	(-3.36)
Firm fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by		**Firm**	**Firm**	**Firm**	**Firm**	**Firm**	**Firm**
N		**255,414**	**255,127**	**258,710**	**258,402**	**258,732**	**258,992**
Adj R^2		**0.020**	**0.020**	**0.022**	**0.022**	**0.020**	**0.021**

(**a**) significant at 1% , (**b**) significant at 5% and (**c**) significant at 10%

Table 8 exhibits the results of equation (11) for the static upper VI case, where we compare the conditional idiosyncratic volatility on days when limits are reached to one day before the limits were reached and two days after the limit events. Table 8 shows that the conditional idiosyncratic volatility is around 21% one day prior to reaching the upper limit. However, when stock prices reach the static upper limits, the conditional idiosyncratic volatility jumps to an average of 82%, an increase of 60% from the day before the static upper limit was reached. Surprisingly, the conditional idiosyncratic volatility decreases the day after the static upper limit is reached and goes back to the same level as the day before the upper limit is reached which is 21%. The conditional idiosyncratic volatility continues to drop to an average of 15% two days after reaching the static upper limits. Thus, we conclude that the conditional idiosyncratic volatility is higher on days when the static upper limits are reached compared to the day before and after, confirming hypothesis 6.

A similar pattern has been observed for the dynamic upper limits. Table 9 illustrates that the conditional idiosyncratic volatility is around 7% one day before the dynamic upper limits are reached but jumps sharply to about 95% on the day the dynamic upper limits are hit. Similar to the static upper limits, the conditional idiosyncratic volatility cools off to 7% the day after the dynamic limits are reached and continues to decrease to reach 3% two days after the dynamic limits are reached. This indicates that the conditional idiosyncratic volatility is higher on days when the dynamic upper limits are reached compared to the day before and after, confirming hypothesis 7.

The conditional idiosyncratic volatility one day prior to reaching the static lower limits is very similar to that of the static upper limits. Table 10 shows that the conditional idiosyncratic volatility is around 26% the day before the static lower limits are reached however, it plummets to -37% when the lower static limits are hit. The conditional idiosyncratic volatility reverts back to the normal range one and two days after the static lower hits to reach 24% then 19%, respectively. These results provide supporting evidence for hypothesis 8 that the conditional idiosyncratic volatility is lower on days when the static lower limit is reached compared to the day before and after.

__Table 8__ reports the results of estimating equation (11). The dependent variable is firm's conditional idiosyncratic volatility measured using EGARCH and GARCH model from estimating the FF 3-factors model, Carhart 4-factors model and FF 5-factors model. The independent variables are "**DayBeforeDUM**" which is a dummy variable for the day before the limit hit event, "**Static Upper**" is a dummy variable that equals one if any of the conditions in (1a) or (1b) is met and zero otherwise, "**DayAfterDUM**" is a dummy variable for the day after the limit hit event, "**2DayAfterDUM**" is a dummy variable for 2 days after the limit hit event, "**ROE**" firm return on equity, "**Size**" is market capitalization, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price , "**Leverage**" is firm debt to asset ratio and "**VROE**" is ROE volatility. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Expected Sign	FF 3 Factors		Carhart 4 Factors		FF 5 Factors	
		E-IVOL (1)	G-IVOL (2)	E-IVOL (3)	G-IVOL (4)	E-IVOL (5)	G-IVOL (6)
DayBeforeDUM	+	**0.22** [a]	**0.22** [a]	**0.20** [a]	**0.20** [a]	**0.21** [a]	**0.21** [a]
		(3.96)	(4.02)	(3.68)	(3.62)	(3.73)	(3.78)
Static Upper	+	**0.80** [a]	**0.80** [a]	**0.83** [a]	**0.83** [a]	**0.83** [a]	**0.82** [a]
		(49.37)	(49.67)	(39.39)	(39.38)	(38.74)	(40.32)
DayAfterDUM	+	**0.18** [a]	**0.18** [a]	**0.21** [a]	**0.21** [a]	**0.21** [a]	**0.20** [a]
		(3.71)	(3.62)	(5.70)	(5.61)	(5.96)	(5.32)
2DaysAfterDUM	+	**0.15** [a]	**0.15** [a]	**0.15** [a]	**0.14** [a]	**0.14** [a]	**0.15** [a]
		(3.47)	(3.61)	(4.12)	(3.92)	(4.04)	(4.09)
ROE	+	**0.21** [a]	**0.21** [a]	**0.23** [a]	**0.23** [a]	**0.22** [a]	**0.22** [a]
		(3.46)	(3.58)	(3.89)	(3.96)	(3.83)	(4.06)
Size	-	**-9.86e-11** [a]	**-1.00e-10** [a]	**-1.19e-10** [a]	**-1.21e-10** [a]	**-1.11e-10** [a]	**-1.09e-10** [a]
		(-5.50)	(-5.53)	(-6.90)	(-7.01)	(-6.54)	(-6.38)
B/M	-	**- 0.01** [c]	**- 0.01** [c]	**- 0.01** [c]	**- 0.01** [c]	**- 0.01** [b]	**- 0.01** [b]
		(-1.86)	(-1.87)	(-1.66)	(-1.74)	(-2.34)	(-2.36)
Leverage	+	**0.002** [a]	**0.002** [a]	**0.003** [a]	**0.003** [a]	**0.004** [a]	**0.003** [a]
		(5.82)	(5.94)	(5.07)	(5.08)	(6.19)	(5.52)
VROE	-	**-2.58e-06** [b]	**-2.62e-06** [b]	**- 0.0001** [a]	**- 0.0001** [a]	**- 0.0001** [a]	**- 0.0001** [a]
		(-2.09)	(-2.13)	(-2.98)	(-2.94)	(-3.49)	(-3.42)
Firm fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by		**Firm**	**Firm**	**Firm**	**Firm**	**Firm**	**Firm**
N		**255,414**	**255,127**	**258,710**	**258,402**	**258,732**	**258,992**
Adj R^2		**0.025**	**0.025**	**0.028**	**0.027**	**0.025**	**0.027**

__Table 9__ reports the results of estimating equation (11). The dependent variable is firm's conditional idiosyncratic volatility measured using EGARCH and GARCH model from estimating the FF 3-factors model, Carhart 4-factors model and FF 5-factors model. The independent variables are "**DayBeforeDUM**" which is a dummy variable for the day before the limit hit event, "**Dynamic Upper**" is a dummy variable that equals one if any

of the conditions in (3a), (3b), or (3c) is met and zero otherwise, "**DayAfterDUM"** is a dummy variable for the day after the limit hit event, "**2DayAfterDUM"** is a dummy variable for 2 days after the limit hit event, "**ROE**" firm return on equity, "**Size**" is market capitalization, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price , "**Leverage**" is firm debt to asset ratio and "**VROE**" is ROE volatility. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Expected Sign	FF 3 Factors		Carhart 4 Factors		FF 5 Factors	
		E-IVOL (1)	G-IVOL (2)	E-IVOL (3)	G-IVOL (4)	E-IVOL (5)	G-IVOL (6)
1 Day before		**0.07** [a]	**0.07** [a]	**0.06** [a]	**0.06** [a]	**0.06** [a]	**0.07** [a]
		(6.40)	(6.36)	(5.75)	(5.78)	(5.63)	(6.36)
Dynamic Upper	+	**0.93** [a]	**0.93** [a]	**0.96** [a]	**0.96** [a]	**0.96** [a]	**0.95** [a]
		(100.74)	(100.84)	(93.87)	(91.75)	(97.30)	(97.11)
1 Day after	+	**0.09** [a]	**0.09** [a]	**0.08** [a]	**0.08** [a]	**0.08** [a]	**0.08** [a]
		(9.79)	(9.58)	(9.47)	(9.35)	(8.94)	(9.07)
2 Days after		**0.04** [a]	**0.04** [a]	**0.03** [a]	**0.03** [a]	**0.02** [c]	**0.03** [a]
		(4.22)	(4.09)	(2.98)	(2.83)	(1.74)	(2.64)
ROE	+	**0.20** [a]	**0.21** [a]	**0.21** [a]	**0.21** [a]	**0.20** [a]	**0.20** [a]
		(4.04)	(4.17)	(4.26)	(4.38)	(4.26)	(4.58)
Size	-	**-7.84e-11** [a]	**-7.99e-11** [a]	**-9.33e-11** [a]	**-9.54e-11** [a]	**-8.62e-11** [a]	**-8.39e-11** [a]
		(-5.05)	(-5.05)	(-6.36)	(-6.51)	(-6.87)	(-5.69)
B/M	-	**- 0.01** [b]	**- 0.01** [b]	**- 0.01** [b]	**- 0.01** [b]	**- 0.01** [a]	**- 0.01** [a]
		(-2.14)	(-2.14)	(-2.06)	(-2.24)	(-2.95)	(-3.05)
Leverage	+	**0.001** [a]	**0.001** [a]	**0.002** [a]	**0.002** [a]	**0.002** [a]	**0.002** [a]
		(3.48)	(3.32)	(5.43)	(5.47)	(7.67)	(6.38)
VROE	-	**-1.62e-06**	**-1.66e-06**	**- 0.0001** [b]	**- 0.0001** [b]	**- 0.0001** [b]	**- 0.0001** [b]
		(-1.23)	(-1.27)	(-2.24)	(-2.21)	(-2.40)	(-2.45)
Firm fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by		**Firm**	**Firm**	**Firm**	**Firm**	**Firm**	**Firm**
N		**255,414**	**255,127**	**258,710**	**258,402**	**258,732**	**258,992**
Adj R^2		**0.083**	**0.083**	**0.088**	**0.087**	**0.082**	**0.086**

Table 11 shows the results of the impact of the dynamic lower VI on the conditional idiosyncratic volatility. It reveals that the conditional idiosyncratic volatility on the day the dynamic lower limits are reached, around -22%, is lower than the day before the dynamic lower limits are hit, about 21%. The conditional idiosyncratic volatility reverts to its normal range, around 20% for the day after the dynamic lower limits are reached and about 15% for two days after the dynamic lower limits are reached.

4.3. Volatility Interruptions and the Volatility Spill-over Hypotheses:

In this section, we examine the volatility spill-over hypothesis under static and dynamic VI mechanism. Kim and Rhee (1997) explain that price limits trigger higher volatility on subsequent days of reaching the price limits (volatility spill-over hypothesis). The literature is divided in the effectiveness price limits in curbing the volatility spill-over over the following days of hitting the limits. This paper provides new evidence on the volatility spill-over hypothesis from the static and dynamic VI mechanism.

We set a range of a two-day window after the limit hits to test for the volatility spill-over hypothesis. The conditional idiosyncratic volatility is our measure of volatility from equations (8) and (9). In equation (11), we introduce $2DaysafterDUM$ in addition to the $DayafterDUM$ to observe the transition of volatility after the limits are reached.

Table 8 shows that the conditional idiosyncratic volatility on the day the static upper limit is reached was around 82% but declines to 21% the day after the limit hit, which is the same level of volatility the day before the static upper limit was reached. Moreover, the conditional idiosyncratic volatility continues to decline two days after the static upper limit was reached to be 15% on average. This suggests that the conditional idiosyncratic volatility diminishes after a stock reached the static upper limits. Such evidence provides support to hypothesis 10.

Table 9 shows similar results for the dynamic upper limit as the static one. The conditional idiosyncratic volatility drops from 95% on the day the dynamic upper limit was reached to 7% on the day after and 3% two days after reaching the limit. It is important to emphasize that the conditional idiosyncratic volatility the day after the dynamic upper hit reached the same level of volatility the day before the limit was reached, both at 7%. So, the conditional idiosyncratic

__Table 10__ reports the results of estimating equation (11). The dependent variable is firm's conditional idiosyncratic volatility measured using EGARCH and GARCH model from estimating the FF 3-factors model, Carhart 4-factors model and FF 5-factors model. The independent variables are "**DayBeforeDUM"** which is a dummy variable for the day before the limit hit event, "**Static Lower"** is a dummy variable that equals one if any of the conditions in (2a) or (2b) is met and zero otherwise, "**DayAfterDUM"** is a dummy variable for the day after the limit hit event, "**2DayAfterDUM"** is a dummy variable for 2 days after the limit hit event, "**ROE**" firm return on equity, "**Size**" is market capitalization, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price , "**Leverage**" is firm debt to asset ratio and "**VROE**" is ROE volatility. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Expected Sign	FF 3 Factors		Carhart 4 Factors		FF 5 Factors	
		E-IVOL (1)	G-IVOL (2)	E-IVOL (3)	G-IVOL (4)	E-IVOL (5)	G-IVOL (6)
1 Day before	+	**0.23** [a]	**0.22** [a]	**0.29** [a]	**0.28** [a]	**0.27** [a]	**0.26** [a]
		(4.87)	(4.55)	(4.68)	(4.57)	(4.07)	(4.34)
Static Lower	-	**- 0.38** [b]	**- 0.39** [b]	**- 0.38** [a]	**- 0.38** [a]	**- 0.34** [b]	**- 0.37** [a]
		(-2.42)	(-2.45)	(-2.64)	(-2.66)	(-2.36)	(-2.64)
1 Day after	+	**0.25** [a]	**0.25** [a]	**0.22** [a]	**0.22** [a]	**0.25** [a]	**0.24** [a]
		(7.03)	(6.91)	(5.85)	(5.94)	(6.60)	(6.49)
2 Days after	+	**0.16** [a]	**0.18** [a]	**0.19** [a]	**0.19** [a]	**0.24** [a]	**0.22** [a]
		(3.31)	(3.92)	(4.11)	(3.93)	(5.06)	(5.10)
ROE	+	**0.20** [a]	**0.20** [a]	**0.22** [a]	**0.22** [a]	**0.21** [a]	**0.21** [a]
		(3.19)	(3.30)	(3.61)	(3.68)	(3.53)	(3.74)
Size	-	**-1.01e-10** [a]	**-1.02e-10** [a]	**-1.21e-10** [a]	**-1.24e-10** [a]	**-1.14e-10** [a]	**-1.11e-10** [a]
		(-5.45)	(-5.49)	(-6.90)	(-7.00)	(-6.57)	(-6.42)
B/M	-	**- 0.01** [c]	**- 0.01** [c]	**- 0.01**	**- 0.01** [c]	**- 0.01** [b]	**- 0.01** [b]
		(-1.80)	(-1.81)	(-1.61)	(-1.69)	(-2.24)	(-2.26)
Leverage	+	**0.002** [a]	**0.002** [a]	**0.003** [a]	**0.003** [a]	**0.004** [a]	**0.003** [a]
		(5.71)	(5.82)	(5.04)	(5.05)	(6.19)	(5.52)
VROE	-	**-2.64e-06** [b]	**-2.69e-06** [b]	**- 0.0001** [a]	**- 0.0001** [a]	**- 0.0001** [a]	**- 0.0001** [a]
		(-2.17)	(-2.20)	(-2.95)	(-2.91)	(-3.41)	(-3.35)
Firm fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by		**Firm**	**Firm**	**Firm**	**Firm**	**Firm**	**Firm**
N		**255,414**	**255,127**	**258,710**	**258,402**	**258,732**	**258,992**
Adj R^2		**0.020**	**0.020**	**0.022**	**0.022**	**0.020**	**0.022**

__Table 11__ reports the results of estimating equation (11). The dependent variable is firm's conditional idiosyncratic volatility measured using EGARCH and GARCH model from estimating the FF 3-factors model, Carhart 4-factors model and FF 5-factors model. The independent variables are "**DayBeforeDUM"** which is a dummy variable for the day before the limit hit event, "**Dynamic Lower"** is a dummy variable that equals one if any

of the conditions in (4a), (4b) or (4c) is met and zero otherwise, "**DayAfterDUM**" is a dummy variable for the day after the limit hit event, "**2DayAfterDUM**" is a dummy variable for 2 days after the limit hit event, "**ROE**" firm return on equity, "**Size**" is market capitalization, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price , "**Leverage**" is firm debt to asset ratio and "**VROE**" is ROE volatility. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Expected Sign	FF 3 Factors		Carhart 4 Factors		FF 5 Factors	
		E-IVOL (1)	G-IVOL (2)	E-IVOL (3)	G-IVOL (4)	E-IVOL (5)	G-IVOL (6)
1 Day before	+	**0.20** [a]	**0.21** [a]	**0.22** [a]	**0.23** [a]	**0.21** [a]	**0.21** [a]
		(17.11)	(17.41)	(16.98)	(17.18)	(16.23)	(16.99)
Dynamic Lower	-	**- 0.24** [a]	**- 0.24** [a]	**- 0.21** [a]	**- 0.22** [a]	**- 0.19** [a]	**- 0.21** [a]
		(-8.45)	(-8.49)	(-6.34)	(-6.36)	(-6.15)	(-6.61)
1 Day after	+	**0.19** [a]	**0.19** [a]	**0.20** [a]	**0.20** [a]	**0.21** [a]	**0.20** [a]
		(20.13)	(19.83)	(17.76)	(17.64)	(19.30)	(19.23)
2 Days after	+	**0.13** [a]	**0.13** [a]	**0.16** [a]	**0.16** [a]	**0.16** [a]	**0.16** [a]
		(12.48)	(12.78)	(16.34)	(16.27)	(14.94)	(14.65)
ROE	+	**0.22** [a]	**0.22** [a]	**0.24** [a]	**0.24** [a]	**0.23** [a]	**0.23** [a]
		(3.60)	(3.72)	(4.09)	(4.16)	(4.02)	(4.26)
Size	-	**-9.98e-11** [a]	**-1.01e-10** [a]	**-1.20e-10** [a]	**-1.22e-10** [a]	**-1.12e-10** [a]	**-1.09e-10** [a]
		(-5.63)	(-5.65)	(-7.05)	(-7.15)	(-6.69)	(-6.51)
B/M	-	**- 0.01** [b]	**- 0.01** [b]	**- 0.01** [c]	**- 0.01** [b]	**- 0.01** [b]	**- 0.01** [b]
		(-2.00)	(-2.01)	(-1.91)	(-2.03)	(-2.56)	(-2.59)
Leverage	+	**0.001** [a]	**0.001** [a]	**0.003** [a]	**0.003** [a]	**0.003** [a]	**0.003** [a]
		(3.99)	(4.02)	(3.89)	(3.89)	(4.86)	(4.26)
VROE	-	**-2.52e-06** [b]	**-2.56e-06** [b]	**- 0.0001** [a]	**- 0.0001** [a]	**- 0.0001** [a]	**- 0.0001** [a]
		(-2.15)	(-2.19)	(-2.78)	(-2.74)	(-3.13)	(-3.12)
Firm fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects		**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by		**Firm**	**Firm**	**Firm**	**Firm**	**Firm**	**Firm**
N		**255,414**	**255,127**	**258,710**	**258,402**	**258,732**	**258,992**
Adj R^2		**0.024**	**0.024**	**0.027**	**0.027**	**0.024**	**0.026**

volatility declines after reaching the dynamic upper limits which provides support to hypothesis 11.

From tables 8 and 9 we can observe that when a stock reaches the upper static or dynamic limits, the conditional idiosyncratic volatility increases but sharply decreases the day after the limit is reached to match the conditional idiosyncratic volatility on the day before the limit was reached. Furthermore, the conditional idiosyncratic volatility continues to decline two days after the limits, showing no evidence of volatility spill-over. This suggests that the static and dynamic VI are in fact effective in curbing the excessive volatility after the limits are reached.

Table 10 shows that the conditional idiosyncratic volatility was around to -37% on the day the static lower limit is reached, then it reverts to 24% on the next day, similar to the level of volatility the day before the limit was reached. The conditional idiosyncratic volatility continues to decline gradually during two days after the limit hit event to be at 19%. This result provide support to hypothesis 12 that the conditional idiosyncratic volatility starts to augment one day after a stock reaches the static lower limits and declines during the second day.

We reach a similar result for the dynamic lower limit as the static lower limit. Table 11 confirms that the conditional idiosyncratic volatility was around -22% on the day the dynamic lower limit is reached but increases the day after to reach 20%, which is the same range as the day before the dynamic lower limit is reached. The conditional idiosyncratic volatility drops even more two days after the limit is reached to around 15%. Tables 10 and 11 also provide supporting evidence for the effectiveness of the static and dynamic VI as there was no evidence of volatility spill-over.

Our results are consistent with the existing body of literature that examines the impact of circuit breakers on volatility spill-over. That is, price limits are effective in lowering the volatility on days following limit hits (i.e Deb, Kalev, and Marisetty (2017) and Brugler, Linton, Noss and Pedace (2018)). We observe similar pattern through the upper and lower static and dynamic limits within a two-day window. We witness that the conditional idiosyncratic volatility goes back to its normal range one day after the limit is reached. Furthermore, we observe that the conditional idiosyncratic volatility continues to drop two days after the limit is reached. This suggests that the static and dynamic VI are effective in curbing the day to day volatility.

5. Conclusion and policy implications:

In this paper, we examine the role of the static and dynamic VI on idiosyncratic volatility and test the volatility spill-over hypothesis. We follow Fu (2009) in estimating the conditional idiosyncratic volatility using EGARCH and GARCH processes. We find that the conditional idiosyncratic volatility surges when a stock reaches the upper static or dynamic limits and declines when it hit the lower static or dynamic limits. We further investigate our hypotheses by looking at the conditional idiosyncratic volatility one day before and one day after the limit hit event. Our earlier results still hold and show that the conditional idiosyncratic volatility on the upper static or dynamic limit hit day is higher than the day before and after. In fact, the conditional idiosyncratic volatility on the day after the limit hit event reverts to the same level of volatility as the day before the event day. Moreover, the conditional idiosyncratic volatility is lower on the lower static or dynamic limit hit day than the day before and after.

In addition, we set a two-day window after the limit hit event to test for the volatility spill-over hypothesis. Our analysis did not show any evidence of volatility spill-over over the next two days of reaching the static and dynamic VI, upper or lower. This indicates that the VI mechanism is effective in limiting the impact of extreme volatility.

References

Abad, D. and Pascual, R., 2010. Switching to a temporary call auction in times of high uncertainty. *Journal of Financial Research, 33(1), pp.45-75.*

Abad, D. and Pascual, R., 2013. Holding back volatility: circuit breakers, price limits, and trading halts. *Market Microstructure in Emerging and Developed Markets: Price Discovery, Information Flows, and Transaction Costs*, pp.303-324.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets, 5(1),* pp.31-56.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61, 259–299.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang. 2009. High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence. *Journal of Financial Economics* 91:1–23.

Arak, M., R. E. Cook, 1997, Do Daily Price Limits Act as Magnets? The Case of Treasury Bond Futures, *Journal of Financial Services Research* 12:1 5-20.

Bali, T., & Cakici, N, 2008, Idiosyncratic Volatility and the Cross Section of Expected Returns. *Journal of Financial and Quantitative Analysis*, 43(1), 29-58.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31, 307–328.

United States. Presidential Task Force on Market Mechanisms and Brady, N.F., 1988. *Report of the presidential task force on market mechanisms*. US Government Printing Office.

Brugler, J. and O. Linton, 2014, Single Stock Circuit Breakers on the London Stock Exchange: Do They Improve Subsequent Market Quality*? Working Paper, University of Cambridge.*

Brugler, James & Linton, Oliver & Noss, Joseph & Pedace, Lucas, 2018. The cross-sectional spillovers of single stock circuit breakers. *Bank of England working papers 759*, Bank of England.

Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of Finance, 52(1),* pp.57-82.

Cho, D.D., Russell, J., Tiao, G.C., Tsay, R., 2003. The magnet effect of price limits: Evidence from high-frequency data on Taiwan Stock Exchange. *Journal of Empirical Finance* 10, 133-168.

Deb, S.S., Kalev, P.S. and Marisetty, V.B., 2010. Are price limits really bad for equity markets? *Journal of Banking & Finance*, *34(10)*, pp.2462-2471.

Deb, S.S., Kalev, P.S. and Marisetty, V.B., 2017. Price limits and volatility. *Pacific-Basin Finance Journal*, *45*, pp.142-156.

Duffee, G.R., 1995. Stock returns and volatility a firm-level analysis. *Journal of Financial Economics*, *37(3)*, pp.399-420.

Enders, W., 2014. Applied econometric time series (4th Edition). John Wiley & Sons.

Fabozzi, F.J., Fung, C.Y., Lam, K. and Wong, W.K., 2013. Market overreaction and underreaction: Tests of the directional and magnitude effects. *Applied Financial Economics*, *23(18)*, pp.1469-1482.

Fama, E.F., 1989. Perspective on October 1987, or What did we learn form the crash?. *Black Monday and the Future of the Financial Markets, Irwin, Homewood, III*.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1), pp.3-56.

Fama, E. F. & French, K. R, 2015. A five-factor asset pricing model. *Journal of Financial Economics*, vol. 116, no. 1: 1–22.

Ferreira, M.A. and Laux, P.A., 2007. Corporate governance, idiosyncratic risk, and information flow. *The Journal of Finance*, 62(2), pp.951-989.

Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of financial Economics*, 91(1), pp.24-37.

George, T.J. and Hwang, C.Y., 1995. Transitory price changes and price-limit rules: Evidence from the Tokyo Stock Exchange. *Journal of Financial and Quantitative Analysis*, 30(2), pp.313-327.

Diacogiannis, G.P., Patsalis, N., Tsangarakis*, N.V. and Tsiritakis, E.D., 2005. Price limits and overreaction in the Athens stock exchange. *Applied Financial Economics*, *15(1)*, pp.53-61.

Kwon, KY., Eom, KS., La, SC., and Park, JH., 2018. The role of dynamic and static volatility interruption: Evidence from the Korean stock markets. *Working paper, University of California, Berkeley*.

Kim, Kenneth A, and Jungsoo Park, 2010, Why do price limits exist in stock markets? A manipulation-based explanation, *European Financial Management* 16, 296–318.

Kim, K.A. and Rhee, S.G., 1997. Price limit performance: evidence from the Tokyo Stock Exchange. *the Journal of Finance*, 52(2), pp.885-901.
Kim, YH., Yang, JJ., 2003, price limits and overreaction. *Working Paper, University of Cincinnati*

Leach, J.C, and A. Madhavan, 1993, "Price Experimentation and Security Market Structure," *Review of Financial Studies*, 6, 375-404

Lehmann, B.N., 1989. Commentary: Volatility, price resolution and the effectiveness of price limits. *Journal of Financial Services Research* 3, 205–209.

Lins, Karl V., Henri Servaes, and Ane Tamayo, 2017, Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*.

Ma, Christopher K., Ramesh, P. Rao, and R. Stephen Sears, 1989a, Volatility, price resolution, and the effectiveness of price limits, *Journal of Financial Services Research* 3, 165-199.

Madhavan, A., 1992. Trading mechanisms in securities markets. *the Journal of Finance, 47(2)*, pp.607-641.

Malkiel, Burton G., and Yexiao Xu, 2003, Investigating the behavior of idiosyncratic volatility, *Journal of Business* 76, 613-644.

Miller, M.H., Hawke Jr, J.D., Malkiel, B. and Scholes, M., 1987. Preliminary Report of the Committee of Inquiry Appointed by the Chicago Mercantile Exchange to Examine the Events surrounding October 19, 1987. *Chicago Mercantile Exchange*.

Harris, L., 1998. Circuit breakers and program trading limits: What have we learned. *Brookings-Wharton papers on financial services*, *63.*

Nelson, D., 1991. Conditional heteroskedasticity in asset returns: a new approach. *Econometrica* 59, 347–370.

Panousi, Vasia and Dimitris Papanikolaou, 2012. "Investment, idiosyncratic risk and ownership," *Journal of Finance*, 67, *no. 3* (June), 1113-1148.

Rogers, W. H., 1983, Analyzing complex survey data, *Rand Corporation memorandum*, Santa Monica, CA.

Rogers, W. H., 1993, Regression standard errors in clustered samples, *Stata Technical Bulletin Reprints* STB-13 – STB-18, 88-94.

Sias, Richard W., 1996, Volatility and the institutional investor, *Financial Analysts Journal*, Mar/Apr 1996,13-20.

Spiegel, Matthew I. and Wang, Xiaotong, 2005. Cross-Sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk. *Yale ICF Working Paper No. 05-13; EFA 2005 Moscow Meetings Paper*.

Subrahmanyam, A., 1994. Circuit breakers and market volatility: A theoretical perspective. *Journal of Finance* 49, 237–254.

Tooma, E.A., 2011. The magnetic attraction of price limits. *International Journal of Business, 16(1)*, p.35.

U.S. Securities and Exchange Commission, 1988. The October 1987 market break. *A report by the Division of Market Regulation.*

Yang, Nien-Tzu., Chu, Hsiang-Hui., Ko, Kuan-Cheng., Lee, Shiou-Wen, 2018, Continuing Overreaction and Momentum in a Market with Price Limits, *Pac. Basin Financ*. J. 48 (2018), 56–71.

Yao, J., Ma, C., He, W.P., 2008. Investor herding behavior of Chinese stock market. *International Review of Economics and Finance*. 29, 12–29

Zimmermann, K., 2013, Price Discovery in European Volatility Interruptions, *Working Paper, Goethe University Frankfurt*.

CHAPTER 2

Stock Return and the Volatility Guards in NASDAQ Stockholm

1. Introduction and motivation:

1.1. Background:

The objective of market regulators and policymakers is to enhance the efficiency of financial markets while preventing markets from a sudden meltdown due to bad news, high frequency trading, manipulations, or market panic. For this, regulators continuously impose new rules and regulations on financial markets. Following the market crash of October 19, 1987 and in light of the Black Monday, a growing number of regulatory reports and academic papers discuss the event of the 1987 crash and whether regulations around that time were effective in withstanding the shock. They also propose different trading mechanisms to help market regulators improve financial markets.

Circuit breakers were first proposed by former United Stated Treasury Secretary, Nicholas Brady, after the 1987 market crash. They were first imposed on the New York Stock Exchange in 1987 after the Dow Jones Industrial Average (DJIA) plunged by 22.6%. The Brady Commission (1988) suggests implementing market wide circuit breakers. The report also suggests that trading halts should not be triggered frequently, suggesting setting high bounds for circuit breakers. Moreover, The Chicago Mercantile Exchange (CME), known as the Miller Report, report that any implementation of price limits should be carefully evaluated and should help issues related to the first hours of trading[4]. However, in 1988, the U.S. Securities and Exchange Commission, SEC,

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[4] For more information see: (1) Commodity Futures Trading Commission (CFTC). "Final Report on Stock Index Futures and Cash Market Activity during October 1987 to the U.S. Commodity Futures Trading Commission." The Division of Economic Analysis and the Division of the Trading and Markets, January 1988. (2) U.S. General Accounting Office. "Financial Markets: Preliminary Observations on the October 1987 Crash." Report to the Congressional Requesters, January 1988. (3) Brown, S. and Warner, J. "Using Daily Stock Returns."/our/ia/ of Financial Economics 14 (1985), 3-31. Chicago Board of Trade. "The Report of the Chicago Board of Trade to the Presidential Task Force on Market Mechanisms." December 1987.

issued a report that was not in favor of any trading halts or price limits mechanisms imposed on stock markets. They claim that mechanisms such as different time openings for different financial markets are more effective in facing market swings.

Lehmann (1989) defines circuit breakers as "devices for halting or limiting trading when prices move too much." In general, circuit breakers halts are imposed when a financial asset reaches a certain threshold, +/-10% for example, depending on the rules of that specific market. Once a halt is triggered, the index or stock in this case cannot be traded for a specific period of time (minutes, hours, or even for an entire day) depending on the regulations of the market, to allow for the volatility of the halted asset to drop. Thus, circuit breakers can be thought of as some temporary pauses on trading a specific financial asset once it reaches a certain threshold. Overall, circuit breakers temporarily put the market on hold, for a short period of time, due to a sudden surge or downfall to allow for the market to adjust and prevent from a massive collapse. Countries such as Japan, France, China, South Korea, and many more followed the United States in imposing circuit breakers in their financial markets.

1.2. <u>Development of Circuit Breakers:</u>

Moser (1990) identifies three types of circuit breakers: order-imbalance circuit breakers, volume induced circuit breakers, and price change circuit breakers. Moser explains that "Order-imbalance circuit breakers are intended to protect the interests of market makers in specialist markets. Volume-induced circuit breakers are intended to protect the viability of back-office operations. Price-change circuit breakers are intended to bring excessive volatility under control."

The 2010 Flash Crash Market questioned the effectiveness of market-wide circuit breakers and encouraged regulators to re-engineer circuit breakers to fit specific market characteristics. Hence, modified versions of circuit breakers have been introduced in many international financial markets.

Abad and Pascual (2013) point out two main types of circuit breakers: price limits and trading halts. They distinguish between two types of price limits, daily price limits and intraday price limits. Daily price limits, also known as the order rejection model, are a volatility-stabilizer mechanism that puts some upper and lower bounds on trading, curbing the day to day volatility.

To explain, regulators set a daily percentage range of trading that is based on previous day's closing price. Thus, stock prices can neither exceed nor go below the price limit bounds, allowing the market to stabilize. Once the daily price limits are triggered, trades beyond price limits cannot be executed. The intraday price limits, known as volatility guards or volatility interruption (VI hereafter), are more sophisticated models of the daily price limits. The VI mechanism combines (1) an intraday price limits, known as the dynamic VI, that are based around the last traded orderbook price, and (2) daily price limits, known as the static VI, that are based around the last auction price, which may have been the price traded in VI from earlier that day, the opening auction, or if there was no trade for either of these then the official closing price of the previous day. The dynamic VI is triggered when the difference between a stock's most recent execution price and potential execution price exceeds a specified price range, while the static VI is triggered when the difference between the price at the previous call auction and the potential execution price exceeds specified price range. Therefore, it is logical for the range of the static VI to be wider than the dynamic one. It is important to note that some markets solely adopt dynamic VI.

Abad and Pascual (2013) also distinguish between two types of trading halts, asset-specific trading halts and market-wide trading halts. The market-wide trading halt is a discretionary model and trading halts are activated under specific circumstances determined by market regulators such as recessions or market turmoil. Unlike the asset-specific trading halts model, trading halts in a market-wide model may include all financial instruments or certain securities.

The objective of this paper is to examine the impact of implementing the static and dynamic VI on stock return in Nasdaq Stockholm. Static and dynamic VI were adopted around the same time. To the best of our knowledge, this is the first paper to study the impact of static and dynamic VI on stock return. In fact, this is the first paper to ever study the relationship between stock return and any type of circuit breakers around the world, not only static and dynamic VI, but also including price limits and trading halts. Previous studies have examined the impact of VI on price discovery, information asymmetry, adverse selection, and market quality, but no study has approached VI impact on stock return.

As far as our contribution is concerned, this paper contributes to the body of literature in many ways. First, this paper enriches the literature on Market Microstructure by providing new evidence from NASDAQ OMX Nordic on the impact of the newly-introduced static and dynamic VI mechanism on the stock market. The mainstream of papers discussing VI in the market microstructure literature focus on their impact on price discovery, market quality, and information asymmetry; hence, this paper expands the VI literature by looking from a different angle, which is stock return. Second, it also adds value to the price limits and circuit breakers literature since VI is one form of price limits as discussed by Abad and Pascual (2013). Third, this paper contributes to the asset pricing literature in two distinctive ways. There are two opposing views on the relationship between idiosyncratic volatility and the cross sectional of stock returns. Ang, Hodrick, Xing, and Zhang (2006) show that there is a negative relation between lagged realized idiosyncratic risk and returns, while Fu (2009) shows a positive relation between conditional idiosyncratic volatility estimated using (EGARCH) models and expected stock returns. This paper sheds the light on the effect of VI on idiosyncratic volatility. This paper also highlights the effect of VI on stock return in the light of the evidence we obtain in Alsunbul (2019) and provide supporting evidence to the literature in the relation between idiosyncratic volatility and return. Finally, this paper contributes to the portfolio management literature by providing evidence on situations when the stock return is expected to be high or low in stock markets.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature review, motivation, and hypotheses development. Section 3 describes the data and methodology used in our analysis. Section 4 presents and interprets the results. Section 5 summarizes the findings and concludes.

2. Literature Review and Motivation & Hypotheses Development:

2.1. Literature Review:

2.1.1. Literature Review Related to Circuit Breaker and Price Limits:

The literature in price limits identifies two opposing views. Some claim that price limits improve the quality financial of markets while others claim the opposite. Lehmann (1989) argues that in markets where price limits are imposed, the imbalance of supply and demand in daily trading causes the prices to reach the limits. Hence, volatility increases in longer horizons, causing liquidity to drop. Subrahmanyam (1994) investigates the impact of circuit breakers on market volatility. The results suggest that the implementation of circuit breakers causes market volatility to surge and therefore, market liquidity to drop. Moreover, Diacogiannis, Patsalis, Tsangarakis, and Tsiritakis (2005) examine the impact of imposing price limits on overreactions in Athens Stock Exchange and find evidence of short-term overreaction during periods of one-day upper limit hit, two-day upper limit hits, three-day upper limit hits, and one-day lower limit hit.

George and Hwang (1995) select a sample of stocks from the Tokyo stocks exchange to examine the volatility of the daily returns based on the opening and closing prices and its relation to price limits. They find that for highly traded stocks in Tokyo stocks exchange, volatility is higher for opening prices compared to closing prices. This indicates that close-to-close returns are higher, because of lower volatility, than open-to-open returns. This finding contradicts with the goal of price limit rule, concluding that price limit rule increases volatility.

Kim and Rhee (1997) study the price limit performance in Tokyo Stock Exchange, beginning by examining the claims of support and opposition of the price limit rule. They state that advocates of the price limits rule believe that such a device helps reduce stock price volatility, does not affect trading movement, and reduces overreaction; while opponents claim that price limits cause higher volatility in the long-run (volatility spillover), negatively affect (delay) the price discovery process, and since price limits restrict trading, opponents argue that trading activity will get affected accordingly. The authors examine both sides of the argument and conclude that price limits do not curb volatility for stocks that reach price limits more frequently as fast as stocks that do not normally hit the price limit, which is in line with the findings of Lehmann (1989) and George and Hwang (1995). They also show that stocks that reach a price limit tend to delay price discovery, compared to stocks that do not reach price limits at all. This is consistent with Fama (1989) who shows that circuit breakers delay price discovery and increase volatility.

Cho, Russell, Tiao, and Tsay (2002) use high frequency data in their empirical work to investigate the magnet effect of price limits in Taiwan Stock Exchange. The magnet effect of price limit is the tendency for a stock price to accelerate towards the upper limit as the stock price gets closer to the upper bound. However, the opposite does not hold true. As a matter of fact, stock prices tend to move solely toward the lower limit as they get closer to the lower bound. The empirical results confirm the existence of the magnet effect, which is caused by the illiquidity risk and investors behavior in Taiwan Stock Exchange. To confirm the accuracy of their model in capturing the magnet effect, they apply their model on the S&P 500 where the price limit rule does not exist. The results show no evidence of the magnet effect.

Tooma (2011) investigates the existence of the magnet effect of price limits in the Egyptian stock exchange for the period from 1997 to 2002, where a 5 percent price limit was imposed. The paper uses pooled time series data for two sub-groups of firms; one for a period where a price limit was imposed and another when it was not to apply a logit model of probability of hitting the 5 percent limit. Results show that the change in the coefficient between periods, when price limits were not imposed compared to the period when price limits were imposed, is consistent with the magnet effect hypothesis. The coefficient indicates that the magnet effect is higher in the period when the price limit was imposed compared to the period when the price limit rule was not in effect. In other words, the probability of reaching the price limit has increased after imposing the price limit rule, consistent with Cho et al (2002).

Advocates of the price limit rule, on the other hand, view price limits positively and claim that price limits reduce price volatility. They argue that setting daily upper and lower bounds for stock prices to move within, helps manage price volatility and gives room for market participants to cool off. This prevents investors from initiating a market panic and avoid overreaction. Thus, allowing volatility to drop.

Yang Chu, Ko, and Lee (2018) study the effect of price limits on continuing overreaction and momentum in Taiwan Stock Exchange and find that imposing price limits reduce investors overreaction. Kim and Yang (2003) investigate whether price limits can play a role in reducing overreaction in Taiwan Stock market under two hypotheses: the cooling-off hypothesis and the magnet hypothesis. They find that overreaction increases as prices are approaching price limits and decreases as prices sequentially hit the price limits.

Deb, Kalev, and Marisetty (2017) apply the propensity score matching techniques to narrow the sample selection bias in Kim and Rhee (1997). They show that price limits are effective in reducing the transitory volatility in days after price limits are hit. Moreover, they find no evidence of the volatility spill-over. These finding contradict with those of Kim and Rhee (1997).

Ma, Rao, and Sears (1989) investigate the effectiveness of price limits in the U.S. future market for four commodities: corn, silver, treasury bonds, and soybeans. The results indicate that price limits can be used as a device to monitor price movement and volatility in volatile markets. Ma et al (1989) point out three benefits for imposing price limits. First of all, price limits can be used to attenuate credit risk. Second, price limits can serve as a tool to prevent the market from overreacting in response to news. Third, price limits can be used to prove that markets are not as liquid.

Kim and Park (2010) introduce a manipulation-based model to test reasons behind the adoption of price limits in stock markets. Their model shows that imposing the price limit rule discourages market manipulation. They also argue that a possible reason, based om their model, for market regulators to impose price limit rules is that the level of manipulation is high. They go on to modify their model to estimate price limits levels and conclude that markets with high levels of corruption and low public enforcement tend to have high price limits.

Deb, Kalev, and Marisetty (2010) investigate whether or not price limits are bad for equity markets. They notice the growing literature criticizing price limits and decide to test it themselves. To do so, they gathere a sample of 58 stock markets, which represents about 80% of the world’s equity markets. Surprisingly, about 71 percent, 41 equity markets, out of the sample impose the price limits rule. They find that markets that impose price limits are characterized by low levels of legal and technical development, less transparency, higher corruption levels, and lower business disclosure. These findings are consistent with their hypothesis even after the robust check.

2.1.2 Literature Review Related to Volatility Interruptions:

Due to the novelty of VI, four papers have discussed the new mechanism. Kwon, Eom, La, and Park (2018) examine the effect of introducing the static and dynamic VI to the pre-existing price limits in the Korean Stock Market. They find that the static VI has a weak impact in stabilizing price discovery, while the dynamic VI has a positive effect in stabilizing price discovery. They also find that static IV has a limited effect as it provides similar results as the existing price limits system.

Brugler and Linton (2014) study the role of static VI on market quality in London Stock Exchange. They argue that market quality worsens after a long suspension from lower static VI events. Nevertheless, they document that lower static VI helps in interrupting poor market quality to other stocks at times when the market is at distress. Finally, they show that upper static VI causes excessive trading spill-overs.

Zimmermann (2013) examine the impact of VI on price discovery in Deutsche Börse Xetra. The study shows that "volatility interruptions contribute to about 36 percent of pre-interruption price uncertainty revelation." The paper also claims that when VIs offers an accurate direction of price discovery, subsequent volatility drops. Lastly, the paper documents that although market quality improves after an VI is triggered, market traders continue to be alert and watchful.

Abad and Pascual (2010) observe the impact of the static VI on the Spanish Stock Exchange. They document a surge in information asymmetry risk prior to a VI halt, hypothesizing that informed traders anticipate their trading strategies arounds VI halts; concluding that VI increases information asymmetry. Finally, the authors conclude that high levels of volatility, illiquidity and trading activities will remain in the market even after the introduction of the static VI mechanism.

2.1.2. Motivation and Hypotheses Development

After the 2010 flash crash, many European exchanges announced the introduction of a new trading mechanism aiming to reduce market volatility. On June 14, 2010, about one month after the flash crash, the Euronext introduced the Static VI, in addition to the pre-existing dynamic VI, to all its exchanges in Amsterdam, London, Paris, Lisbon, Brussels, and Dublin. Three months later, on September 30, 2010, NASDAQ OMX Nordic introduces an updated VI to its Nordic markets to protect investors and listed companies form excess volatility. Nordic markets include Stockholm, Helsinki, Copenhagen, and Iceland exchanges.

Similar to European exchanges, Asian exchanges followed suit. On September 1, 2014, The Korean Stock Exchange introduced the dynamic VI and on June 15, 2015, they announced the introduction of the static VI.

In this paper, we only focus on one type of circuit breaker, the VI mechanism, both static and dynamic. We examine the impact of VI on idiosyncratic volatility in Stockholm stock exchange. We chose Stockholm stock exchange for two main reasons. First, Stockholm stock exchange is the largest market in Nasdaq OMX Nordic and is the fact that it is managed by Nasdaq implies that the level is efficiency is much higher compared to those locally-managed in other European markets. Second, it adopts the VI mechanisms, both static and dynamic. To the best of our knowledge, this is the first paper to study the impact of VI on stock return.

The early work of Merton (1987) suggests that firm's idiosyncratic risk is priced due to the imperfect diversification. He argues that investors who cannot hold a market portfolio should be rewarded. Thus, firms with higher idiosyncratic volatility should offer a return premium to compensate investors for the undiversified risk they create, indicating a positive relationship between idiosyncratic volatility and expected return. Malkiel and Xu (2002) find similar results. Moreover, Spiegel and Wang (2005) examine the relationship between idiosyncratic volatility and liquidity and find that expected return increases as idiosyncratic volatility increases. In addition, Fu (2009) find a significantly positive relationship between the conditional idiosyncratic volatility and expected return. Chau, Goh, and Zhang (2010) find similar results.

In the previous paper, we have shown that the conditional idiosyncratic volatility increases when stocks reach the upper static or dynamic upper limit. Therefore, and based on the previous papers we just reviewed, it is logical to observe a positive stock return when stock prices hit the upper static or dynamic limits. Thus, we expect stock return to increase as stock prices approach upper static and dynamic limits:

H_1: Stock return increases when stocks hit the upper static limit.
H_2: Stock return increases when stocks hit the upper dynamic limit.

On the other hand, we also expect the opposite to hold true which leads us to investigate the following hypotheses:

H_3: Stock return decreases when stocks hit the lower static limits.
H_4: Stock return decreases when stocks hit the lower dynamic limits.

To further investigate hypotheses 1 and 2, we look at stock return one day before and day after the limit hit day for both upper static and dynamic. We expect our earlier hypotheses to hold. That is, stock return is higher on the upper limit hit day compared to the day before and the day after the limit hit. We test the following hypotheses:

H_5: Stock return is higher on days when the static upper limit is reached compared to the day before and after.
H_6: Stock return is higher on days when the dynamic upper limit is reached compared to the day before and after.

Similarly, we further investigate hypotheses 3 and 4 and test the following hypotheses:

H_7: Stock return is lower on days when the static lower limit is reached compared to the day before and after.

H_8: Stock return is lower on days when the dynamic lower limit is reached compared to the day before and after.

Furthermore, Chang and Dong (2006) point out that large firms tend to have lower idiosyncratic volatility, and Fu (2009) shows that "Small firms tend to have higher idiosyncratic volatilities than larger firms." This motivates us to investigate the impact of stock size on the relation between stock return and static and dynamic VI. Higher idiosyncratic volatility is only observed within the upper limits, while low idiosyncratic volatility is observed within the lower bounds. For this reason, we only focus on the static and dynamic upper limits. So, we sort stocks by their size and create two portfolios, large market cap and small market cap. Since small stocks tend to have higher idiosyncratic volatility than larger stocks, then we expect smaller stocks to have higher returns than larger stocks:

H_9: Small market cap stocks that hit the upper static limit tend to have higher stock returns than larger market cap stocks.

H_{10}: Small market cap stocks that hit the upper dynamic limit tend to have higher stock returns than larger market cap stocks.

3. Data and Methodology:

We obtain daily stock prices and related financial data from DATASTREAM. Data for Stockholm spans from September 30, 2010 to December 29, 2017. We chose September 30, 2010 to be the starting date for our sample because this is the date when static and dynamic VI first came into effect. There are 378 stocks traded in Stockholm Stock Exchange. We drop stocks that were listed after December 29, 2017 or have observations less than one week. The final sample consists of 344 firms. The table below summarizes the static and dynamic VI range in Nasdaq Stockholm:

Exchange	Static Limit (stock)	Static Limit (Index)	Dynamic Limit (stock)	Dynamic Limit (Index)	Suspension time for static	Suspension time for dynamic
Stockholm	+/- 15% from opening	+/- 10% from opening	+/- 5% from the last traded price	+/- 3% from the last traded price	3 minutes	1 minute

To identify static and dynamic limit hit occurrences, we follow these steps. We assume upper static limits are reached when any of the following conditions occur:

$$H_t \geq O_t + \textit{Static limit (15\%)} \quad (1a)$$

$$C_t \geq O_t + \textit{Static limit (15\%)} \quad (1b)$$

where H_t and C_t represent Day t's high and close price, respectively, and O_t represents Day t's open price.

We assume Lower static limits are reached when any of the following conditions occur:

$$C_t \leq O_t \text{ - } Static\ limit\ (15\%) \quad (2a)$$

$$L_t \leq O_t \text{ - } Static\ limit\ (15\%) \quad (2b)$$

where L_t represent Day t's low and price

Similarly, we assume upper dynamic limits are reached when any of the following conditions are met:

$$H_t \geq O_t + Dynamic\ limit\ (5\%) \quad (3a)$$

$$C_t \geq O_t + Dynamic\ limit\ (5\%) \quad (3b)$$

$$C_t \geq H_t + Dynamic\ limit\ (5\%) \quad (3c)$$

And Lower dynamic limits are reached when any of the following conditions are met:

$$L_t \leq O_t \text{ - } Dynamic\ limit\ (5\%) \quad (4a)$$

$$C_t \leq O_t \text{ - } Dynamic\ limit\ (5\%) \quad (4b)$$

$$C_t \leq L_t \text{ - } Dynamic\ limit\ (5\%) \quad (4c)$$

Once we determine the number of upper and lower hits from static and dynamic VI, we study the impact of static and dynamic VI on stock return. Following Chua, Goh, and Zhang (2010), we estimate the following regression:

$$R_{i,t} = a_0 + a_1\ LimitDUM_{i,t} + \sum_{i=1}^{n} b_i\ Controls_{i,t} + Time\ Dummies + Firm\ Fixed\ Effects + \varepsilon_{i,t}$$
(12)

where $R_{i,t}$ is the logarithmic return, $LimitDUM$ is the VI dummy associated with conditions (1) to (4), and we control for size, book-to-market, and lagged return to control for the momentum effect. We extend their work to control for volatility, illiquidity, and return on equity.

To examine hypotheses 5 to 8, to estimate the following regression:

$$R_{i,t} = a_0 + a_1\, LimitDUM_{i,t-1} + a_2\, LimitDUM_{i,t} + a_3\, LimitDUM_{i,t+1} + \sum_{i=1}^{n} b_i\, Controls_{i,t} + Time\ Dummies + Firm\ Fixed\ Effects + \varepsilon_{i,t} \quad (13)$$

where $LimitDUM_{t-1}$ is a dummy that takes the value of 1 for the day before the limit hits and zero otherwise and $LimitDUM_{t+1}$ is a dummy that takes the value of 1 for the day after the limit hits and zero otherwise.

It is important to point out that panel data settings might suffer from inflated t-statistics which could possibly lead to inaccurate inferences and conclusions. For this, we follow Rogers' (1983, 1993) method to correct for heteroscedasticity, serial correlation, or contemporaneous cross-sectional correlations of error terms by adjusting standard errors for clustering at the firm level. In addition to clustering the standard error, we include a year fixed effect dummy for each year in the sample to control for any economic changes as suggested by and Lins et al (2017).

4. Results and Interpretations:

4.1. Descriptive Statistics:

Table 1 shows the summary statistics of 344 stocks in Nasdaq Stockholm during the period from September 30, 2010 to December 29, 2017. The minimum stock return is -2.28% and the maximum is 2.32% with an average of -0.0016% stock return. We do not observe high spikes in stock return and this is due to the VI mechanism that restricts stocks from increasing or decreasing above or below certain range. Stocks liquidity is relatively higher in Nasdaq Stockholm as indicated by the Amihud (2002) measure with a mean of -12.40. Moreover, stock volatility is considerably low with an average of 0.02%. As far as stock profitability is concerned, the average return on equity is 9.37% and the median is 11.67% indicating that stocks in Nasdaq Stockholm are profitable. The average book to market ratio is 61.52%. Hence, stocks in Nasdaq Stockholm are characterized by being profitable, liquid, and having low level of volatility for the period following the imposition of the VI mechanism from September 30, 2010 to December 29, 2017.

Table 2 shows the VI occurrences for both static and dynamic limits sorted by year, market capitalization, and market sector. In total, 59,445 times the VI were triggered from September 30, 2010 to December 29, 2017. Static limits were reached 3,618 times (2,252 static upper hits and 1,366 static lower hits) compared with 55,827 for dynamic limits (27,259 and 28,568 limits hit for dynamic upper and lower limits, respectively). It is not surprising to observe greater dynamic VI occurrences than static because of the limit range. It is common to observe a stock reaching 5% from opening price but not common to observe a stock reaching 15% from yesterday's closing price, and this explains why we have more dynamic occurrences compared to their static counterparts.

The year following the implementation of the VI rules, 2011, witnessed the highest VI occurrences with a total of 10,501 limit reaches. Out of the 10,501 hits, 288 static upper hits, 228 static lower hits, 4,234 dynamic upper hits, and 5,751 dynamic lower hits. Moreover, small market cap stocks witnessed the highest VI occurrences with 30,882 compared with 8,173 and 20,390 for large and medium market cap stocks, respectively. It can be observed here that small market cap stocks are more volatile compared to large and medium market cap stocks. Moreover, medium market cap stocks are more volatile than larger market cap stocks. This is consistent with the literature that small size firms tend to be more volatile compared to their larger counterparts. Fu (2008) shows that "Small firms tend to have higher idiosyncratic volatilities than larger firms."[5] Furthermore, we sort stocks by their market sectors. Nasdaq Stockholm is divided into ten main sectors: Basic Materials, Consumer Goods, Consumer Services, Financials, Health Care, Industrials, Oil and Gas, Technology, Telecommunications, and Utilities. Industrials and Health care sector observed the highest VI occurrences with 13,549 and Conversely, Utilities and Telecommunications sectors witnessed the lowest VI occurrences with 533 and 639 limit hits, respectively.

4.2. Stock return and Volatility Interruptions:

In this section, we report the results of examining the impact of static and dynamic limit hits on stock returns. We estimate equation (12) for static upper and lower limits as well as dynamic upper and lower limits. We execute this view by regressing return on the upper and lower limits and other control variables. The first column in each regression includes control variables suggested by Chua, Goh, and Zhang (2010). It is well documented that volatility (i.e. Chua, Goh,

[5] See also Duffee (1995) for more information.

Table 12: Summary Statistics

This table shows summary statistics for 344 stocks listed in Nasdaq Stockholm during the period from September 30, 2010 to December 29, 2017. "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**B/M**" Book – to - Market," **Leverage**" Total liabilities to total assets ratio, "**ROE**" Net income over the difference between total assets and total liabilities, "**ILLIQ**" stock daily Amihud's (2002) illiquidity, "**Closing price**" stock daily closing price, "**Daily returns**" stock daily return, "**Volatility**" daily return simple volatility. "**Lagged Return**" is one day lagged return.

	Descriptive Statistics				
	Mean	**Median**	**Std. Dev.**	**Min**	**Max**
Closing price	79.28	52.05	94.20	0.02	1,767.17
Daily returns	- 0.0016%	0.00%	1.38%	-2.28%	2.32%
Volatility	0.071%	0.0091%	1.37%	0.0%	858.63%
Lagged Return	-0.003%	11.67%	1.39%	-2.25%	2.35%
ILLIQ	-12.402	-12.19	3.09	-22.58	2.21
ROE	9.37%	11.67%	13.24%	-18.63%	26.50%
B/M	61.52%	50.44%	40.35%	14.04%	138.45%
Size	8.9	2.4	13.4	0.21	42.3

***Table 13 "Volatility Interruptions Occurrences"**:* This table shows the volatility interruptions occurrences categorized by Static and Dynamic hits for 344 stocks listed in Nasdaq Stockholm during the period from September 30, 2010 to December 29, 2017.

Panel A: *VI occurrences by year*

Year	Static Upper	Static Lower	Dynamic Upper	Dynamic Lower	Occurrences Per Year
2010	64	52	718	670	**1,504**
2011	288	228	4,234	5,751	**10,501**
2012	314	215	3,369	3,972	**7,870**
2013	361	169	3,305	3,145	**6,980**
2014	295	193	3,255	3,380	**7,123**
2015	330	194	4,479	4,204	**9,207**
2016	335	177	4,519	4,527	**9,558**
2017	265	138	3,380	2,919	**6,702**
Total No. of Occurrences	**2,252**	**1,366**	**27,259**	**28,568**	**59,445**

Panel B: *VI occurrences by Market Capitalization:*

Size	Static Upper	Static Lower	Dynamic Upper	Dynamic Lower	Occurrences MC
Large Cap	118	82	3,987	3,986	**8,173**
Medium Cap	641	325	9,987	9,437	**20,390**
Small Cap	1,493	959	13,285	15,145	**30,882**
Total No. of Occurrences	**2,252**	**1,366**	**27,259**	**28,568**	**59,445**

Panel C: *VI occurrences by Sectors:*

Sector	Static Upper	Static Lower	Dynamic Upper	Dynamic Lower	Occurrences Sector
Basic Materials	114	56	1,915	1,787	**3,872**
Consumer Goods	133	75	2,271	2,342	**4,821**
Consumer Services	163	95	2,560	2,515	**5,333**
Financials	227	130	3,024	3,374	**6,755**
Health Care	602	310	5,985	6,474	**13,371**
Industrials	387	248	6,288	6,626	**13,549**
Oil & Gas	30	16	620	530	**1,196**
Technology	558	423	4,058	4,334	**9,373**
Telecommunications	8	5	274	352	**639**
Utilities	30	8	264	234	**533**
Total No. of Occurrences	**2,252**	**1,366**	**27,259**	**28,568**	**59,445**

and Zhang (2010)), illiquidity (i.e. Amihud (2002) and Amihud et al (2015)) and return on equity impact return, so we extend the control variables by Chua, Goh, and Zhang (2010) to control for these variables. In the second column we include the illiquidity measure of Amihud (2002) in addition to other control variables in the first column, which is calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock:

$$ILLIQ_{i,t} = \frac{|R_{i,t}|}{VO_{i,t} * CP_{i,t}} \tag{14}$$

Where $R_{i,t}$ is the return for stock i in day t, and $VO_{i,t}$ is the daily trading volume for stock i in day t, and $CP_{i,t}$ is the daily closing price for stock i in day t.

In columns 3 and 4 we include volatility and return on equity, respectively. Here, we proxy simple volatility for volatility. Table 14 reports the results from estimating equation 12. The coefficient of static upper in the first column is 0.14 and is statistically significant at 1% level of significance. Even after controlling for illiquidity in column 2, volatility in column 3, and ROE in column 4, the coefficient is consistent at 0.15 and statistically significant at 1% level of significance. This indicates that return increases by an average of 15% when a stock reaches the static upper limit compared to a stock that did not reach the static upper limit. This provides confirmation for our first hypothesis that stock return increases as the stock reaches the static upper limit.

Table 15 reaches the same conclusion as in Table 14. The coefficients of dynamic upper limit in all four models are 6% and statistically significant at 1% level of significance. This indicates that stock return on average increases by 6% when stocks reach the dynamic upper limit, supporting our second hypothesis. Furthermore, we can conclude that although stock return is positive whenever it reaches the upper bound, whether static or dynamic, stock return is even higher when it hits the static upper bound than when it hits the dynamic upper bound by about 8% to 9%, on average. One reason to explain such a phenomenon could be attributed to their level of idiosyncratic volatility. Recall that Spiegel and Wang (2005) and Fu (2009) show that stock return increases as the conditional idiosyncratic volatility increases. Since we have previously provided supporting evidence that conditional idiosyncratic volatility increases when stocks reach the upper static or dynamic upper limit, then it is expected to observe an increase in stock return for both upper limits, static and dynamic.

Table 16 presents the results of regressing stock return on the static lower limit dummy and other control variables. In all four models, static lower is negatively significant at 1% level of significance. The coefficient in the first column is -0.14 and when we add illiquidity to other control variables, the coefficient becomes -0.16. However, no significant change is observed for the coefficient of static lower when we include volatility and ROE to other control variables in columns 3 and 4, it remains the same at -0.18. Hence, we can conclude that stock return decreases when stocks reach the static lower limit by an average of -14% to -18% compared to those that did not reach the static lower bound, confirming our third hypothesis.

Table 17 reports the results of examining the impact of stocks reaching the dynamic lower limit on stock return. The coefficients of dynamic lower are -0.05 across all four models and are negatively significant at 1% level of significance. This indicates that stock return decreases by an average of 5% when stocks reach the lower dynamic limit, confirming our fourth hypothesis.

Form Tables 16 and 17, we conclude that whenever stocks reach the lower bound, static or dynamic, stock return decreases. Another point worth noting is that static limits, upper or lower, have a greater impact on stock returns compared to dynamic limits, upper or lower. We have shown from tables 3 and 4 that stock return increases by an average of 14% to 15% when stocks hit the upper static limits compared to an average of 6% when they reach the dynamic upper limit. Similarly, stocks reaching the static lower limits observe a greater return loss compared to stocks reaching the dynamic lower bound. Hence, stocks that frequently hit the static limits, upper or lower, are riskier than those that frequently hit the dynamic lower limit. This can be attributed to the fact that static limits have a wider VI range of 15% compared to a 5% dynamic limits rage. With a wider range, stocks accumulate higher levels of volatility before they reach the limits compared to tighter range. In this case, investors need to be compensated for holding such volatile stocks and this explains the greater impact of static limits on stock return compared to dynamic limits.

Table 14 reports the results of estimating equation (12). The dependent variable is the logarithmic return. The independent variables are "**Static Upper**" which us a dummy variable that equals one if any of the conditions in (1a) or (1b) is met and zero otherwise, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Log (Return)	**Log (Return)**	**Log (Return)**	**Log (Return)**
Static Upper	**0.14** [a]	**0.15** [a]	**0.15** [a]	**0.15** [a]
	(46.54)	(18.48)	(18.18)	(18.17)
B/M	**- 0.0008** [b]	**- 0.0008** [b]	**- 0.0008** [b]	**- 0.0008** [b]
	(-2.15)	(-2.22)	(-2.33)	(-2.25)
Size	**7.17e-09** [a]	**7.09e-09** [a]	**7.67e-09** [a]	**7.62e-09** [a]
	(3.05)	(3.15)	(3.29)	(3.72)
Lagged Return	**- 0.07** [a]	**- 0.09** [a]	**- 0.09** [a]	**- 0.09** [a]
	(-8.35)	(-6.52)	(-6.59)	(-6.60)
ILLIQ		**- 0.0003** [a]	**- 0.0006** [a]	**- 0.0006** [a]
		(-4.57)	(-9.83)	(-9.41)
VOL			**3.48** [a]	**3.44** [a]
			(8.69)	(8.57)
ROE				**0.006** [a]
				(6.40)
Firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**	**Firm**	**Firm**
N	**425,692**	**358,233**	**358,233**	**358,171**
Adj R^2	**13.26%**	**14.41%**	**14.59%**	**14.62%**

(a) significant at 1% , **(b)** significant at 5% and **(c)** significant at 10%

Table 15 reports the results of estimating equation (12). The dependent variable is the logarithmic return. The independent variables are "**Dynamic Upper**" which is a dummy variable that equals one if any of the conditions in (3a), (3b) or (3c) is met and zero otherwise, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm

	Log (Return)	Log (Return)	Log (Return)	Log (Return)
Dynamic Upper	**0.06** [a]	**0.06** [a]	**0.06** [a]	**0.06** [a]
	(46.55)	(33.81)	(36.69)	(36.68)
B/M	**- 0.0008** [c]	**- 0.0009** [b]	**- 0.0009** [b]	**- 0.0008** [b]
	(-1.94)	(-2.15)	(-2.17)	(-2.10)
Size	**1.18e-08** [a]	**9.81e-09** [a]	**9.75e-09** [a]	**9.72e-09** [a]
	(2.75)	(3.11)	(3.04)	(3.49)
Lagged Return	**- 0.07** [a]	**- 0.08** [a]	**- 0.09** [a]	**- 0.09** [a]
	(-5.81)	(-5.25)	(-5.86)	(-5.87)
Illiquidity		**- 0.0007** [a]	**- 0.0009** [a]	**- 0.0008** [a]
		(-9.67)	(-9.37)	(-9.22)
VOL			**0.49** [a]	**0.49** [a]
			(5.33)	(5.33)
ROE				**0.006** [a]
				(5.93)
Firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**	**Firm**	**Firm**
N	**425,692**	**358,233**	**358,233**	**358,171**
Adj R^2	**22.49%**	**24.11%**	**25.89%**	**25.92%**

a) significant at 1% , (**b**) significant at 5% and (**c**) significant at 10%

We further investigate hypotheses one to four by looking at stock return one day before and after limit hits. Table 18 shows the results of estimating equation 13 for the static upper limit. Through all four models, stock return increases when it reaches the static upper limit by an average of 15% but decreases the day before and after the static upper limit hit by an average of 1%. This result is consistent with our earlier findings and provide support to our fifth hypothesis that stock return is higher on days when the static upper limit is reached compared to the day before and after.

Table 19 reports the results of estimating equation 13 for the dynamic upper limit, which proves our sixth hypothesis that stock return is higher on days when the dynamic upper limit is reached compared to the day before and after. As predicated, stock return increases by 6% when it reaches the dynamic upper limit but drops by 1% the day before the limit hit and an average of 0.1% the day after the limit hit event.

Our results for the upper limits, both static and dynamic, suggest that stock return surges when it hits the upper limits. This should not be surprising since we know that the conditional idiosyncratic volatility increases when stocks reach the upper limits as well. These results are consistent with Fu (2009) who shows a positive relation between conditional idiosyncratic volatility estimated using (EGARCH) models and expected stock returns.

We have previously shown that the conditional idiosyncratic volatility decreases when a stock price reaches the lower bounds, static or dynamic. Since Fu (2009) establishes a positive relationship between the conditional idiosyncratic volatility and expected stock returns, we should observe a stock return loss when a stock price reaches the lower bounds.

Table 20 reports the results of estimating equation 13 for the static lower limit. Stock return still makes an average loss of - 17% when it reaches the static lower limit, even after comparing the return to the day before and after the limit hit day. This evidence provides support to our earlier finding from hypothesis three and offers a support to hypothesis seven which argues that

__Table 16__ reports the results of estimating equation (12). The dependent variable is the logarithmic return. The independent variables are "**Static Lower**" which is a dummy variable that equals one if any of the conditions in (2a) or (2b) is met and zero otherwise, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Log (Return)	**Log (Return)**	**Log (Return)**	**Log (Return)**
Static Lower	**- 0.14** [a]	**- 0.16** [a]	**- 0.18** [a]	**- 0.18** [a]
	(-17.77)	(-14.34)	(-20.33)	(-20.31)
B/M	**- 0.0008** [b]	**- 0.0008** [b]	**- 0.0008** [b]	**- 0.0007** [b]
	(-2.24)	(-2.29)	(-2.45)	(-2.38)
Size	**7.73e-09** [a]	**9.12e-09** [a]	**9.21e-09** [a]	**9.18e-09** [a]
	(3.61)	(3.98)	(4.42)	(4.88)
Lagged Return	**- 0.05** [a]	**- 0.07** [a]	**- 0.07** [a]	**- 0.07** [a]
	(-5.15)	(-4.71)	(-6.41)	(-6.42)
Illiquidity		**- 0.0001**	**- 0.0003** [a]	**- 0.0003** [a]
		(-1.21)	(-6.37)	(-5.82)
VOL			**0.93** [a]	**0.93** [a]
			(7.44)	(7.45)
ROE				**0.005** [a]
				(5.92)
Firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**	**Firm**	**Firm**
N	**425,692**	**358,233**	**358,233**	**358,171**
Adj R^2	**7.38%**	**8.75%**	**14.94%**	**14.96%**

a) significant at 1% , (**b**) significant at 5% and (**c**) significant at 10%

__Table 17__ reports the results of estimating equation (12). The dependent variable is the logarithmic return. The independent variables are "**Dynamic Lower**" which is a dummy variable that equals one if any of the conditions in (4a), (4b) or (4c) is met and zero otherwise, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm

	Log (Return)	**Log (Return)**	**Log (Return)**	**Log (Return)**
Dynamic Lower	**- 0.05** [a]	**- 0.05** [a]	**- 0.05** [a]	**- 0.05** [a]
	(-40.63)	(-28.80)	(-34.22)	(-34.25)
B/M	**- 0.0005** [b]	**- 0.0006** [b]	**- 0.0005** [b]	**- 0.0005** [b]
	(-2.17)	(-2.07)	(-2.23)	(-2.15)
Size	**6.53e-09** [a]	**9.76e-09** [a]	**9.80e-09** [a]	**9.76e-09** [a]
	(3.28)	(3.90)	(4.09)	(4.32)
Lagged Return	**- 0.05** [a]	**- 0.07** [a]	**- 0.07** [a]	**- 0.07** [a]
	(-4.59)	(-4.15)	(-5.36)	(-5.36)
Illiquidity		**0.0002** [a]	**0.00001**	**0.00003**
		(2.70)	(0.2)	(0.5)
VOL			**0.83** [a]	**0.83** [a]
			(7.08)	(7.08)
ROE				**0.004** [a]
				(5.05)
Firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**	**Firm**	**Firm**
N	**425,692**	**358,233**	**358,233**	**358,171**
Adj R^2	**14.86%**	**16.42%**	**21.51%**	**21.53%**

a) significant at 1% , (**b)** significant at 5% and (**c)** significant at 10%

stock return is lower on days when the static lower limit is reached compared to the day before and after.

The results from Table 21 for the dynamic lower limit are similar to those of Table 20 for the static lower limit. The results suggest that stock return experience an average of – 5% loss when it hits the dynamic lower limit, in all four models, even after controlling for the day before in which a stock gains an average of 1% return and the day after where a stock gains 0.3% return. Our findings here are the same as our previous findings from hypothesis four and offer support to hypothesis eight.

4.4.Market Capitalization and Volatility Interruptions:

In this section, we investigate whether stock size plays a role in the impact of static and dynamic VI on stock return. This hypothesis is motivated by the body of literature that studies the relationship between stock market cap and idiosyncratic volatility. Chang and Dong (2006) point out that large firms tend to have lower idiosyncratic volatility, and Fu (2008) shows that "Small firms tend to have higher idiosyncratic volatilities than large firms." So, these two papers show a negative relationship between stock market cap and idiosyncratic volatility. Fu (2009) also show a positive relationship between idiosyncratic volatility and expected stock return. Hence, from these papers, it can be argued that if small firms tend to have higher idiosyncratic volatilities than large firms and that there is a positive relationship between expected stock return and the conditional idiosyncratic volatility, it is logical to assume that small stocks enjoy higher stock returns, because of their higher conditional idiosyncratic volatility, than large stocks. In other words, since small stocks tend to have higher idiosyncratic volatility than large stocks, then we expect small stocks to have higher return than larger stocks.

This motivates us to investigate the role of firm size on the relation between stock return and static and dynamic VI. High idiosyncratic volatility is only observed within the upper limits, while low idiosyncratic volatility is observed within the lower bounds. For this reason, we only focus on the static and dynamic upper limits. So, we sort stocks by their size and create two portfolios, large market cap and small market cap. Then we estimate equation 5 for the two portfolios.

Table 18 reports the results of estimating equation (13). The dependent variable is the logarithmic return. The independent variables are "**DayBeforeDUM**" which is a dummy variable for the day before the limit hit event, "**Static Upper**" which us a dummy variable that equals one if any of the conditions in (1a) or (1b) is met and zero otherwise, "**DayAfterDUM**" is a dummy variable for the day after the limit hit event "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Log (Return)	Log (Return)	Log (Return)	Log (Return)
DayBeforDUM	**-0.01**	**-0.01**	**-0.01**	**-0.01**
	(-1.24)	(-1.03)	(-1.09)	(-1.09)
Static Upper	**0.15** [a]	**0.16** [a]	**0.15** [a]	**0.15** [a]
	(42.36)	(18.19)	(17.70)	(17.69)
DayAfterDUM	**-0.01** [a]	**-0.01** [b]	**-0.01** [a]	**-0.01** [a]
	(-3.77)	(-2.44)	(-2.82)	(-2.78)
B/M	**- 0.001** [b]	**- 0.001** [b]	**- 0.001** [b]	**- 0.001** [b]
	(-2.17)	(-2.24)	(-2.36)	(-2.28)
Size	**7.15e-09** [a]	**7.07e-09** [a]	**7.67e-09** [a]	**7.62e-09** [a]
	(3.12)	(3.22)	(3.36)	(3.79)
Lagged Return	**- 0.06** [a]	**- 0.08** [a]	**- 0.08** [a]	**- 0.08** [a]
	(-8.24)	(-6.02)	(-5.99)	(-6.00)
Illiquidity		**- 0.0003** [a]	**- 0.001** [a]	**- 0.001** [a]
		(-4.86)	(-10.49)	(-10.05)
VOL			**3.60** [a]	**3.56** [a]
			(9.43)	(9.31)
ROE				**0.006** [a]
				(6.50)
Firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**	**Firm**	**Firm**
N	**425,692**	**358,233**	**358,233**	**358,171**
Adj R^2	**13.41%**	**14.47%**	**14.66%**	**14.69%**

a) significant at 1% , (**b)** significant at 5% and (**c)** significant at 10%

Table 19 reports the results of estimating equation (13). The dependent variable is the logarithmic return. The independent variables are "**DayBeforeDUM**" which is a dummy variable for the day before the limit hit event, "**Dynamic Upper**" which us a dummy variable that equals one if any of the conditions in (3a) (3b) or (3c) is met and zero otherwise, "**DayAfterDUM**" is a dummy variable for the day after the limit hit event "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Log (Return)	**Log (Return)**	**Log (Return)**	**Log (Return)**
DayBeforeDUM	**-0.01** [a]	**-0.01** [a]	**-0.01** [a]	**-0.01** [a]
	(-5.09)	(-5.38)	(-5.77)	(-5.77)
Dynamic Upper	**0.06** [a]	**0.06** [a]	**0.06** [a]	**0.06** [a]
	(44.55)	(34.01)	(36.62)	(36.61)
DayAfterDUM	**-0.002** [c]	**-0.001**	**-0.001**	**-0.001**
	(-1.91)	(-0.92)	(-1.28)	(-1.26)
B/M	**- 0.001** [b]	**- 0.001** [b]	**- 0.001** [b]	**- 0.001** [b]
	(-1.97)	(-2.20)	(-2.23)	(-2.15)
Size	**1.09e-08** [a]	**8.98e-09** [a]	**8.81e-09** [a]	**8.78e-09** [a]
	(2.80)	(3.18)	(3.09)	(3.55)
Lagged Return	**- 0.06** [a]	**- 0.08** [a]	**- 0.08** [a]	**- 0.08** [a]
	(-4.23)	(-3.95)	(-4.41)	(-4.43)
Illiquidity		**- 0.001** [a]	**- 0.001** [a]	**- 0.001** [a]
		(-10.37)	(-9.99)	(-9.84)
VOL			**0.51** [a]	**0.51** [a]
			(5.44)	(5.45)
ROE				**0.01** [a]
				(6.14)
Firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**	**Firm**	**Firm**
N	**425,692**	**358,233**	**358,233**	**358,171**
Adj R^2	**22.81%**	**24.38%**	**26.23%**	**26.26%**

a) significant at 1% , (**b)** significant at 5% and (**c)** significant at 10%

Table 20 reports the results of estimating equation (13). The dependent variable is the logarithmic return. The independent variables are "**DayBeforeDUM**" which is a dummy variable for the day before the limit hit event, "**Static Lower**" which us a dummy variable that equals one if any of the conditions in (2a) or (2b) is met and zero otherwise, "**DayAfterDUM**" is a dummy variable for the day after the limit hit event "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Log (Return)	Log (Return)	Log (Return)	Log (Return)
DayBeforeDUM	**0.05** [a]	**0.05** [a]	**0.03** [c]	**0.03** [c]
	(2.85)	(2.76)	(1.91)	(1.92)
Static Lower	**- 0.14** [a]	**- 0.17** [a]	**- 0.18** [a]	**- 0.18** [a]
	(-25.62)	(-14.89)	(-20.96)	(-20.94)
DayAfterDUM	**0.01** [b]	**0.001**	**-0.005**	**-0.005**
	(2.45)	(0.46)	(-1.56)	(-1.54)
B/M	**- 0.001** [b]	**- 0.001** [b]	**- 0.001** [b]	**- 0.001** [b]
	(-2.25)	(-2.31)	(-2.47)	(-2.40)
Size	**7.43e-09** [a]	**8.86e-09** [a]	**9.06e-09** [a]	**9.03e-09** [a]
	(3.54)	(3.92)	(4.34)	(4.83)
Lagged Return	**- 0.05** [a]	**- 0.07** [a]	**- 0.07** [a]	**- 0.07** [a]
	(-5.08)	(-4.73)	(-6.26)	(-6.26)
Illiquidity		**- 0.0001**	**- 0.0003** [a]	**- 0.0003** [a]
		(-1.36)	(-6.48)	(-5.92)
VOL			**0.91** [a]	**0.91** [a]
			(6.92)	(6.92)
ROE				**0.01** [a]
				(6.22)
Firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**	**Firm**	**Firm**
N	**425,692**	**358,233**	**358,233**	**358,171**
Adj R^2	**8.18%**	**9.32%**	**15.16%**	**15.18%**

a) significant at 1% , (**b)** significant at 5% and (**c)** significant at 10%

Table 21 reports the results of estimating equation (13). The dependent variable is the logarithmic return. The independent variables are "**DayBeforeDUM**" which is a dummy variable for the day before the limit hit event, "**Dynamic Lower**" which us a dummy variable that equals one if any of the conditions in (4a), (4b) or (4c) is met and zero otherwise, "**DayAfterDUM**" is a dummy variable for the day after the limit hit event "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm

.

	Log (Return)	**Log (Return)**	**Log (Return)**	**Log (Return)**
DayBeforeDUM	**0.01** [a]	**0.01** [a]	**0.01** [a]	**0.01** [a]
	(5.98)	(6.16)	(5.14)	(5.15)
Dynamic Lower	**- 0.05** [a]	**- 0.05** [a]	**- 0.05** [a]	**- 0.05** [a]
	(-37.34)	(-28.69)	(-33.23)	(-33.26)
DayAfterDUM	**0.004** [a]	**0.003** [a]	**0.003** [a]	**0.003** [a]
	(5.27)	(3.54)	(3.62)	(3.65)
B/M	**- 0.001** [b]	**- 0.001** [b]	**- 0.0005** [b]	**- 0.0005** [b]
	(-2.23)	(-2.23)	(-2.29)	(-2.21)
Size	**6.06e-09** [a]	**9.35e-09** [a]	**9.45e-09** [a]	**9.41e-09** [a]
	(3.44)	(3.99)	(4.17)	(4.51)
Lagged Return	**- 0.04** [a]	**- 0.06** [a]	**- 0.06** [a]	**- 0.06** [a]
	(-3.18)	(-3.)	(-4.09)	(-4.09)
Illiquidity		**0.0002** [a]	**- 2.98e-06**	**0.00002**
		(2.65)	(-0.05)	(0.32)
VOL			**0.82** [a]	**0.82** [a]
			(7.07)	(7.07)
ROE				**0.004** [a]
				(4.80)
Firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**	**Firm**	**Firm**
N	**425,692**	**358,233**	**358,233**	**358,171**
Adj R^2	**15.59%**	**17.12%**	**22.01%**	**22.03%**

a) significant at 1% , (**b)** significant at 5% and (**c)** significant at 10%

Table 22 reports the estimation of equation 12 for large and small market cap stocks reaching the static upper limit. We find that large stocks gain 14% return when they reach the static upper limit, while small stocks gain 16% return. Table 23 reports the estimation of equation 12 for large and small market cap stocks reaching the dynamic upper limit. We find that large stocks gain 0.56% return while small stocks gain 0.71% return as they reach the dynamic upper limit.

Hence, these findings indicate that small stocks tend to gain higher return greater than large stock as they reach the upper limits, static or dynamic. These results, which are statistically significant at 1% significance level, provide support to our hypotheses nine and ten.

5. Conclusion:

This paper studies the impact of the static and dynamic VI on stock return. Motived by Fu (2009) and Chang and Dong (2006) as well as our previous findings, we find that stocks that reach the upper static or dynamic limits experience a gain in return, while stocks that reach the lower static or dynamic limits experience a loss in return. Our results are in favor of our hypotheses.

Nevertheless, it can be argued that the return gain or loss of reaching limits is subsequent of historical event. Thus, to avoid any speculations, we look at stock return one day before and after the event day. Our results still hold that stocks that reach the upper static or dynamic limits experience a gain in return, while stocks that reach the lower static or dynamic limits experience a loss in return.

We also investigate whether stock size plays a role in the impact of static and dynamic VI on stock return. We sort stocks by their size and find that when small stocks reach a static or dynamic limit, they tend to gain higher returns compared to larger stocks.

Table 22 reports the results of estimating equation (12). The dependent variable is the logarithmic return. The independent variables are "**Static Upper**" which is a dummy variable that equals one if any of the conditions in (1a) or (1b) is met and zero otherwise, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Large Market Cap	**Small Market Cap**
	Log (Return)	
Static Upper	**0.14** [a]	**0.16** [a]
	(11.35)	(13.24)
B/M	**- 0.0003** [b]	**- 0.003** [a]
	(-2.09)	(-4.09)
Size	**1.17e-08** [a]	**1.52e-06** [a]
	(4.20)	(3.88)
Lagged Return	**- 0.04** [a]	**- 0.12** [a]
	(-5.63)	(-4.75)
Illiquidity	**- 0.0003** [a]	**- 0.0002** [b]
	(-4.18)	(-2.11)
VOL	**3.90** [a]	**0.26**
	(7.98)	(0.31)
ROE	**0.001**	**0.01** [a]
	(1.32)	(4.61)
Firm fixed effects	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**
N	**137,828**	**98,679**
Adj R^2	**4.37%**	**20.45%**

a) significant at 1% , (**b)** significant at 5% and (**c)** significant at 10%

Table 23 reports the results of estimating equation (12). The dependent variable is the logarithmic return. The independent variables are "**Dynamic Upper**" which is a dummy variable that equals one if any of the conditions in (3a), (3b) or (3c) is met and zero otherwise, "**B/M**" Book-to-market ratio calculated as the book value per share relative to the closing price, "**Size**" is the market value "in thousands of Swedish Krona" calculated as the stock closing price times the number of ordinary shares in issue, "**ILLIQ**" is Amihud's (2002) illiquidity measure calculated as the ratio of the absolute daily stock return over the Krona traded volume for each stock, "**VOL**" is the simple volatility, and "**ROE**" is firm return on equity. In parentheses are t-statistics calculated using Rogers' (1983, 1993) corrected standard errors. The sample period is from September 30, 2010 to December 29, 2017 for 344 stocks listed in Nasdaq Stockholm.

	Large Market Cap	**Small Market Cap**
	Log (Return)	
Dynamic Upper	**0.056** [a]	**0.071** [a]
	(28.66)	(19.09)
B/M	**- 0.0002**	**- 0.003** [a]
	(-1.23)	(-4.63)
Size	**1.27e-08** [a]	**2.45e-06** [a]
	(3.64)	(4.49)
Lagged Return	**- 0.04** [a]	**- 0.10** [a]
	(-6.15)	(-3.42)
Illiquidity	**0.0004** [a]	**0.001** [a]
	(3.54)	(5.92)
VOL	**-5.95** [a]	**-14.94** [a]
	(-7.49)	(-11.85)
ROE	**0.003** [a]	**0.01** [a]
	(3.57)	(4.45)
Firm fixed effects	**Yes**	**Yes**
Time fixed effects	**Yes**	**Yes**
S.E. Clustered by	**Firm**	**Firm**
N	**137,828**	**98,679**
Adj R^2	**18.17%**	**28.16%**

a) significant at 1% , (**b)** significant at 5% and (**c)** significant at 10%

References

Abad, D. and Pascual, R., 2010. Switching to a temporary call auction in times of high uncertainty. Journal of Financial Research, 33(1), pp.45-75.

Abad, D. and Pascual, R., 2013. Holding back volatility: circuit breakers, price limits, and trading halts. *Market Microstructure in Emerging and Developed Markets: Price Discovery, Information Flows, and Transaction Costs*, pp.303-324.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets, 5(1),* pp.31-56.

Amihud, Y., Hameed, A., Kang, W. and Zhang, H., 2015. The illiquidity premium: International evidence. *Journal of Financial Economics, 117(2),* pp.350-368.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61, 259–299.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang. 2009. High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence. *Journal of Financial Economics* 91:1–23.

Arak, M., R. E. Cook, 1997, Do Daily Price Limits Act as Magnets? The Case of Treasury Bond Futures, *Journal of Financial Services Research* 12:1 5-20.

Bali, T., & Cakici, N. (2008). Idiosyncratic Volatility and the Cross Section of Expected Returns. *Journal of Financial and Quantitative Analysis*, 43(1), 29-58. doi:10.1017/S002210900000274X

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31, 307–328.

United States. Presidential Task Force on Market Mechanisms and Brady, N.F., 1988. *Report of the presidential task force on market mechanisms*. US Government Printing Office.

Brugler, J. and O. Linton, 2014, Single Stock Circuit Breakers on the London Stock Exchange: Do They Improve Subsequent Market Quality*? Working Paper, University of Cambridge.*

Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of Finance, 52(1),* pp.57-82.

Chang, E.C., Dong, S., 2006. Idiosyncratic volatility, fundamentals, and institutional herding: evidence from the Japanese stock market. *Pac. Basin Financ*. J. 14 (2), 135–154

Cho, D.D., Russell, J., Tiao, G.C., Tsay, R., 2003. The magnet effect of price limits: Evidence from high-frequency data on Taiwan Stock Exchange. *Journal of Empirical Finance 10*, 133-168.

Chua, C., Goh, J. and Zhang, Z, 2010. Expected Volatility, Unexpected Volatility and the Cross-section of Stock Returns. *Journal of Financial Research, 33(2)*, 103-123.

Deb, S.S., Kalev, P.S. and Marisetty, V.B., 2010. Are price limits really bad for equity markets? *Journal of Banking & Finance, 34(10),* pp.2462-2471.

Deb, S.S., Kalev, P.S. and Marisetty, V.B., 2017. Price limits and volatility. *Pacific-Basin Finance Journal, 45*, pp.142-156.

Duffee, G.R., 1995. Stock returns and volatility a firm-level analysis. *Journal of Financial Economics*, *37(3)*, pp.399-420.

Fabozzi, F.J., Fung, C.Y., Lam, K. and Wong, W.K., 2013. Market overreaction and underreaction: Tests of the directional and magnitude effects. *Applied Financial Economics, 23(18),* pp.1469-1482.

Fama, E.F., 1989. Perspective on October 1987, or What did we learn form the crash?. *Black Monday and the Future of the Financial Markets, Irwin, Homewood, III*.

Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of financial Economics*, 91(1), pp.24-37.

George, T.J. and Hwang, C.Y., 1995. Transitory price changes and price-limit rules: Evidence from the Tokyo Stock Exchange. *Journal of Financial and Quantitative Analysis*, 30(2), pp.313-327.

Diacogiannis, G.P., Patsalis, N., Tsangarakis*, N.V. and Tsiritakis, E.D., 2005. Price limits and overreaction in the Athens stock exchange. *Applied Financial Economics, 15(1),* pp.53-61.

Kwon, KY., Eom, KS., La, SC., and Park, JH., 2018. The role of dynamic and static volatility interruption: Evidence from the Korean stock markets. *Working paper, University of California, Berkeley.*

Kim, Kenneth A, and Jungsoo Park, 2010, Why do price limits exist in stock markets? A manipulation-based explanation, *European Financial Management* 16, 296–318.

Kim, K.A. and Rhee, S.G., 1997. Price limit performance: evidence from the Tokyo Stock Exchange. *the Journal of Finance*, 52(2), pp.885-901

Kim, YH., Yang, JJ., 2003, price limits and overreaction. *Working Paper, University of Cincinnati*

Leach, J.C, and A. Madhavan, 1993, "Price Experimentation and Security Market Structure," *Review of Financial Studies*, 6, 375-404

Lehmann, B.N., 1989. Commentary: Volatility, price resolution and the effectiveness of price limits. *Journal of Financial Services Research* 3, 205–209.

Lins, Karl V., Henri Servaes, and Ane Tamayo, 2017, Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. The Journal of Finance.

Ma, Christopher K., Ramesh, P. Rao, and R. Stephen Sears, 1989a, Volatility, price resolution, and the effectiveness of price limits, *Journal of Financial Services Research* 3, 165-199.

Madhavan, A., 1992. Trading mechanisms in securities markets. *the Journal of Finance*, *47(2)*, pp.607-641.

Malkiel, Burton G., and Yexiao Xu, 2003, Investigating the behavior of idiosyncratic volatility, *Journal of Business* 76, 613-644.

Merton, R., 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42, 483–510.

Miller, M.H., Hawke Jr, J.D., Malkiel, B. and Scholes, M., 1987. Preliminary Report of the Committee of Inquiry Appointed by the Chicago Mercantile Exchange to Examine the Events surrounding October 19, 1987. *Chicago Mercantile Exchange*.

Harris, L., 1998. Circuit breakers and program trading limits: What have we learned. *Brookings-Wharton papers on financial services*, *63.*

Rogers, W. H., 1983, Analyzing complex survey data, *Rand Corporation memorandum*, Santa Monica, CA.

Rogers, W. H., 1993, Regression standard errors in clustered samples, *Stata Technical Bulletin Reprints* STB-13 – STB-18, 88-94.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19(3)*, pp.425-442.

Spiegel, Matthew I. and Wang, Xiaotong, 2005. Cross-Sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk. *Yale ICF Working Paper No. 05-13; EFA 2005 Moscow Meetings Paper*.

Subrahmanyam, A., 1994. Circuit breakers and market volatility: A theoretical perspective. *Journal of Finance* 49, 237–254.

Tooma, E.A., 2011. The magnetic attraction of price limits. *International Journal of Business*, *16(1)*, p.35.

U.S. Securities and Exchange Commission, 1988. The October 1987 market break. *A report by the Division of Market Regulation.*

Yang, Nien-Tzu., Chu, Hsiang-Hui., Ko, Kuan-Cheng., Lee, Shiou-Wen, 2018, Continuing Overreaction and Momentum in a Market with Price Limits, *Pac. Basin Financ*. J. 48 (2018), 56–71.

Yao, J., Ma, C., He, W.P., 2008. Investor herding behavior of Chinese stock market. *International Review of Economics and Finance*. 29, 12–29

Zimmermann, K., 2013, Price Discovery in European Volatility Interruptions, *Working Paper, Goethe University Frankfurt*.

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