Financial Volatility and The Leverage Effect

A study of the Swedish Stock Exchange

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Finansiell Volatilitet och ”Leverage-effekten”
En studie av den svenska aktiemarknaden

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Abstract
In today’s financial markets, volatility is a fundamental concept in regards of the risk assessment of assets and instruments. Financial volatility is commonly used to measure the quantitative aspects of risk and is given a significant amount of attention in past literature and research. The leverage effect refers to the well-established negative relationship between return and future volatility. The relation is usually explained by the increased leverage ratio that arises from a drop in the share price for a firm. A lower price means lower value of the equity and while the debt remains unchanged, the leverage ratio will rise. The leverage ratio affect how risky the equity is from an investor’s perspective, hence affects the volatility of the stock. This paper aims to analyse whether the theory is applicable on the Swedish stock exchange and takes both individual stocks and the OMXS30-index into account. Further theories related to the model is acknowledged in order to enhance the analysis of the findings. The study is performed by a regression model where volatility, estimated through an EGARCH model, represents the dependent variable. Lagged return, together with a number of control variables, constitutes the explanatory variables. The findings claims that the leverage effect is present for individual stocks but can be rejected on the index level. Additionally, significant improvement was noticed when a dynamic approach was added to the model. The conclusions drawn is that the Swedish stock exchange facilitates the leverage effect for individual firms but it is off-set by other theories such as risk-return trade-off and volatility clustering for the index.

Key-words
Volatility, Leverage effect, Risk, Return, Clustering, Modigliani and Miller, EGARCH, Capital structure, Leverage ratio
Sammanfattning

Nyckelord
Volatilitet, Leverage-effekt, Risk, Avkastning, Klustring, Modigliani and Miller, EGARCH, Kapitalstruktur, Skuldsättningsgrad
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Foreword

To begin with, we would like to enlighten our gratitude towards our mentor, Ulrika Stavløt at the Royal Institute of Technology for invaluable input and support throughout the thesis process. We would also like to thank Kristofer Månsson at Jönköping University for valuable support and insights related to our models. Not to forget, we would like to thank our fellow students at the Royal Institute of Technology for valuable discussions and advice.
1 Introduction

1.1 Background

In today’s financial markets, volatility is a fundamental concept in regards of the risk assessment of assets and instruments. The financial volatility is commonly used to measure the quantitative aspects of risk and is given a significant amount of attention in past literature and research.

While the most common view is that higher volatility will impose higher expected returns in order to cover up for the increased risk, Bae et al. (2007) showed in their study that increased volatility went hand in hand with lower expected returns on stocks. They further stressed the fact that the relationship between these factors are problematic to disentangle. In financial markets, the risk and return on investments are essential for participants involved in the valuation of an asset. The trade-off between risk and return have previously been widely studied. As mentioned, most common is that a larger expected return are required from the investor if the risk of the asset is relatively high (Glosten et al. 1993). Numerous studies have highlighted the importance of volatility management during the recent years. Financial volatility has been ranked as the highest emerging risk in the 2012 fifth annual survey of emerging risks. (Ladd 2012) The survey stated that volatility was one of top three concerns among almost three quarters of the respondents. In a similar study, Sawers (2012) showed that the reduction of earnings volatility was, once again, one of top three main objectives for over 90% of the respondents. The research was conducted on corporate treasurers around the world and offers a hint of just how widespread the matter is.

The negative relation between risk and return is by now more or less generally acknowledged and the dynamic behaviour of this risk has been given increased attention during the past years. As showed, volatility is of high concern for practitioners and decision makers in the industry and the ability to forecast stock market volatility is vital in the timing of investment decisions. Of course, forecasting of a specific phenomena requires an understanding of what triggers it in the first place and extensive efforts are made trying to determine the drivers behind financial volatility. (Hamilton & Gang 1996) Analyses of market behaviour and risk is continuously performed by actors within the industry. Large Swedish and Nordic banks like Nordea and SEB continuously performs macroeconomic analyses for both internal and external use. This highlights the major efforts put into risk analyses in order to accurately decide which level of
risk that optimally should be utilized in terms of investment decisions (Nordea Markets 2018)(SEB 2018). Hence, it is of great value for financial institutions, banks and corporations to deeper understand the precedes of stock volatility to use their resources as efficiently as possible and provide transparent and accurate advice to their clients.

As demonstrated above, several studies have been conducted examining drivers behind stock market volatility. This thesis aim to focus on one effect in particular, the leverage effect. According to the leverage effect, as first stated by Black (1976), there is a negative relationship between current return and future volatility. Black (1976) argues that this relation derives from the increased debt-ratio that arises when stock prices goes down and the value of equity decreases. While Black (1976), Christie (1982) and Duffee (1995) argues that they found evidence of the leverage effect as such, other researchers have discussed additional causes to the relation. Hence, the objective of this paper is to decide whether the return is significant as an inverse driver of future volatility on the Swedish stock exchange. The findings state that there is a negative and significant relationship between lagged return and volatility for firms on an individual level, hence the leverage effect is assumed to be present. In contrast, the leverage effect could not be proven on an index level where the relation between return and future volatility was found to be positive.

1.2 Objective and Purpose

The main purpose of this paper is to investigate if the leverage effect holds for the Swedish stock market. More precisely, if there is a negative relation between stock return and future stock volatility. The ability to forecast risk appropriately when taking on new investments is of great importance in order to be efficient and profitable on the market for both large institutions and private consumers. Understanding how and why the volatility fluctuates is a key factor when efficiently forecasting future risk. This paper provides additional and significant information to actors within the Swedish financial industry, enhancing their ability to forecast future risk. While previous research is focused primarily on the US market and to a small extent Chinese, European and Korean markets, this paper extends the literature by engaging solely in the Swedish stock exchange. It provides more accurate information to investors on the Swedish market but will also widen the understanding of how the possible existence of a leverage effect might differ on a smaller country, highly dependent on the state of the global economy.
1.2.1 Research Question

Is the leverage effect significantly applicable on the Swedish stock market?

1.2.2 Hypotheses

H0: There is a significant and negative relation between financial volatility and lagged return.

1.3 Limitations

Due to limitations in time and resources, the number of stocks investigated in this research is restricted. The firms included in the research are the ones composing the OMSX30 as of December 2017. The stocks included in the OMXS30 index are the most traded shares on the Swedish stock market. Taking a larger set of stocks into account, including smaller and more illiquid shares, could have provided us with different results. Further, there are most likely room to extend the estimators in order reach even more efficient results. Lastly, this paper is limited to examine the leverage effect only. Volatility is an extensive subject and is most likely dependent on a large number of factors beyond those included in this model.

1.4 Ethical and sustainable application

This thesis is relevant from an ethical and sustainable perspective in terms of transparency and integrity on the financial market. Increased awareness of factors affecting the movements and volatility of the market will yield higher transparency. A greater understanding within this area is beneficial for both institutional and private investors in terms of risk management and return on investment. Sustainability and transparency on the financial markets are currently a relevant subject and the implementation of regulations like MIFID II and GDPR are some examples of that (Finansinspektionen 2018). Hence, this research is an important factor in the progress towards a more open, transparent and sustainable stock market.

1.5 Structure of the Paper

This paper will start by presenting the theory related to the research question and then continue with an overview of previous research and their findings. The theoretical framework presents theories, related to volatility and the leverage effect, that will have an impact on the study and the interpretation of the results.
Further, the methodology is presented and the models, control variables and the data-set is described in detail. The result section objectively goes through the findings, starting of by presenting the results related to individual shares, later moving on to the results of the OMSX30 index. Finally, a discussion is held based on the results in accordance the theoretical framework and previous literature and is followed by concluding remarks as well as suggestions for future research.
2 Theoretical Framework

The theoretical framework section presents theories related to volatility and the leverage effect that will have an impact on the study and the interpretation of the results.

2.1 Financial Volatility

It is today well known that the volatility of financial markets is of a dynamic nature that changes with time. The fact that it is fundamental in most risk and return theories make the drivers behind it vital to study. (Lettau & Y. Campbell 1999) Attempting to assess the affecting factors of the time-varying volatility in the market is a widespread interest of research but unfortunately not always successful (Hamilton & Gang 1996).

Volatility can be explained in both a mathematical and a non-mathematical perspective and before moving further into previous research on the subject, it is important to clarify what it meant by financial volatility. Auinger (2015) defines volatility as "the tendency for prices to change with respect to new information regarding the value of the underlying asset or due to the demand for liquidity by impatient traders". The mathematical perspective of volatility is often measured as the standard deviation ($\sigma$) of the return, or the square root of the variance ($\sigma^2$).

\[ Var(R) = \frac{1}{N} \sum_{i=1}^{N} (R_i - \overline{R})^2 \quad (1) \]

Standard Deviation($\sigma$) = $\sqrt{Var(R)} \quad (2)$

Equation 1 shows the calculations for the variance of the returns. The standard deviation is then received by taking the square root of the variance, as shown in equation 2.

2.1.1 Volatility Types

When measuring volatility it is sometimes important to define which type of volatility that is suitable for the specific occasion. Normally, one can distinguish between three different types of volatility namely, realized volatility, model volatility and implied volatility. Realized volatility is also called "historical volatility" and is determined using past volatility observations. However, the volatility variable in this paper is mostly concerned with the model volatility in terms of the EGARCH model applied to determine the financial volatility. Model volatility
ca be calculated by data and is a virtual variable used in theoretical models which is accurate in this case. (Auinger 2015) Further, implied volatility is a measurement supposed to reflect the underlying asset's forecasted volatility by taking reported option prices into consideration (Blenman & Wang 2012). This paper takes implied volatility into account in terms of the VIX-index used as a control variable in the regression analysis. The VIX-index reflects the rates of the S&P500 options (Cboe 2018) and is an implied volatility measurement for the S&P500 index.

2.1.2 Volatility Clustering

Volatility is shown to be an appropriate predictor of future volatility since periods of high volatility are usually followed by periods of high volatility. In the same way, low volatility precedes periods of low volatility. This phenomena is referred to as "volatility clustering" and is of great utility when aiming to understand and forecast the patterns of volatility (Zabiulla 2015). Oh et al. (2007) studied volatility clustering behaviours on the S&P500 index as well as the 28 stocks on the NYSE with largest liquidity during the years 1993 to 2002. They showed in their study that the degree of volatility clustering was reduced significantly when the GARCH(1,1)-model was applied to the financial time series.

2.2 The Leverage Effect

The leverage effect states that there is a negative relationship between stock return and future volatility. The theory claims that a price drop in a certain stock will decrease the value of the firm’s equity, hence increase the leverage-ratio since the value of the debt will remain the same. The increased leverage-ratio will, in turn, impose higher risk on the equity and the stock will be more volatile during next period. Reasons for the price drop in first place can be company announcements or other news related to the stock or industry. (Black 1976) The theory stands in direct relation to other theories, such as the capital structure of a firm, which will be explained in more detail later on.

2.2.1 The Leverage Effect vs. The Volatility Feedback Model

The causal relationship between the volatility and stock return is hard to disentangle. While the leverage effect argues that the relation between the two variables is of negative nature and explains why a negative return leads to increased volatility in the next period (Black 1976) (Christie 1982), the volatility feedback theory provides an alternative explanation to the phenomena. The
volatility feedback theory suggests that larger volatility in one period provides negative returns in the next period (Bollerslev et al. 2006).

2.3 Capital Structure and Expected Return

Model 4 and 3 below are vital parts of the valuation of a firm and usually used in corporate finance literature (Berk 2016). The models consist of information in terms of expected return on equity and the effect of capital structure on the pricing of a stock. The capital structure is defined as the relationship between debt and equity, in other words, how much of the capital that consists of debt versus equity. This division between debt and equity affects the valuation of a firm in terms of return on investment \( r_{WACC} \), as stated in equation (3) below. The WACC formula emphasizes that changes in the expected return of equity and debt, along with the capital structure of the firm, directly affect the expected return on the investment, \( r_{WACC} \), and is the discount rate to which a firm’s future cash flows are discounted in order to calculate the present value of the firm.

\[
r_{WACC} = \frac{E}{(E + D)} \cdot r_e + \frac{D}{(E + D)} \cdot r_d \cdot (1 - \tau)
\]  

(3)

The Capital Asset Pricing Model (CAPM) (4) is used to calculate the expected return on equity \( r_e \). The return on equity is directly affecting the \( r_{WACC} \) and the valuation of a firm. The CAPM-model consists of the risk free rate \( r_f \), the beta of the firm \( \beta \) and the risk premium \( (R_m - r_f) \). More often than not, a firm specific risk premium is additionally added to the CAPM-model to estimate the final expected return on equity. (Berk 2016).

\[
r_e = r_f + \beta (R_m - r_f)
\]  

(4)

As illustrated by these two models, both risk and capital structure is highly relevant to the valuation of a firm. If one were supposed to evaluate a stock, the capital structure of the firm as well as the risk would be taken into consideration and affect the final value.

2.4 The Modigliani and Miller (MM) Propositions

The Modigliani and Miller (MM) (Modigliani 1958) theory argues a classic principle regarding the relationship between capital structure of a firm and its total value. The principle states that a firm with leverage should have higher equity volatility than it would have on its total value otherwise. The relationship between leverage and equity will impose systematic and asymmetric stock volatil-
ity returns. A negative stock return will increase firm leverage due to decreasing value of equity and fixed debt and will result in increased equity volatility. The reversed will be true for positive returns. This theory are according to Modigliani (1958) only valid in perfect capital markets. Below are the definition for perfect capital markets as well as the two MM-propositions stated.

Cited definition of perfect capital markets (Modigliani 1958):

1. Investors and firms can trade the same set of securities at competitive market prices equal to the present value of their future cash flows.

2. There are no taxes, transaction costs, or issuance costs associated with security trading.

3. A firm’s financing decisions do not change the cash flows generated by its investments, nor do they reveal new information about them.

**MM Proposition I**: In a perfect capital market, the total value of a firm is equal to the market value of the total cash flows generated by its assets and is not affected by its choice of capital structure.

**MM Proposition II**: The cost of capital of levered equity increases with the firm’s market value debt-equity ratio.

As illustrated above, the MM principle I states that firms with leverage exhibits increased risk of equity. However, leverage does not affect the total value of the firm, meaning that the allocation between debt and equity in terms of cash flow has drifted. Thereby, equity holders will require a higher return in opposite to the debt holders due to the higher risk concerning their investment.

The four equations 5, 6, 7 and 8 below explains the relationship between total firm value, debt and equity. The first equation (5) illustrates the first step in the proposition made by MM. Where, E=Market value of equity, D=Market value of debt, U=Market value of unlevered Equity, A = Market value of a firms total assets. This equation states that regardless of the firm being leveraged or not, the total value of all assets equals the total market value of the firm. The second equation (6), represents the WACC-rate but differ from equation (3) in terms of taxes. Equation (6) is influenced by perfect capital markets, hence no taxes are accounted for to fit the proposition made by MM. Equation, (7) can be derived from (6) by solving for $R_E$. It contains the return of levered equity and provides an illustration of the effect of leverage on the return. The equations indicates that the unlevered return plus an additional value, added to account for the risk
of leverage, equals the levered return. This relation illustrates that the return of levered equity increases when stock prices are increasing (\(R_u > R_D\)), and the opposite is accurate when prices decrease (\(R_u < R_D\)). This relationship is true for realized return according to MM and are also valid for expected return. (Modigliani 1958).

\[
E + D = U = A
\]  

\[
R_U = \frac{E}{(E + D)} \cdot R_E + \frac{D}{(E + D)} \cdot R_D
\]  

\[
R_E = \underbrace{R_U}_{\text{Risk without leverage}} + \underbrace{\frac{D}{E} \cdot (R_U - R_D)}_{\text{Additional risk due to leverage}}
\]

\[
r_E = r_U + \frac{D}{E} \cdot (r_U - r_E)
\]

Even though the theories of Modigliani (1958) somewhat contradicts the arguments of the leverage effect, it provides a basic understanding of the relation between capital structure, risk and return. Several authors have based their research of the leverage effect on theories and assumptions from the MM propositions Christie (1982) and it is important to distinguish the causal relationship between volatility and return. While the MM theory take the effect of volatility on expected return into consideration, the leverage effect focuses on how the return affects future volatility. The theory is also widely used in textbook literature regarding firm valuation and corporate finance. (Berk 2016).

### 2.5 Risk-Return Trade-off

To what is known this far, the causal relation between the return and volatility generates quite different results. While the leverage effect argues for a negative relation between return and future volatility, the MM-theory states that increased volatility affects expected return positively. This theory is also known as the Risk-Return Trade-off. A risk averse investor wants to discount the cash flows of an risky investment with an appropriate risk premium in addition to the interest rate. The market risk premium is the expected return of the market portfolio minus the risk free rate as shown in section 2.3, equation 4. The rate of this risk premium will be higher when the risk is higher and vice versa. Thereby, the investor will only hold a more volatile stock or portfolio if they ex-
pect to receive and earn a higher return. (Berk 2016)

Figure 1 below, illustrate a fictional relationship between the expected return and the risk in terms of volatility. The expected return are located on the y-axis with increasing values and risk on the x-axis, also with increasing values. The line illustrates how the expected return rises as the volatility increases. The holdings in the figure is placed according to their level of risk. As example, a Treasury bill is often referred to as the risk free rate. It is considered to have very low risk and according to the figure, it also has the lowest expected return. However, the "Stocks Small Cap" holding is interpreted as riskier and investors expect a higher return given the higher volatility.

![Figure 1: Risk-return Trade-off](image)

The theory and the positive relationship between volatility and return has been accepted by some (French et al. 1987) and discarded by others (Glosten et al. 1993). The results related to this fundamental principles can possibly be explained by other theories. The negative relationship argued by the leverage effect, discards the Trade-Off theory to some extent and can be explained by the financial state of firms. For example, a firm with previous value losses are related to the negative relationship while a firm in which investors recently experienced gains are related to the positive relationship. One possible explanation of this could be that some investors are effected by reference-dependent presence, a phenomena related to behavioural finance. These investors might discard the normal preference and traditional view of a positive risk-return relationship as stated by the Trade-off theory. (Wang et al. 2017)
3 Literature review

This chapter provides an overview of previous research and empirical studies, with main focus on volatility and the leverage effect.

3.1 Financial Volatility

To answer the research question of this thesis, an overall understanding of financial volatility is crucial to understand the drivers behind it. Research related to financial volatility have frequently analysed different macroeconomic variables and their effects on volatility. According to William Schwert (1989), the stock market volatility is interesting to study since the fluctuations impact the business cycle through fundamental variables such as consumption and capital investments. William Schwert (1989)’s findings indicates that macroeconomic factors such as the interest rate and bond prices influences the volatility. However, even though his results indicated quite small effects on the volatility, the foundation of the study has been fundamental to many studies in this area. William Schwert (1989)’s research is based on the theory of future cash flows, a model commonly used in company valuation. The literature and theories on stock valuation usually stresses the interest rate as an important fraction of the model, meaning that the risk-free rate should have a direct impact on the expected value of the stock (Berk 2016). Beltratti & Morana (2006) argues that changes in monetary policy has a significant impact on stock return volatility, indicating that money growth and the interest rate affects the volatility of the financial returns. A significant amount of research has been dedicated to examining the relation between the market volatility and expected stock returns. Diebold & Yilmaz (2008) conducted a cross country study were a possible link between time-average volatility and fundamental volatility were analysed. Using consumption and real GDP as fundamental factors, the study provided indications of a relation between the macroeconomic factors and the financial volatility. Further, the relationship between exchange rate volatility and stock volatility is examined by Kennedy & Nourzad (2016). With the volatility of S&P500 as an dependent variable they set up a model with several macroeconomic control variables to adjust the model accordingly. Their research concluded that the exchange rate had a significant affect on the financial volatility of the stock market.
3.2 The Leverage Effect

3.2.1 Origin of the Leverage Effect

The empirical literature and on volatility modeling has mainly concerned the relationship found between stock market returns and volatility. However, the fundamentals behind the observed relation has been frequently discussed and findings is not fully consistent between the studies (Bollerslev et al. 2006). The negative relationship between stock return and stock return volatility has by now been documented in a number of empirical studies that aims to prove the relation but also to provide an explanation to it. The leverage effect is one of the frequently acknowledged theories used to explain the relation. Black (1976) were first to observe and discuss this phenomena and is often seen as the originator of the literature on the leverage-effect. According to Black (1976), the leverage effect claims that a price drop would increase the firms leverage ratio, hence, the volatility of equity will increase, making the stock less valuable and pushing the price down. Christie (1982) extends Black (1976)’s paper by putting further effort in understanding the background to the relation. He aims to expand the literature by looking into the Modigliani and Miller theory mentioned in section 2.4. Christie (1982) studies the relation between the variance of equity returns and several explanatory variables and finds that equity variances have a strong positive relation on both financial leverage and interest rates. In other words, Christie (1982) illustrates a negative relation between the value of equity and volatility, which he concludes to be strongly attributable to the leverage effect.

Duffee (1995) continued the research of Christie (1982). He found evidence of a strong and positive relation between the current stock price return and current volatility, but further strengthened the findings of Black (1976) and Christie (1982) by showing a negative relation between lagged stock returns and financial volatility. Like Black (1976) and Christie (1982), Duffee (1995) conducted his study on the US stock market. The data set consisted of daily returns for 2 494 firms stocks traded on NYSE or AMEX between 1977-1991. Duffee (1995)’s study were conducted on a broader set of data, including both large and small firms in contrast to previous research by Black (1976) and Christie (1982) who both focused solely on larger firms. Duffee (1995)’s research was based on a multifactor model using frequencies of both monthly and daily stock returns.

Similar to Black (1976), Duffee (1995) and Christie (1982), French et al. (1987) examines the relation between stock market volatility and stock returns on the
US market. Using daily returns of NYSE common stocks over 1928-1984, French et al. (1987) find that the market risk premium (defined as the expected stock portfolio return less the Treasury bill yield) is positively correlated to the stock return volatility. Their findings show a positive relation between ex-ante volatility and the expected risk premium, which in turn will impose a negative relation between changes in the volatility and the period return. However, even though French et al. (1987) show evidence of a leverage effect, they suggest that alternative explanations of the relation should be concerned due to the large variability of realized stock returns. They argue that the negative relation between returns and changes in volatility in fact are too big to be explained solely by those terms.

3.2.2 Recent studies

Bouchaud et al. (2001) extends the work of Black (1976) and Christie (1982) while investigating the leverage effect quantitatively. They differentiate the outcome by looking at both indices and individual stocks. Investigating both the US market, in terms of 437 stocks constituent of the S&P 500 index, and seven major international indices (S&P 500, NASDAQ, CAC 40, FTSE, DAX, Nikkei, and Hang Seng), they find the relation to be of different amplitude between the two groups. The negative correlation between returns and future volatility is much stronger for indices while more moderate for individual stocks (Bouchaud et al. 2001).

The causality of the relation between risk and return has also been of interest in previous literature. (Bollerslev et al. 2006), (Lee 2012), (Carr & Wu 2017) investigated the reversed causal relation, sometimes referred to as the volatility feedback theory. In opposite to Black (1976), Christie (1982) and Duffee (1995) who state that the return effects volatility in the next period, the volatility feedback theory implies that increased volatility induces a higher risk of the stock which makes it less attractive and pushes down the stock price. Bollerslev et al. (2006) builds on previous work by examining the negative relationship using high-frequency aggregate equity index data. While the research so far has almost exclusively focused on daily returns, Bollerslev et al. (2006) suggests an improvement by looking at five-minute returns on the S&P500 index. They argue that low-frequency data makes the causal relation between volatility and return more difficult to distinguish due to the immediate relation appearance. In contrast, high-frequency data allows to differentiate between the leverage effect and the volatility feedback mechanism more clearly. In line with previous research, the results of Bollerslev et al. (2006) reveal a negative correlation be-
tween current and lagged returns and volatility. What is new for this study is the correlation between lagged volatility and the returns. The correlation between the two turns out to be close to zero, hence could work as evidence of a non-existent feedback volatility effect. Together with the negative correlation proved to exist between current and lagged returns and volatility, it strengthens that the leverage effect is more significant at an intra-day level. Hence, Bollerslev et al. (2006)'s findings are consistent with the leverage effect documented in existing literature.

While most research in this area has been conducted on the US market, Lee (2012) investigate the leverage effect and its causality using time series from the Korean Composite Stock Price index through the period November 1997 to September 2010. The measurements are taken from the cross-correlation coefficient of different time lags, based on the time series of return and volatility. This resulted in a negative correlation between future volatility and past return. Lee (2012) used the absolute value of the return instead of the root mean square value when calculating volatility. Similar to Bollerslev et al. (2006), the author also investigated the direction of the hypothesized causal relation between lagged volatility and return, the volatility feedback effect. However, in line with the findings of Bollerslev et al. (2006), Lee (2012) showed the causal relation to exist rather between the lagged return and volatility, as argued by the theory of the leverage effect.

Figlewski & Wang (2000) is one of the more recent papers concerning the relation between stock returns and the volatility of returns by extending the work of Black (1976), Christie (1982), French et al. (1987) and Duffee (1995) among others. In their paper, Figlewski & Wang (2000) aim to establish whether the so called “leverage effect” actually is an effect of leverage. The conclusion drawn is that leverage is one explanation of the phenomena but not the only one. In order to reach this conclusion Figlewski & Wang (2000) examine daily returns of stocks constituting the S&P100 index in December 1992, but also the returns of the index itself. In the research, Figlewski & Wang (2000) consider both the realized and implied volatility. The data of realized volatility were sampled between the years 1977-1996 while the implied volatility covered a shorter time period during the years 1991-1996. A simple regression analysis were conducted with the natural log of the realized volatility (computed on a monthly basis) as the dependent variable and the logarithmic return of the underlying stock (or index) on the right hand side. The results suggested a negative relation on both a monthly and quarterly interval which could work as an indication of an existent leverage effect. However, the coefficient is not statistically signif-
icant. To extend the analysis, a “down market” dummy variable is included in order to decide whether the effect is stronger when the returns are negative. This time, Figlewski & Wang (2000) showed that a change in the “leverage effect” is noticeable when the “down market” dummy is included. They argue that the theoretical relationship between financial leverage and volatility should be symmetrical to both positive and negative moves in the market and states that this clearly is contradicted by their results. A very strong effect was obtained on the realized volatility when the returns are negative but a “reverse” leverage effect emerged with positive returns. The results found indicated that the volatility increased even when market moves were positive. This results were the same for both the index and individual stocks and open up for future discussions and further research within this area.

Carr & Wu (2017) argue in their paper that the variation in the equity index volatility interacts with the index return from any of three possible channels. Thereby, they propose a model to examine each relative contribution. First, they mean that the volatility of an index increases with the aggregate financial leverage of the the market. Second, they argue a negative relation between return and volatility of an index, deriving from positive volatility shocks that increases the cost of capital and hence, reduces the valuation of future cash flows. This can be referred to as the volatility feedback model also analyzed by Bollerslev et al. (2006) Lee (2012), and further argues that the relation exists regardless of the level of leverage. Third, large negative market disruptions show self-exciting behaviors. Looking at both S&P500 index options as well as individual stock options for five selected companies, Carr & Wu (2017) concludes that the leverage effect has the largest impact on long-dated options while the volatility feedback effect shows itself mainly in the short-term options. When looking at individual companies, the leverage effect has stronger presence for companies with a more passive behaviour to capital structure and is weaker for companies, like banks, that more actively manage their capital structure.
4 Methodology

A quantitative approach is applied to answer the research question of this paper. The coming section will begin with an explanation of the data set and models applied in order to investigate the possible existence of a leverage effect on the Swedish stock market. Further, a short explanation of the volatility estimation model and reason of its applicability.

4.1 Empirical Model

Examining the relation imposed by the leverage effect, a regression analysis will be conducted to study the effect of lagged return on volatility while controlled for by a number of control variables. With volatility as dependent variable, the right hand side of the regression will be set up by lagged return of stock prices, change in the VIX-index, the 10 year Swedish government bond and a dummy for market trends. Lagged volatility will in some models be included as a regressor to account for the possible affect previous volatility has on next-period volatility. According to the results of Black (1976), Christie (1982) and Duffee (1995), our regression is hypothesized to predict a negative correlation between the lagged stock return and volatility in order to prove the leverage effect. Hence, in our specified regression model

\[ y_{it} = \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + u_{it} \]  

(9)

where the error term \((u_{i,t})\) equals

\[ u_{it} = \alpha_i + \epsilon_{it} \]  

(10)

we assume the volatility \((y_{it})\) to be negatively correlated with the lagged return \(x_{1it}\), in line with the leverage effect as stated by Black (1976), Duffee (1995) and Christie (1982) etc. To test this relationship, a number of control variables are included. These are interest rate (10-year bond) \(x_{2it}\), the change in the VIX-index \(x_{3it}\) and a bi-variate dummy variable, baisse \(x_{4it}\). The error term \((u_{i,t})\) is divided in two parts and represents both the and the idiosyncratic error \((\epsilon_{it})\) and the individual-specific effects \((\alpha_i)\).

4.1.1 Baisse market

In consistency with the work of Figlewski & Wang (2000), a bi-variate dummy variable representing a negative market, or as we call it, a "baisse market" is included in the regression analysis. The variable is meant to represent the
effect of a negative market on the volatility. It is constructed to take a value of zero in a positive market trend, defined as a stock return greater than 0 \( (r_i > 0) \) and will hence not affect the model. In the case of a negative market trend, defined as a negative return \( (r_i < 0) \), the "baisse" variable will take the value one in order to affect the model results.

4.1.2 The VIX-index

The VIX index, or the Volatility Index, was introduced in 1993 by The Chicago Board Options Exchange (CBOE) (Auinger 2015). It reflects the real time rates of the S&P500 options and is a key measure of the markets expectations of future volatility (Cboe 2018). The S&P500 index consist of 500 American stocks from different major industries (Bloomberg Markets 2018) hence, the VIX index can be seen as a representation of the implied volatility on the US stock market. Our model includes a control-variable representing the change of the VIX-index closing price. The variable is included in order to account for the possibility that the volatility in current period is affected by how the market-expectations of future volatility varies. The variable is therefor expected to have a positive effect on the dependent variable.

4.1.3 Interest rate

The interest rate is concerned in previous research (William Schwert 1989), (Beltratti & Morana 2006), (Berk 2016) as a variable related to volatility but is also included in the theory of firm valuation mentioned in section 2.4. Elyasiani & Mansur (2004) discuss that bank managers, investors etc. take changes of the interest rate into consideration since it might affect the margins of their return. The author conducted studies on the short- and long-term interest rate volatility and its impact on the return and found it to have a significant impact on the portfolios. The change in daily rates of the Swedish 10-year government bond is included in the model since it occurs to have a positive impact on the volatility and firm valuation.

4.2 Estimation of Volatility

In contrast to a direct measures of simple variables such as price, volatility estimations reflects an average value and calculations of volatility involves the challenge to estimate an accurate average. Several statistical models can be used to estimate the volatility and different arguments need to be considered before the estimation is conducted (Sinclair 2013). The GARCH-model has by today become a standard practice when measuring financial volatility (Molnár
The model is particularly suitable for the financial market because it takes conditional clustering into consideration, a phenomena common for financial volatility and explained in 2.1.2. Nelson (1991) proposed an extended GARCH-model with the use of an exponential GARCH (EGARCH)-model for financial time-series. This model is significant in order to capture the asymmetric response to good and bad news. The model does this by interpolating absolute residuals into the conditional variance equation and hence relax the non negative constraints by taking a log form (Nelson 1991). The assymetric relation between return and volatility is captured by the use of an EGARCH-model and has been stressed by several papers (Figlewski & Wang 2000). Implementing an EGARCH-model in the analysis will further extend, and most likely enhance, the work and findings of Figlewski & Wang (2000).

According to the literature presented above, the GARCH-model is suitable when estimating financial volatility since it deals with clustering effects. Further, it is applicable to both time series data and panel data which applies to our model. Furthermore, the EGARCH-model has been shown useful in previous research regarding the leverage effect and the EGARCH (1,1) model will therefor be used for volatility estimation in this thesis.

### 4.3 Description of the Data Set

To our knowledge, no study of the application of a leverage effect have been conducted on the Swedish stock market. The studies so far are mostly conducted on the US market, with some exceptions for indices on the Japanese, Chinese and European market.

To examine the implications of a leverage effect on the Swedish stock market, our data set is sampled from a number of reliable sources. We will examine stocks of major firms, for which the most efficient market pricing can be expected (Figlewski & Wang 2000). Hence, our data set is based on the stocks included in the OMXS30 index as of December 2017, in consistence with the method of Figlewski & Wang (2000). The OMXS30 index consists of the 30 most traded shares on Nasdaq Stockholm and is the most traded index on Nasdaq Nordic exchange. It is a market weighted index, meaning that every share within it affects the index price with a weight proportional to its total market capitalization. Its combined price movements are supposed to reflect the movements of the entire stock market and is therefor considered a good fit to our model. (NASDAQ 2018)
Our dependent variable volatility or the EGARCH estimation of conditional variance, as well as the lagged return are both derived from daily closing prices gathered from Nasdaq Nordic. Daily closing prices of the VIX index are gathered from The Chicago Board Options Exchange (CBOE) (Cboe 2018) and the interest rate, defined as daily rates of the Swedish 10-year government bond, is collected from the Swedish Riksbank (Sveriges Riksbank 2018).

Our analysis and model is divided into two parts. On one hand, we have the pure time series data set consisting of the OMXS30-index itself.

Table 1: Time series data summary

<table>
<thead>
<tr>
<th>Time variable:</th>
<th>time (daily observations 2000 to 2017)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta:</td>
<td>1 unit</td>
</tr>
<tr>
<td>n:</td>
<td>1</td>
</tr>
<tr>
<td>T:</td>
<td>4517</td>
</tr>
</tbody>
</table>

On the other hand, we have a panel data set covering the shares included in the OMXS30-index as of December 2017. To create the data sets, daily closing prices of the 30 stocks included in the index, as well as closing prices of the index itself, between the years 2000-2017 are collected. However, because not all of the shares included in the index as of December 2017 were a part of it for the full 18 years in question, all firms lacking data were dropped in order to reach a balanced data set for the panel-data model.

Table 2: Panel data summary

<table>
<thead>
<tr>
<th>Panel variable:</th>
<th>firm (strongly balanced)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time variable:</td>
<td>time (daily observations 2000 to 2017)</td>
</tr>
<tr>
<td>Delta:</td>
<td>1 unit</td>
</tr>
<tr>
<td>n:</td>
<td>23</td>
</tr>
<tr>
<td>T:</td>
<td>4517</td>
</tr>
</tbody>
</table>

This provides us with a strongly balanced data set, meaning that $T_i = T$ for all $i$ (Cameron 2009) and we end up with a long panel of 23 firms over 18 years with daily intervals (4517 dates), resulting in a panel data set of 103 891 observations. Through the use of panel data as well as time-series, we are allowed to further contribute to previous research in the area by creating a regression model that captures the variation in both time and units (Cameron 2009), building on the work of Figlewski & Wang (2000), Bollerslev et al. (2006), Lee (2012), Kristoufek (2014) and Carr & Wu (2017).
4.3.1 The Panel-Data model

Firstly, our data is analysed, studied and tested to be able to establish the best fitted model for the data set to obtain as efficient results as possible. These tests and the different steps are stated below. The panel data consist of data based on the included individual firms.

Panel data are usually constructed with consistent time intervals. The fact that we have a strongly balanced data set means that we also have consistent time variables. The data set used in this study is a long panel, meaning that it consists of many time periods (18 years, 4517 daily observations) and fewer individuals (23 firms). A possible problem with panel data is that the probability of correlated errors are very high. Consequently, we must keep this in mind when looking at and testing the data. Summing the data set provides us with expected results. The time-invariant variable "firm" has zero within variation while the individual variant variable "time" is a time trend and has zero between variation. Also our control variables baisse market, the change in VIX-index and the 10-year interest rate has zero between variation due to the fact that their values are the same for each and every one of the firms.

When studying our main variables volatility and return, we found both of them to be normally distributed. While the returns are normally distributed with two tails, the volatility estimated as the conditional variance of the returns by the EGARCH model are shown to be normally distributed with one tail.

As shown in figure 2, representing collapsed volatility of the 23 firms included in our panel data set, the conditional variance experience some striking val-
ues, preventing us to overlook the overall trends. After further investigation of our data set we recognised these abnormal values to derive from the SCA’s hygiene brand (Essity) carve-out in June 2017. The carve-out were conducted by a rights issue of Essity shares where one SCA B-share gave one Essity B-share. As a result of this, the stock price of SCA B fell approximately 78% during a single day. (VA Finans 2017) This pattern is clearly visible in figure 3 where firm number 20 represents the returns of SCA B. To be able to follow the overall trends of the collapse volatility, figure 4 is adjusted for the extreme values of SCA B. Here we can recognize an expected pattern where the volatility were considerably high around 2008 and the financial crisis and observably more stable during last years. Still, it is important to have in mind that the trend could be affected by individually deviant values, even though they might be much less significant than the SCA/Essity division.

Figure 2: Conditional variance, Panel data, All firms included
Figure 3: Stock return, Individual firms

Figure 4: Conditional variance, Panel data, Adjusted
In order to acknowledge whether we are experiencing serially correlated standard errors in our panel data model we control for auto-correlation between the dependent variable volatility and its lags on a five order level. The results are shown in table 5 and indicates strongly that the errors are serially correlated. Cluster-Robust standard errors are therefor needed in further estimation and analysis.

Table 5: Auto-correlation for panel-data

<table>
<thead>
<tr>
<th></th>
<th>volatility</th>
<th>L1.vol</th>
<th>L2.vol</th>
<th>L3.vol</th>
<th>L4.vol</th>
<th>L5.vol</th>
</tr>
</thead>
<tbody>
<tr>
<td>volatility</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.gc</td>
<td>0.8090</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L2.gc</td>
<td>0.6567</td>
<td>0.8090</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L3.gc</td>
<td>0.5347</td>
<td>0.6567</td>
<td>0.8090</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L4.gc</td>
<td>0.4368</td>
<td>0.5347</td>
<td>0.6567</td>
<td>0.8090</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>L5.gc</td>
<td>0.3581</td>
<td>0.4368</td>
<td>0.5347</td>
<td>0.6567</td>
<td>0.8090</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

To test for stationary in our model, a Dicker-Fuller unit root test is conducted. The null hypothesis of the test, states that the panels contain unit roots, hence and a rejection of the null hypothesis tells us that the data set is stationary (Cameron 2009). For our model, p-values very close to zero were obtained and the null hypothesis is therefor rejected at a 1% level, meaning that our data set is stationary. Since the mean and variance is constant over time, stationary data provide more reliable results and since the panels are stationary without any lag, further estimations doesn’t necessarily need to take any difference into consideration. Testing for stationary is mainly applied in time series but can also be used on panel data when testing for cross-section heterogeneity (Cameron 2009).

To a large extent, a fixed effects estimator (FE) has been used in previous literature when conducting research on financial panel data (Lee 2010), (Valera et al. 2017). The FE estimator allows for and accept endogeneity to a certain level, meaning that the model allows for correlation between the regressors $x_{it}$ and the individual specific error term $u_i$ (Cameron 2009). Further, a Robust Hausman-test were conducted to test whether random effects (RE) or fixed effects (FE) is more appropriate for the model. Since the regular Hausman-test requires the RE-model to be sufficient, we perform the RobustHausman-test by the method of Wooldrigde which allows for an inefficient RE-model. The null hypothesis states that the RE-estimator is more appropriate for the model, say-
ing that the individual effects are random. (Cameron 2009) In our case we are
able to reject the null hypothesis at a 1% level, meaning that the fixed-effects
model should be used rather than a random-effects model. Hence, this model-
ing starts with a fixed-effect model, fitted for long panels, to establish whether
it is an appropriate estimator for our data. Even though the estimator allows for
some endogeneity in the model, the idiosyncratic error $\epsilon_{it}$ and the regressors
are assumed to be uncorrelated. (Cameron 2009) Due to the existence of
auto-correlation discovered in table 5, robust standard errors are therefor used
in the fixed-effects model. To further support the use of robust standard errors
in our model, we run the Breusch-Pagan/Cook-Weisberg test for heteroskedas-
ticity. The null hypothesis of homoscedasticity or constant variance is clearly
rejected as regards of the test results, hence we can assume to experience
heteroskedasticity in our model, resulting in incorrect default OLS standard er-
rors. (Cameron 2009) To correct for this, robust standard errors should be used.

To further account for the probability of correlation between a given firm over
time and the error term $u_{it}$, cluster robust standard errors are used in estimat-
ing a pooled ordinary least square model. Cluster robust errors are crucial for
panel data estimation since the use of default standard errors could provide
us with misleadingly small results. However, due to the probable correlation
between the the lagged dependent variable and the error term $u_{it}$, the pooled
OLS estimator is likely to be biased upwards. (Cameron 2009) Clustering on the
individual, or the firm in our case, the model provides us with a firm average
estimator and is stated in equation 11.

$$y_{it} = \gamma y_{i,t-1} + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \alpha_{it} + (\alpha_{it} - \alpha + \epsilon_{it})$$ (11)

Due to the fact that we have a long panel where $T$ is extensively larger than $n$, a
model for serial correlation in the error is required. (Cameron 2009) This is also
shown by previous test results. We will hence consider pooled OLS and PFGLS
models which are fitted for long panel data. The estimators allow the error $u_{it}$
the lagged dependent variable and the error term $u_{it}$, the pooled
OLS estimator is likely to be biased upwards. (Cameron 2009) Clustering on the
individual, or the firm in our case, the model provides us with a firm average
estimator and is stated in equation 11.

$$y_{it} = \gamma y_{i,t-1} + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + \alpha_{it} + (\alpha_{it} - \alpha + \epsilon_{it})$$ (11)

Due to the fact that we have a long panel where $T$ is extensively larger than $n$, a
model for serial correlation in the error is required. (Cameron 2009) This is also
shown by previous test results. We will hence consider pooled OLS and PFGLS
models which are fitted for long panel data. The estimators allow the error $u_{it}$
to be correlated over individuals and to be heteroskedastic. The PFGLS es-

imates extends the pooled OLS and associated standard errors even further,
assuming the model for the errors is the correct one. If the model is correctly
specified, the PFGLS estimators are more efficient. (Cameron 2009)
4.3.2 Dynamic approach

This far we have considered a model of a pure linear nature, taking both FE-OLS and GLS estimators into account. To further extend the research, a dynamic approach will be examined by adding a lag of the dependent variable to the model as stated in the extended regression model

\[
y_{it} = \gamma y_{i,t-1} + \beta_1 x_{1it} + \beta_2 x_{2it} + \beta_3 x_{3it} + \beta_4 x_{4it} + u_{it} \tag{12}
\]

where the error term \(u_{it}\) equals the individual-specific effects \(\alpha_i\) plus the idiosyncratic error \(\epsilon_{it}\).

\[
u_{it} = \alpha_i + \epsilon_{it} \tag{13}\]

The lag of the dependent variable \((y_{i,t-1})\) is added to the model because we suspect the volatility to be highly dependent on the volatility in previous periods, as discussed partly in section 2.1.2. Including a lag of the dependent variable in the right hand side of the regression provides us with a dynamic approach to the model.

Even though robust standard errors are used, it is of importance to understand that the dynamic approach of our model might constitute non-sufficient results in the FE-, OLS- and PFGLS models as they are of pure linear nature. (Cameron 2009) Thereby, we extend the results further by looking at estimators suggested to increase the efficiency of dynamic panel data models. Including a lag of the dependent variable as a regressor is relevant in order to account for the effect volatility in the previous period has on current volatility. However, the lagged volatility will most likely be correlated with the error-term to some extent. Because the individual-specific error \(\alpha_i\) is fixed over time, the first-difference will equal zero, as shown in equation 14, and the application of a first-difference (FD) model therefor allows for elimination of the individual-specific error \(\alpha_i\) which reduce some of the endogeneity in our specified model.

\[
\Delta \alpha_i = \alpha_i - \alpha_i = 0 \tag{14}
\]

This model will be stated as

\[
\Delta y_{i,t} = \gamma \Delta y_{i,t-1} + \beta_1 \Delta x_{1it} + \beta_2 \Delta x_{2it} + \beta_3 \Delta x_{3it} + \beta_4 \Delta x_{4it} + \Delta \epsilon_{it} \tag{15}
\]

and will only include the idiosyncratic error \((\epsilon_{it})\).

To deal with the inconsistency the OLS estimator can impose on dynamic data
because of the correlation between the lagged dependent variable and the error term, the Anderson-Hsiao (AH) estimator offers a way to conduct an IV estimation where the second lag of the dependent variable is used as instrument for the endogenous regressor. By first-differencing, the individual-specific error ($\alpha_i$) will be dropped as demonstrated in equation 14 and 15. However, the model is still biased because the FD lagged volatility ($\Delta y_{i,t-1}$) is also correlated with the FD idiosyncratic error term ($\Delta \varepsilon_{i,t}$). The Anderson-Hsiao (AH) estimator suggests a solution to this bias by the use of further volatility lags ($y_{i,t-2}$) as instrument for the endogenous variable ($\Delta y_{i,t-1}$). This is possible due to the lack of correlation between the second lag of the dependent variable ($y_{i,t-2}$) and the first-differenced error term ($\Delta \varepsilon_{i,t}$). (Cameron 2009)

4.3.3 The Time-Series Model

The time series data is based on OMXS30 daily closing prices in which the daily return and lagged return was calculated. All variables included in the dataset are stated in table 4 Testing for normal distribution are conducted by plotting histograms of the different variables. The OMXS30 stock returns are normally distributed with two tails and the volatility who only contain positive values is normally distributed with one tail as illustrated in figure 6 and figure 5 below.
To obtain an efficient and reliable volatility the conditional variance was estimated by an EGARCH model. The EGARCH estimation, or volatility, is illustrated in figure 7. As shown in the figure, the estimation indicates significant fluctuations throughout the years. Higher volatility can be observed during the beginning of the time-period, around year 2000, and also around year 2008, which is in line with expectations related to historical financial crises.

A Dicker Fuller test is performed to control the data for stationary. The null hypothesis states that there is unit roots present while a rejection of the null hypothesis result in stationary data (Cameron 2009). By comparing the test statistic and the interpolated Dicker Fully value for different critical values was the data stationary. The null hypothesis was rejected at a 1% critical value.

The possibility of serially correlated standard errors in the time-series model
was controlled for by an auto-correlation table. Table 6 consists of data between the dependent variable volatility and its lags on a five order level, it indicates that the errors are serially correlated.

Table 6: Auto-correlation time series

<table>
<thead>
<tr>
<th></th>
<th>Volatility</th>
<th>L1.gc</th>
<th>L2.gc</th>
<th>L3.gc</th>
<th>L4.gc</th>
<th>L5.gc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volatility</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.gc</td>
<td>0.9763</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L2.gc</td>
<td>0.9558</td>
<td>0.9763</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L3.gc</td>
<td>0.9365</td>
<td>0.9558</td>
<td>0.9762</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L4.gc</td>
<td>0.9203</td>
<td>0.9364</td>
<td>0.9556</td>
<td>0.9762</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>L5.gc</td>
<td>0.92048</td>
<td>0.9202</td>
<td>0.9363</td>
<td>0.9556</td>
<td>0.9762</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

Henceforth, a Jarque-Bera test was conducted in order to test for normally distributed error terms. The null hypothesis demonstrates normal distributed errors. The null hypothesis is rejected if the \( \text{di}_b \) value is larger than the \( \text{di}_c \text{hi-critical value} \), both received from the test. Our test rejected the null hypothesis and the data doesn't have normal distributed errors.

Lastly, in order to acknowledge whether we are experiencing heteroskedasticity or homoscedacity, the Breusch-Pagan test was conducted. Constant variance is the null hypothesis which is related to homoscedacity. We reject the null hypothesis and heteroskedasticity is exiting.

To summarize the different tests, the data is normally distributed, stationary, the errors appear to be serially correlated with non normal distributed errors and the time series is heteroskedasticity. The use of standard robust errors are therefor necessary in order to receive reliable results.
5 Results

In this section, the results of the models are presented. First, the results for the panel data model of individual shares are described followed by the time-series of the OMXS30-index.

5.1 Individual shares

The panel data model includes, as stated earlier, daily returns of each share included in the OMXS30 index, as of December 2017, over 15 years. Table 7 represents estimators of the pure linear panel data models while the dynamic extension of the model is presented in table 8.

<table>
<thead>
<tr>
<th>variables</th>
<th>FE</th>
<th>OLS</th>
<th>PFGLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>lagged return</td>
<td>-0.0804136</td>
<td>-0.0803648***</td>
<td>-0.0803648***</td>
</tr>
<tr>
<td></td>
<td>(0.0795221)</td>
<td>(0.0029663)</td>
<td>(0.00028127)</td>
</tr>
<tr>
<td>tenyrate</td>
<td>0.0022256</td>
<td>0.0022261**</td>
<td>0.0022261**</td>
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<td>-0.0022649***</td>
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<td>0.0079</td>
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Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1

The main findings obtained from the panel data models of non-dynamic nature are listed in table 7. It presents results from three different estimators, the variables included in each regression, their coefficients, significance level and robust standard errors. All three models have 103890 observations the FE and OLS estimator have the same R-squared of 0.79.

The Fixed effect (FE) estimator is stated under the header “FE”. As previously mentioned in section 4.3.1 the FE model allow for some endogeneity while it assumes the regressors to be uncorrelated with the idiosyncratic error (εit). The main findings from the robust FE estimator show a negative but insignificant value of -0.0804136 for the lagged return. Hence, according to the FE estimator, a one unit change in the lagged return have an impact of -
0.0468834 on the volatility. However, the relationship is not significant at a 10% level and will therefore allow us to reject the null hypothesis (H0) of a significant and negative correlation between the financial volatility and the lagged return, even though the relation is negative. By rejecting the null hypothesis, the existence of a leverage effect within this model can be eliminated.

The coefficient of the control variables 10-year government bond (tenyrate) and baisse market (baisse) is negative but insignificant in line with expectations. However, the negative effect of the change in VIX index (VIXchange) was more unexpected.

The second model, the pooled OLS (OLS) estimator, provided a negative but significant effect of the lagged return (-0.0803648). The FE and OLS models has the same R-squared of 0.0079, a seemingly low value telling us that the variance in the dependent variable is explained to 0.79% by the model. Overall, the results of the OLS model are very similar to the ones of the FE model with the essential difference that the OLS estimator provides significant results on a 1% and 5% level for all variables except for VIXchange. The standard errors are also slightly lower for OLS than FE and OLS can be assumed to generate the more efficient estimator of these two. The PFGLS estimator is very similar to the pooled OLS and the FE models but is supposed to extend the efficiency of the OLS model even further. The results indicate this to be accurate with coefficients same or similar to the OLS model but even lower standard errors. The PFGLS estimator provides a significant coefficient of -0.0803648 for the lagged return, just like the OLS model, but standard errors of 0.00028127 which is lower than 0.0029663 for the OLS model.

The control variables had similar impact on each of the models. However, the tenyrate and baisse variables were only significant in the OLS and PFGLS models while VIXchange was insignificant in all three cases. The positive relation between the tenyrate and the volatility shows that the volatility increases as a result of a positive change in the interest rate. Similarly, a baisse market has a negative impact on the volatility. Because the baisse variable is a bivariate variable, taking the value of 1 in a negative market and 0 in a positive market 4.1.1, it will only be considered when the returns are negative. This tells us that a negative market trend, will have a positive impact on the volatility. In other words, when the closing prices are decreasing and negative returns are present, the volatility will increase. The relation between the change in VIX-index and volatility is of a small but negative nature in all three models, saying that volatility will decrease slightly when VIXchange increases and vice versa.
While the OLS and PFGLS models provide similar results, the PFGLS is preferred because it generates lower standard errors and more efficient results.

5.1.1 Dynamic Panel Data

When including a lag of the dependent variable in the specified model, a dynamic approach is necessary to keep the sufficiency of the model. While first-differencing the data eliminates the individual-specific error $\alpha_i$, the model will still be biased to a certain extent since the FD lagged volatility $(\Delta y_{i,t-1})$ is also correlated with the FD idiosyncratic error term $(\Delta \epsilon_{i,t})$. The Anderson-Hsiao (AH) estimator proposes the use of a second lag of the dependent variable $(y_{i,t-2})$ as an instrument for the endogenous variable $(\Delta y_{i,t-1})$ to solve this problem. (Cameron 2009) The results from the Anderson-Hsiao (AH) models are presented in Table 8 and the difference between the AH1 and AH2 models is that the baisse variable is included in AH2. Adding the baisse variable to the second model allows to compare our results to the ones of Figlewski & Wang (2000). His results indicated that the leverage effect overall is existent but not significant. Including a dummy variable of a baisse market, the results indicated an even stronger relationship and significant coefficients, hence the leverage effect are stronger when returns are negative. Both models contain 103866 observations and has similar R-squared values of 65.93% and 66.27%.

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Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 8: Dynamic panel data estimators, Summary table

Both the AH1 and AH2 model provided a negative relation between the return in previous period and the volatility. The coefficients were significant.
for both models, hence allows to reject H0 at 1% level and conclude that the leverage effect is present. In accordance to Figlewski & Wang (2000), the relationship becomes stronger when adding the baisse variable, indicating that the leverage effect is slightly more relevant in a negative market, even though the results were still significant in model AH1 where the baisse variable is not included. The endogenous variable lagged volatility is positively correlated with the dependent variable volatility and significant at a 1% level. The result indicates that increased volatility in previous period will increase the volatility in next period. The dummy variables tenyrate and VIXchange are both insignificant in accordance to the results of previous models.

The most essential effect of adding the lagged volatility as a regressor in the model is by far the relevant increase of the R-squared values. While the AH1 model generates a degree of explanation (65.93%) that is significantly higher than the FE, OLS and GLS models (0.79%), adding the baisse variable to the model AH2 increases the R-squared even more to 66.27%. Hence, taking lagged volatility into consideration allows the model to explain the variance in the dependent variable to 65.93%. Adding the baisse variable improves the model even further by increasing the degree of explanation to 65.93%, slightly decreasing the standard errors and indicating a stronger relation between the lagged return and the volatility be increasing the absolute value of the coefficient. This far, the results obtained are in line with the conclusions of Figlewski & Wang (2000).

5.2 Time-Series

To study the leverage effect on the Swedish stock market in a wider perspective, returns of both individual shares and the OMXS30 index is considered. Section 5.1 above focused on the results of the individual shares with a cross sectional viewpoint by the application of panel data models fitted for our data set. In the coming section, the results obtained by modeling the OMXS30-index returns in a pure time-series model will be examined and explained.

The results presented in this section represents four different estimations. They are all estimators of how the independent variables lagged return, tenyrate and VIXchange affect the dependent variable volatility. However, there are some structural differences between the four different models. The first two estimators, OLS1 and OLS2, take all variables mentioned above into consideration with the difference that OLS2 further includes the bivariate variable baisse. Further, OLS3 and OLS4 is extended versions of OLS1 and OLS2 by including
a lag of the dependent variable volatility into the right hand side of the model.

A summary of the results is presented in table 9 below. The main difference between OLS1 and OLS2 is the lagged return, which is insignificant in OLS1 with a coefficient of 0.0005789 but significant on a 5% level for OLS2 taking on a coefficient of 0.0014032. Hence, taking the baisse market into consideration increases the significance and the impact of the lagged return on volatility. Despite these differences, the the two models are similar in terms of robust standard errors and low R-squared values of 0.00019 (OLS1) and 0.00021 (OLS2).

Table 9: Time series estimators, Summary table

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<th>OLS 3</th>
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Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

5.2.1 Extended models

Moving on to the extended models OLS3 and OLS4, which in addition to previous models consider the lagged volatility as a regressor, they both offers a positive and significant relationship between the lagged return and the volatility. In OLS3, the lagged return has a 0.0001976 unit impact on the volatility while OLS4 stated a 0.00034 impact for the same variable. The two models also differ in significance of the lagged return where OLS4 provides a higher significance level of 5% while the OLS3 coefficient for the same variable is significant only on a 10% level.

Investigating the robust standard errors, further differences between the estimations is to be found. Including the lagged volatility as a regressor is shown
to slightly decrease the standard errors from OLS1 and OLS2. However the most striking result gained by including a dynamic approach to the model is its effect on the R-squared values. Moving from strikingly low explanatory degrees of 0.019% versus 0.021% in the first two models, adding the lagged volatility offer a completely different value of 95.32% and 95.33%. These results show that lagged volatility increases the degree to which the variance in volatility can be explained by the model essentially, hence indicating that volatility is somewhat dependent of volatility in previous periods.

Just like the lagged return, both the baisse market and the lagged volatility has a positive and significant impact on volatility. Neither of the four estimators summarized in table 9 show a negative and significant relationship between lagged return and volatility. The null-hypothesis (H0) of a negative and significant relation between the financial volatility and the lagged return is hence rejected by these four models. Following, the existence of a leverage effect can be eliminated from the OMXS30-index. To summarize the results from the time series data over the OMXS30-index, the degree of explanation increases when the lagged volatility is added to the model. The "baisse" variable strengthens the effect of the lagged return on volatility when included in the OLS1 and the OLS3 models. However, the null hypothesis is still rejected for all estimators due to the lack of a negative relationship, meaning that non of them illustrated evidence of presence of the leverage effect.
6 Discussion

Results obtained when testing for the leverage effect on the Swedish stock exchange differs between individual firms and the OMXS30-index. For the panel data set of individual firms, a small but negative relation between the lagged return and the volatility was noticed. The effect was significant for the OLS, GLS and AH estimators and these models allow us to keep H0 of a significant and negative relationship between the financial volatility and the lagged return, hence, we cannot exclude that the leverage effect is present. However, results obtained through the time-series data of the OMXS30-index displayed a positive relationship between lagged return and volatility. In contrast to the results of individual firms, this allows us to reject H0 and conclude that the leverage effect cannot be applied to the index return-volatility relation.

6.1 Application on previous research

The results presented above both strengthens and contradicts the findings of Black (1976), Christie (1982), Duffee (1995) and others whom found evidence of a leverage effect on the US stock market. In accordance to their results, the leverage effect is present on an individual stock level. However, the existence of a leverage effect is surprisingly enough rejected on the index level in this study. Neither when looking to the work of Bouchaud et al. (2001), who differentiated their study between individual firms and indices in accordance to this paper, we find any explanation to the contradicting results obtained. While this study rules out the leverage effect on an index level, Bouchaud et al. (2001) states that the effect is even stronger for indices than individual stocks. To a large extent, recent studies have all concluded presence of a leverage effect on both an individual and index-level. Important to notice when analysing the contradicting results of this study is the fact that the index represents the market as a whole while individual shares represents the state of a single company. With this in mind, the fact that the leverage in our case is only to be found on individual shares is not that incomprehensible. The leverage effect focus a lot on the risk of the equity within a specific firm, saying that it is riskier for an investor to hold positions in a share with a higher leverage ratio. Holdings of the OMXS30-index is differentiated and represents the state of 30 different companies within different sectors. Hence, the investor should not find the index as risky as a single share in terms of the leverage ratio since it consist of multiple firms with different leverage ratios. One can therefore interpret the results knowing that any leverage effect within individual firms might have been evened out when adding them all together into an index.
6.2 A risk-return perspective

With the above analysis in mind, the fact that evidence of the leverage ratio is only found for individual shares and is rejected on the index level, might not be as surprising as it first seemed to be. The positive relation between lagged return and volatility rules out presence of the leverage ratio but instead welcomes theories such as the risk-return trade-off. While the leverage effect insists that lower return decreases the value of equity which increases the leverage ratio and imposes a higher risk on equity, hence higher volatility of the return, the trade-off theory argues that higher volatility affects the expected return positively. This relation derives from the perspective of an investor. If the holdings contain higher volatility, the investor will require a higher return in order to account for the risk. However, it is important to stress that this relation is not necessary derived from reality but rather a theoretical view of the relation between risk and return where higher risk should be accompanied by higher return in order to be attractive and efficient for the investor. The positive relation found in this study is between return and next-period volatility which makes it slightly more difficult to argue from a risk-return view point. Even though higher return theoretically, according to the trade-off theory, should allow for higher risk, it is hard to motivate it in reality. One would probably think that higher returns should decrease the volatility, as would be the case if the leverage effect held, since the risk of equity would be smaller. However, the results are based on daily returns of the OMXS30-index, hence the time interval is very small and the leverage ratio is not as relevant for an investor. It is possible that the relation would be more relevant for weekly or monthly returns since the effect of the return would have more time to impact the volatility, hence it is possible that the results would look different for another time interval.

6.2.1 Application of volatility clustering

Looking at the results over the OMXS30 index, one of the more important factors to consider is the significant increase in the degree of explanation (R-squared) to the model when the lagged volatility is included. Adding a lag of the volatility as an regressor in order to account for its possible effect on future volatility increased the R-squared value from 0.021% to 95.33%. This is an extraordinary improvement to the model, indicating that the volatility clustering theory might be of high relevance to our research. Volatility clustering refers to the phenomena that periods of high volatility usually are followed by periods of high volatility and vice versa and its utility in explaining the fluctuations of volatility is highlighted by Zabiulla (2015). While the lagged return implies a weak but positive relation to to the volatility on a 10% level (baisse not in-
and a 5% level (baisse included), the lagged volatility show a strong and highly significant (1%) positive relation to the volatility while improving the R-squared noticeably. Increasing volatility in previous period hence affects the volatility in this period positively allows to assume that volatility clustering is a highly possible explanation to the results of the OMXS30-index.

6.3 Impact of positive- and negative market trends

One of the more interesting findings to discuss in connection to our results is the ones of Figlewski & Wang (2000) whom argued that the volatility increased even when the returns were positive. According to the leverage effect the relation should be reversed in case of a positive return, meaning that it should decrease the volatility due to lower leverage ratio, hence lower risk on equity. They therefor claimed that other factors than the leverage effect is relevant for the negative relation between lagged return and volatility since the effect should have been the same in both positive and negative market moves. The authors illustrated that a change in the “leverage effect” is noticeable when including a “down market” dummy variable into the model. To examine these findings the dummy variable “baisse” were included in our models. However, including the “baisse” market did not generate significantly different results of our models as it did for Figlewski & Wang (2000). For the dynamic panel data of individual shares, the degree R-squared increased some and the negative impact of lagged return on volatility strengthened slightly when “baisse” was included but in total the results did not change much. Similar results was obtained for the index as well. While Figlewski & Wang (2000) argued that the shift in results from adding the “baisse” variable worked as evidence of a non-existence leverage effect, we cannot really interpret anything new from our models by doing the same. They further argued that, in order for the leverage effect to be “true”, a permanent change in leverage should mean a permanent change in stock volatility because the financial leverage of a firm is a “level” variable. They mean that the amount of leverage in a firm, and not the change in leverage, should determine the volatility and the effect should therefore not die out over time as showed by Bouchaud et al. (2001) for example. However, the leverage effect as early influencers like Black (1976) and Christie (1982) described it, is not an effect of the amount of leverage in the capital structure but rather an effect of changed values of equity, hence the debt-to-equity ratio which would increase with decreased equity. Neither, Figlewski & Wang (2000) consider the “human factor” when presenting these arguments. With this in mind, the immediate effect on volatility after a decrease in the stock price could be an expression of initial “fear” of higher risk among the investors that is much likely
to level out over time if the stock show signs of stabilization. Due to reasons stated above, this thesis has not considered to what extent the effect “dies out” but is nevertheless comfortable to draw conclusions about the leverage effect.

6.4 The Modigliani and Miller Propositions

Modigliani (1958) state that a negative stock return, increases a firm’s leverage ratio due to lower value of equity in relation to the fixed debt. This theory stands in direct relation to the leverage effect, further claiming that the increased leverage ratio also increases the equity volatility. The findings of this thesis indicate that the leverage effect is present for individual firms where a significant and negative relation between volatility and lagged return is found. Hence, our panel data results are in line with the MM propositions on a theoretical level. However, the MM proposition and theory can not be stated as valid at the index level because its findings did not illustrate any evidence of an negative relationship between past return and volatility. However, one must remember that the MM proposition only is valid when certain market conditions are reached. The conditions for the perfect capital markets applied on the theory is stated in section (2.4). Among other things, taxes and transactions costs are assumed to be non existing for the perfect capital markets while the firms included in our models and most real-life applications are affected by these kinds of factors. For example, the CAPM and WACC theories stated in (2.3) includes taxes and implies that holding debt increases the value of the tax shield, which in turn increases the value of the firm. These formulas are frequently used for firm valuation within the financial industry. Thereby, one must have the markets conditions in mind when analyzing the stock returns from this perspective even though we can state that the MM propositions are valid both in theory and in reality for the individual shares examined.

6.5 Further discussion

To this point, different theories and causes are brought up aiming to explain the given results. Even though the results alone are quite straight-forward to understand, what becomes clear is that a precise interpretation of the reasons behind obtained relations between return and volatility is hard to distinguish. A negative and significant relation was found between volatility and lagged return for individual stocks. This allowed us to accept H0 of a significant and negative relation between financial volatility and lagged return and we can not rule out the existence of a leverage effect on this level. However, this paper is limited to only research the relation as such and not the causes behind it. Even though
analysis of previous research and together with our obtained results invites to argue that the leverage effect is present, we cannot know for sure that is the real cause behind the relation without further research. Lee (2012) and Bollerslev et al. (2006) both aimed to distinguish the causal relation between return and volatility. They investigated whether the volatility feedback model, claiming that higher volatility impacts the return negatively and explained in chapter (2.2.1), could be an alternative cause of the relation. As mentioned earlier the time interval in this research is quite small, by estimating the returns on a daily basis, and could complicate the analysis of the causal relation between the variables.

To summarize, this far, many has argued for evidence of the existence of a leverage effect (Black 1976), (Christie 1982), (Duffee 1995). Others are more suspicious and aims to find alternative explanations for the negative relation between return and volatility (Lee 2012), (Bollerslev et al. 2006), (Carr & Wu 2017) and (Figlewski & Wang 2000). Our results can be analysed from different perspective, applying either reality based models such as the leverage effect, or more theory based models such as the trade-off theory. The subject of volatility is extensive and sometimes complicated since it depends to a large extent on the human mind and risk aversion which is not always possible to predict.
7 Concluding remarks

The objective of this paper was to find out whether the leverage effect is significantly applicable on the Swedish stock market. Throughout the paper, financial volatility is discussed and theories related to volatility and the leverage effect was presented before setting up the appropriate regression model and analysing the results. While previous studies on the subject mainly is set on the US market, we contribute to the area of research by focusing on the Swedish market solely and distinguishing the results between individual shares and the OMXS30-index. The final remarks of the results presented above is that the leverage effect cannot be rejected for individual stocks on the Swedish stock market. On the contrary, the effect is proven not to be present for the OMXS30-index, which is supposed to represent the Swedish Stock market. Hence, the results is strengthen by the Modigliani (1958) (MM) theory on an individual level. The MM-theory is related to the leverage effect and further takes other relevant theories into account, for example the volatility clustering and the trade-off theory.

Overall, the thesis discusses the importance for participants in the financial industry to gain understanding of financial volatility and factors that affects it. Knowledge of the leverage effect and its presence is a key factor to that overall understanding, even though it is far from enough. Further, the research in this thesis present additional knowledge to previous research. This paper has an empirical relevance but is significantly important for reality based analysis and represents an overall economical level of interest. Highlighting factors that affect financial volatility and investment decisions of market participants in turn, creates a foundation for future development towards transparency and sustainability within the market place.

The conclusions that can be drawn from this paper is that the leverage effect cannot be rejected for individual firms on the Swedish stock market and is rather likely to exist as a result of the discussion. However, the effect is excluded for the OMXS30-index and off-set by other theories such as risk-return trade-off and volatility clustering which provides more significant explanations to the positive return observed at this level. To answer the research question of this paper, the negative and significant relation observed between volatility and lagged return in our model of individual firms, together with the application of relevant theory as discussed in (6), we can state that the leverage effect is significantly applicable on the Swedish stock exchange on an individual basis.
7.1 Suggestions for further research

Financial volatility is an extensive subject hence, there is a lot of room for further research within this area. To begin with, our research could be further extended by looking into a larger set of stocks on the Swedish market. The stocks included in this paper is the ones that constitutes the OMSX30-index. Even though various industries are represented within the index, all of the stocks included are the most traded firms on the Swedish stock exchange. Further research could be extended to differentiate between certain industries to test whether the leverage effect is stronger or weaker within different branches. It would be highly relevant to look into industries containing firms with various capital structures since the capital structure and the level of debt is of high relevance within this topic. Further, previous research have applied different GARCH-models to estimate the volatility. This thesis ended up using the EGARCH-model but it could be relevant to test different models in order to really understand their impact on the results and their levels of efficiency. Conducting further research with another choice of method could possibly improve the accuracy and efficiency of the results.

As discussed in the last chapter, other theories, such as the risk-return trade-off theory and clustering effects, are analysed as other ways to interpret the results. Interesting for future research is to extend the results presented in this thesis, looking further in to the capital structure of the firms and aim to establish whether the obtained results are a direct effect of the leverage effect or if other causes behind the negative relation between return and volatility is more likely. As mentioned in the discussion, this research focus on the actual relationship and does not fully prove the cause of it even though its relevance is discussed.
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