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The Impact of Leverage on Return-Volatility Relationship -An Empirical Study of the Nordic Equity Markets

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Abstracts

Prior studies have documented mixed evidence regarding the relationship between stock returns and equity return volatilities. The purpose of this thesis is to contribute to the debate about the direction of the risk-return relationship and to seek further explanation for this phenomenon. The aim of this thesis is therefore two-fold. Firstly, it examines the risk-return relationship in the Nordic stock markets. Secondly, it seeks to explain the impact of leverage on risk-return relation using a range-based measure of volatility. Different estimation techniques are applied on both cross-sectional and panel data in order to enhance robustness of the results. After controlling for size, value, momentum factors, variation across industry and over time, as well as a number of firm-level characteristics, the regression results suggest a positive and statistically significant relationship between (range-based) volatilities and stock returns in the Nordic equity markets. The conclusion is that low volatility effect that has been documented in international stock markets does not prevail in the Nordic equity markets. Additionally, the regression results show that low leverage firms not only have higher volatility but also higher return although the leverage-return relationship has somewhat weaker statistical significance. While Dutt et al. (2013) suggest that operating performance might explain why low volatility stocks in developed and emerging equity markets outside North America generate higher returns, the findings of this thesis indicate that leverage has a negative impact on the risk-return relation. Therefore, a firm's financial leverage could be an additional explanation to the positive risk-return relationship that is present in the Nordic equity markets.

Keywords: Risk-return relation, low volatility effect, leverage, volatility, Nordic stock market, Fama-French three factors

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1. INTRODUCTION

1.1. Background

Even though stock and option markets had been in existence since the 1600s, it is not until the 1960s that theoretical and empirical foundations were laid to understand risk (Perold, 2004). Markowitz (1959) postulates that an investor who is risk-averse only cares about the mean and variance of their one-period investment return. Since the work of Markowitz (1959), the trade-off between risk and return has received considerable attention in the research literature. The classical Capital Asset Pricing Model (CAPM) was introduced by Sharpe (1964), Treynor (1962), Lintner (1965a,b), and Mossin (1966) based on the idea of the modern portfolio theory in Markowitz (1959). The CAPM gives us insights about what kind of risk is related to returns by postulating that the expected returns on securities is a positive linear function of their market beta, i.e. investors should be compensated for taking higher risk through higher returns on their investment. Nevertheless, later empirical studies have found conflicting results regarding the relationship between return and volatility. The positive risk-return relation predicted in the CAPM is supported by Bollerslev, Tauchen, Zhu (2009); Rachwalski, Wen (2016) and Tariq, Valeed Ahmad (2017). While Fama and French (1992); Haugen and Baker (1996) claim that the relation between market beta and average return is flat, other studies document a reversed relationship between risk and return (Ang, Hodrick, Xing and Zhang ,2006, 2009; Blitz and Vliet 2007, Bali and Whitelaw, 2011; Blau and Whitby, 2017). The latter is usually termed low volatility effect. Fu (2009) and Li, Yang, Hsiao and Chang (2005) report similar findings and further claim that the relationship between volatility and returns is fragile and substantially sensitive to how volatility is estimated.

Contemporaneously, research has shown that financial leverage has some impact on both equity return and volatility. However, just as risk-return relation, the answer to the question regarding what impact leverage has on stock return and volatility remains inconclusive. Positive relation between financial leverage and stock returns has been documented in the influential study on capital structure of Modigliani and Miller (1958) and other empirical researches e.g. Artikis and Nifora (2011); Min, Jiwen and Toyohiko (2016). However, Dutt et al. (2013) suggest a negative relation between the firm's leverage in terms of Debt/Asset and yearly stock returns after controlling for market, level of volatility and a number of corporate characteristics. Similarly, mixed results are found in regard to leverage-volatility relationship. In contrast to the theory of mechanical leverage effect which postulates that leverage is positively associated with volatility, Brandt, Brav, Graham, Kumar (2010) suggest a negative and statistically significant relation between volatility and leverage.

Furthermore, Dutt et al. (2013) find that the low volatility effect could be explained by the firm's operating performance (measured by EBIT/Assets ratio). They further clarify that low volatility firms experience better operating performance and since these firms have stronger fundamentals this will drive stock returns. Overall, research has shown that there is a connection between volatility, return and leverage. Hence, it could be reasonable to argue that leverage might have some impact on the risk-return relationship. This reasoning is the starting point and the foundation of the thesis.

1.1. Research questions

In view of stated purposes, the research questions of this thesis can be formulated as following:

- What is the relationship between stock return volatility and leverage in the Nordic equity markets?
- What is the relationship between leverage and stock returns in the Nordic equity markets?
- What is the relationship between volatilities and returns in the Nordic stock markets? Does leverage have any impact on the risk-return relationship?

2. LITERATURE REVIEW

This section is an overview of previous studies on the subject, namely the relationship between volatility and stock returns as well as the impact of leverage on both volatility and equity returns. Both international evidence and findings at country/exchange-level will be discussed.

2.1. Positive relationship between stock return volatility and stock returns

One of the very first studies investigating the relationship between stock return and stock return volatility were conducted by Sharpe (1964), Treynor (1962), Lintner (1965a,b), and Mossin (1966) who developed the classical Capital Asset Pricing Model (CAPM). The CAPM postulates that the expected returns on securities is a positive linear function of their market beta, i.e. investors should be compensated for taking higher risk through higher returns on their investments. In the CAPM, the expected return is determined solely by market beta, i.e. idiosyncratic risk has absolutely no relation with expected returns in the single-period model. Based on the single-period CAPM, Merton (1973) further develops the Intertemporal Capital Asset Pricing Model ICAPM in which it is assumed that security returns are distributed over multiple time periods. Even in this intertemporal model of capital market, the positive relationship between expected returns and volatility remains unchanged, as predicted in the classical CAPM.

Many later studies document similar findings on both domestic and international stock markets. However, in contrast to the classical theory of market betas and returns, the attention has been turned to idiosyncratic volatility. Rachwalski et al. (2016) document that the negative relation between idiosyncratic risk innovations and returns is short-lived. However, high idiosyncratic volatility stocks persistently earn high returns. The most recent study conducted by Tariq et al. (2017) predicts a positive relation between idiosyncratic volatility and future stock returns. However, when examining a subsample consisting of small stocks Tariq et al. (2017) find that the positive idiosyncratic volatility-return effect is concentrated among small stocks. The positive relationship between stock returns and volatility is further supported by Fu (2009) who takes into account the fact that volatility is time-varying, therefore uses GARCH to measure volatility. On the other hand, Bollerslev, Tauchen, Zhu (2009) measure both realized and implied variation and still come to the same conclusion.

2.2. Negative relation between stock return volatility and stock returns – the low volatility effect

The positive relation between stock returns and volatility described in the classical CAPM, not so long after its birth, became subject to criticism by various researchers. The relationship was later on proven to be flat in the US stock market (Fama and French,1992; Haugen and Baker, 1996) or even reversed in other studies. By observing idiosyncratic volatility in the US stocks, Ang et al. (2006, 2009) conclude that monthly stock returns are negatively related to the one-month lagged idiosyncratic volatilities and the puzzle of low returns to high-idiosyncratic-volatility stocks is not a market-specific but much likely a global phenomenon. According to Ang et al. (2006) one of the explanations for this phenomenon is due to the fact that stocks with high idiosyncratic volatilities may have high exposure to aggregate or market volatility risk, which lowers their average returns. Bali and Cakici (2008) as well as Bali et al. (2011) argue that the negative relationship reported in Ang et al. (2006) is not robust as the high return phenomenon might only be present among small and illiquid stocks with lottery-like payoffs. In order to address this issue, Blitz and Vliet (2007) investigate a global large-cap stock sample consisting of the US, European and Japanese equity market over the 1986 – 2006 period. Blitz et al. (2007) find that the portfolios ranked on volatility provide considerably lower alphas relative to those ranked on beta. Blitz et al. (2007) document that when performing the analysis using simple returns not much evidence of anomalous behaviour of the volatility portfolios is found. However, the picture changes when risk-adjusted returns are used. After controlling for factors such as size, value and momentum and measurement period, Blitz et al. (2007) conclude that the result is still robust and low-volatility effect is a distinct effect that is not related to any of the classic effects, namely size, value and momentum.

In addition to earlier studies of stocks in developed markets, Blitz, Pang and Vliet (2013) show that the volatility effect also holds in emerging markets for the period 1988-2010, after controlling for size, value and momentum factors. The relation between risk and return is negative and becomes more strongly when volatility is used instead of beta to measure risk. In response to existing critiques, Blitz et al. (2013) also account for the effect of small illiquid stocks by excluding 50 % of smallest least liquid stocks from the sample.

Based on other studies on this subject, Dutt et al. (2013) test the theory using stocks in emerging and developed markets outside of North America and confirm the finding. Furthermore, Dutt et al. (2013) find that one possible explanation for the low volatility effect is because low volatility stocks tend to have superior operating performance (measured by EBIT/Assets ratio), which drives stock returns. Thus, operating performance could be an explanatory reason to why low volatility stocks generate higher returns.

Prior researches have used standard deviation of returns or GARCH models to measure and forecast volatility. Blau and Whitby (2017) on the other hand use a rang-based measure of volatility where range is the difference between the highest price and the lowest price during a particular month. Their analysis documents a significant, negative return premium associated with range-based volatility for the US stock market.

2.3. The impact of financial leverage on stock returns

In their influential research on capital structure, Modigliani and Miller (1958) propose a positive relation between financial leverage and equity returns. According to Modigliani et al (1958), the explanation is that an increase in leverage adds financial risk, and thus increases the expected returns of equity. Unfortunately, just as the risk-return relation, the effect of financial leverage on stock returns has also been controversial across stock markets. Positive effect of leverage on stock returns has been predicted by Kallunki et al. (1997); Artikis and Nifora (2011); Min, Jiwen and Toyohiko (2016);

In a similar study, Penman, Richardson and Tuna (2007) decompose book-to-price ratio into an enterprise book-to-price (reflecting operating risk) and a leverage component (pertaining to financing risk). Their finding is that the leverage component, which is measured by Net Debt/Equity is negatively associated with future stock returns while there exists a positive relation between the enterprise book-to-price ratio and returns. This finding survives under controls for size, estimated beta, return volatility and momentum. In addition, Dutt et al. (2013) find a negative relation between leverage in terms of Debt/Asset and yearly stock returns after adjusting for market, level of volatility (volatility quintile) and a number of corporate characteristics. In line with prior studies, Acheampong, Agalega and Shibu (2014) state that financial leverage has a negative impact on stock returns for manufacturing firms listed on Ghana Stock Exchange when industrial data is used. However, this relation is not stable at the individual firm level.

When examining US stock samples, Hu and Gong (2018) find that a firm’s leverage position relative to its target leverage (a reference point) combined with market conditions places firms in either a gain or a loss domain. The firm’s observed leverage is measured as Total liabilities/(Total liabilities + Market Capitalization). This leads to different leverage–return relationships. Hu et al. (2018) conclude that leverage and expected returns generally exhibit positive and negative relationships in gain and loss domains, respectively.

2.4. The relation between leverage and equity return volatility

Higher leverage is often associated with more risk or higher volatility. The relation between volatility and leverage can be described through so called mechanical leverage effect which dates back to Black (1976) and Christie (1982). The mechanical leverage effect postulates that as a firm’s stock price (equity) declines the firm’s leverage mechanically increases given a fixed level of debt outstanding. This increase in leverage induces a higher equity-return volatility. The positive relation between leverage and volatility has also been documented in various modern studies. When examining stocks in non-US markets Dutt et al. (2013) find that firms with high Debt/Asset ratio are more likely to be in the high-volatility quintile. This evidence appears to be stronger in emerging markets including Asian and European markets.

On the contrary, when using the ratio book debt to the sum of book debt and market equity as the proxy for leverage Brandt et al. (2010) state that relation between idiosyncratic volatility and leverage is statistically significantly negative.

3. METHODOLOGY AND DATA

This chapter describes the data sample, the variables as well as the econometric models used throughout the thesis. It should be mentioned that all the regressions discussed in this chapter and the results reported in later parts of the thesis are retrieved from the statistical software STATA.

3.1. Methodology

3.1.1. Ordinary Least Squares regression OLS

According to Stock and Watson (2015), the OLS is commonly used to estimate the regression coefficients (βs) specified in equation (2.1) in Theory Review section. It basically minimizes the sum of squared prediction errors,

$$\sum_{i=1}^{n} (Y_i - b_0 - b_1 X_{1i} - \cdots - b_k X_{ki})^2 \tag{3.1}$$

Mathematically, the formula for the OLS estimator can be derived by solving the First Order Condition FOC with respect to each element of the coefficient vector. The FOC of the sum of squared prediction errors w.r.t. the j^{th} regression coefficient is

$$\frac{\partial}{\partial b_j}\sum_{i=1}^{n}(Y_i - b_0 - b_1 X_{1i} - \cdots - b_k X_{ki})^2 = 0$$

$$= -2\sum_{i=1}^{n} X_{ji}(Y_i - b_0 - b_1 X_{1i} - \cdots - b_k X_{ki}) = 0$$

For $j = 0, \dots, k$ where for $j = 0, X_{0j} = 1$ for all i. The same approach can be applied to obtain the OLS estimator $\widehat{\boldsymbol{\beta}}$ in matrix form.

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X'X})^{-1}\boldsymbol{X'Y}$$

Where $(\boldsymbol{X'X})^{-1}$ is the inverse of the matrix $\boldsymbol{X'X}$**.**

OLS is applied in this thesis to estimate the relationship between stock returns and volatility, leverage as well as other control variables (See Table for model specification).

3.1.2. Ordered Logit Model

When the dependent variable is an ordinal variable, i.e. when it has order or ranking, ordered logit model can be used to estimate the non-linear relationship between the dependent and independent variable(s). This model is based on the idea that *one* underlying latent variable y_i^* is used to observe y_i (consider the situation where the dependent variable has M alternatives, numbered from 1 to M. Hence $y_i = 1,2, \dots, M$). The relation between y_i^* and y_i can be expressed as follows:

$$y_i^* = x_i'\beta + \varepsilon_i \tag{3.2}$$

$$y_i = j \text{ if } \gamma_{j-i} < y_i^* \leq \gamma_j$$

Where $\gamma_0 = -\infty, \gamma_1 = 1$ and $\gamma_M = \infty$. The probability that alternative j is chosen is the probability that the latent variable y_i^* is between the range γ_{j-i} and γ_j. Assume that ε_i is i.i.d. with logistic distribution we have ordered logit model (Verbeek, 2004).

A good example on Ordered Logit Model, which is commonly used in qualitative survey studies is illustrated in Hosmer and Stanley (2000). Respondent ith (i=1,…,N) in a survey has $M > 2$ alternatives (outcomes). The variable D_i represents the degree of deprivation for ith respondent in the survey, the higher D_i the higher degree of deprivation. D_i can be expressed as a linear function of the predictors (as in equation 3.3) such that the outcome chosen by the ith respondent can be assigned to discrete choice set Y_i by imposing a threshold on D_i.

$$D_i = \sum_{k=1}^{K} \beta_k X_{ik} + \varepsilon_i = \alpha_i + \beta' x \tag{3.3}$$

where $k = 1, \dots, K$ is the number of factors for the ith respondent.

Then the probability that Y_i takes three levels 1,2,3 is expressed below:

$$\log\left(\frac{P(Y=1)}{P(Y=2)+P(Y=3)}\right) = \alpha_1 + \beta' x$$

$$\log\left(\frac{P(Y=1)+P(Y=2)}{1-P(Y\leq 2)}\right) = \alpha_2 + \beta' x$$

$$P(Y=1) = 1 - P(Y>1)$$

$$\log\left(\frac{P(Y=1)+P(Y=2)}{1-P(Y\leq 2)}\right) = \alpha_1 + \beta' x$$

The probabilities can be written in logit form as follows:

$$P(Y=1) = Logistic\ (D_1) = \left(\frac{\exp(\alpha_1 + \beta' x)}{1-\exp(\alpha_1 + \beta' x)}\right)$$

$$P(Y=2) + P(Y=1) = Logistic(\alpha_2 + \beta' x)$$

$$P(Y=2) = P(Y \leq 2) - P(Y \leq 1)$$

$$= Logistic\ (\alpha_2 + \beta' x) - Logistic(\alpha_1 + \beta' x)$$

$$\text{Thus } P(Y=2) = \left(\frac{\exp(\alpha_2+\beta' x)}{1-\exp(\alpha_2+\beta' x)}\right) - \left(\frac{\exp(\alpha_1+\beta' x)}{1-\exp(\alpha_1+\beta' x)}\right)$$

$$\text{And } P(Y=3) = 1 - \left(\frac{\exp(\alpha_2+\beta' x)}{1-\exp(\alpha_2+\beta' x)}\right)$$

The odds ratio (OR):

$$OR_m = \frac{\Pr(Y_i \leq m)}{\Pr(Y_i > m)}$$

The coefficients of the independent variables in the ordered logit model imply the increase (or decrease) in probability that the outcome m occurs.

3.1.3. Fixed Effects Regression

Fixed effects regression is a method used to control for omitted variables in panel data when the omitted variables vary across entities but not over time. A fixed effects model can be expressed as in equation (3.4):

$$Y_{it} = \beta_1 X_{it} + \alpha_i + u_{it} \tag{3.4}$$

Where α_i with ($i = 1, \dots, n$) are treated as unknown intercepts to be estimated, one for each entity. In other words, the intercept α_i can be thought of as the "effect" of being in entity i. $\alpha_1, \dots, \alpha_n$ are also known as entity fixed effects. The variation in the entity fixed effects comes from omitted variables that vary across entities but not over time. Fixed effects models can be estimated using OLS with $n-1$ regressors, or binary variables representing $n-1$ entities to be specific. We cannot include all n binary variables representing n entities, for if we do the regressors will be multicollinear. Therefore, the first binary variable in the regression will be omitted.

Equivalently, the fixed effects regression model can be written in the form of terms of $n - 1$ binary variables representing all but one entity:

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \gamma_2 D2_i + \gamma_3 + D3_i + \cdots + \gamma_n Dn_i + u_{it}$$

Where $D2_i = 1$ if $i = 2$ and $D2_i = 0$ otherwise and so forth (Stock et al., 2015).

The standard errors for fixed effects regressions are so-called clustered standard errors, which allow for heteroskedasticity and autocorrelation within an entity but treat the regression errors as uncorrelated across the entities. Just as heteroskedasticity-robust standard errors in cross-sectional data regressions, clustered standard errors are valid whether or not there is heteroskedasticity, autocorrelation, or both.

3.1.4. Quantile Regression

Similar to classical linear regression methods which estimate models for conditional mean functions based on the idea of minimizing sums of squared residuals, quantile regression methods are intended to estimate models for the conditional median function, and the full range of other conditional quantile functions. With the techniques for estimating an entire family of conditional quantile functions, quantile regression is capable of providing a more complete statistical analysis of the stochastic relationships among random variables. For any random variable Y with probability distribution function

$$F(y) = Prob\ (Y \leq y)$$

the τth quantile of Y is defined as:

$$Q(\tau) = inf\{y: F(y) \geq \tau\}$$

where $0 < \tau < 1$. Thus, the median is $Q(1/2)$.

For a random sample $\{y_1, \dots, y_n\}$ of Y, the sample median is the minimizer of the sum of absolute deviations

$$min_{\xi\in\mathbf{R}}\sum_{i=1}^{n}|y_i - \xi|$$

Similarly, the general τth sample quantile $\xi(\tau)$, which is the analogue of $Q(\tau)$, may be found by solving the following optimization problem

$$min_{\xi\in\mathbf{R}}\sum_{i=1}^{n}\rho_\tau\,(y_i - \xi)$$

where $\rho_\tau\,(z) = z(\tau - I(z < 0)), 0 < \tau < 1$, with $I(\cdot)$ denoting the indicator function.

Just like the sample mean, which minimizes the sum of squared residuals

$$\hat{\pi} = argmin_{\mu\in\boldsymbol{R}}\sum(y_i - \mu)^2$$

can be extended to the linear conditional mean function $E(Y\,|X = x) = x\,'\beta$ by solving

$$\hat{\beta} = argmin_{\beta\in\boldsymbol{R}^p}\sum(y_i - x'_i\beta)^2$$

the linear conditional quantile function, $Q_Y(\tau\,|X = x) = x'_i\beta(\tau\,)$, can be estimated by solving

$$\hat{\beta}(\tau) = argmin_{\beta\in\boldsymbol{R}^p}\sum\rho_\tau\,(y_i - x'_i\beta)$$

for any quantile τ ∈ (0, 1). The quantity $\hat{\beta}(\tau\,)$ is called the τth regression quantile. The case $\tau = 1/2$, which minimizes the sum of absolute residuals, is known as median regression (Koenker, 2005).

3.2. Data description

3.2.1. Data sample

The data sample consists of active stocks being listed on the Nordic stock exchanges including Stockholm Stock Exchange, OMX Nordic Exchange Copenhagen, Oslo Bors, Helsinki Stock Exchange and Nasdaq OMX Iceland. The data are retrieved from Thomson Reuters Datastream in EURO (where applicable) and cover the time period 2003–2017. The initial idea was to cover a 20-years period (from 1997 to 2017). However due to the lack of daily data on stock prices, which are used to calculate range-based volatility, the time period is limited to 2003-2017. The choice of time period is also based on the interest of examining the Nordic stock markets in most recent years. Stock prices, dividend per share, market capitalization, trading volume, market-to-book value are obtained at the monthly and yearly level whereas bid and ask prices which are needed for the estimation of range-based volatility are daily data. The monthly data on stock prices are needed for the calculation of Sharpe ratios as well as the computation of the factors. Since the aim of this thesis is to seek to explain the return-volatility relationship with respect to leverage, the yearly data including stock prices and the firms' fundamentals serve the purpose. The companies' fundamentals, downloaded from Datastream are Worldscope data. Table 5 in the appendices provides Worldscope definitions of each balance sheet item together with the definition of each variable.

After excluding dead stocks and stocks whose daily data were not available in Datastream, the bottom 10 % of smallest illiquid stocks are excluded. This is done by first sorting all stocks based on their free float market value (in EUR). The stocks are then divided into quintiles. Later, the bottom 10 % of the stocks in the quintile with lowest free float market value is eliminated. The removal of small illiquid stocks is conducted in line with Ang et al. (2006) and Bali et al. (2008) to addresses the issue regarding small illiquid stocks effect. A manual screening of the stocks shows that a large proportion of the stocks lack price data for the period prior to 2003. After excluding stocks with unavailable price data, the remaining 334 active stocks, ranging from small to large market cap and covering the period 2003-2017 are kept for the analysis in this thesis. It is noteworthy that the data used in this thesis are book values, which in many cases do not reflect the real value of the companies' assets. Book values can also be manipulated and are sensitive to accounting rules since the accounting of assets might vary between companies and industries, sometimes even within the same industry. Therefore, using book values to measure leverage might not be optimal. In addition, as market values of equity are used for the purpose of estimating returns market values of debt would be a more appropriate measure of debts compared to book values. However due to limited accessibility to market values of debts, book values will be used throughout the thesis.

Table 1 reports statistics that summarize the data sample. It can be seen from Panel A that the average stock in Nordic equity market earns a return of 20.7%. Ln (Returns) is negatively skewed and has a relatively large kurtosis, however considerably lower than Return. Sharpe on the other hand seems to be more normally distributed compared to Ln(Returns). The skewness and kurtosis of (Range-based) Volatility indicate that the variable is approaching a Gaussian distribution, supporting the statement of Blau et al. (2017). WML has a mean of 0.680, the largest among the factors which implies that momentum portfolios on average have outperformed size and value portfolios during the period 2003-2017 in the context of Nordic equity market. This contradicts the results reported in Blau et al. (2017). According to Blau et al. (2017) size portfolios seem to have outperformed momentum and value portfolios in the US stock market during 1980-2012. The variable EBIT/Assets is heavily negatively skewed and has a high level of kurtosis, indicating the presence of outliers in the data. Robust regression, which accounts for outliers would therefore be an appropriate estimation technique.

Panel B shows the correlation matrix of the variables used throughout the thesis. Volatility appears to be negatively correlated with both Returns and Sharpe ratio. In addition, factors are highly correlated with volatility. While HML is positively correlated with volatility, WML has correlation coefficient of -0.496 indicating a strong negative correlation with volatility. These results are inconsistent with Blau et al. (2017) who report that range-based volatility Is positively correlated with SMB, HML and WML factors in the US stock market.

Table 1. Descriptive statistic and correlation

Panel A. Descriptive statistics

	Ln (Returns)	Return	Sharpe	Volatility	Ln Assets	Ln Capex	SMB	HML	WML	Debt /Assets	EBIT /Assets
Mean	0.061	0.207	0.989	2.932	12.977	8.946	-0.163	0.196	0.680	0.098	0.033
Median	0.110	0.116	0.424	3.052	12.822	9.022	-0.106	0.222	0.599	0.137	0.059
Std. Dev	0.523	0.713	1.988	1.006	2.310	2.717	0.250	0.159	0.330	0.304	0.216
Skewness	-0.926	5.486	0. 805	-0.173	0.259	-0.233	-2.092	-0.02	1.919	-0.725	-5.542
Kurtosis	8.240	71.263	3.559	2.422	2.971	2.693	7.796	2.076	7.471	3.88	58.744

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B. Correlation Matrix

	Ln (Returns)	Volatility	Sharpe	SMB	HML	WML	Lagged EBIT/ Assets	Lagged Debt/ Assets
Ln (Returns)	1							
Volatility	-0.0489***	1						
Sharpe	-0.113***	-0.164***	1					
SMB	-0.222***	-0.328***	0.331***	1				
HML	-0.0272	0.240***	-0.0591***	0.214***	1			
WML	0.254***	-0.496***	0.152***	0.620***	0.263***	1		
Lagged EBIT/Assets	0.0745***	0.114***	0.124***	-0.0327*	0.00497	-0.100***	1	
Lagged Debt/Assets	-0.0036	0.0239	0.0695***	-0.0398**	0.0208	-0.0210	0.104***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1 and 2 show the development of stock returns, volatility and leverage on Nordic stocks listed on Stockholm Stock Exchange, OMX Nordic Exchange Copenhagen, Oslo Bors and Helsinki Stock Exchange over the past 2003-2017 period. Both graphs show that the return volatility in Nordic equity market has risen considerably from 2003 to 2017. During 2006-2007 volatility and return seem to move in reverse direction and later decline at the same time. After the financial crisis 2008-2009 there is a rise in both volatility and return. The graphs show that there is no clear direction in the relationship between volatility and return for the entire period 2003-2017. Leverage (measured as Debt/Assets) has remained almost constant over this period.

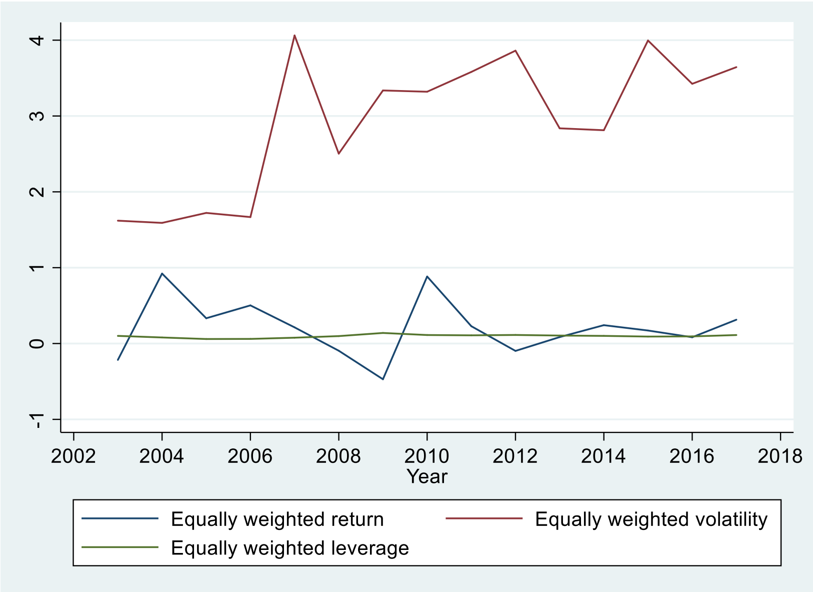

Figure 1. Equally weighted returns, volatility and leverage on Nordic stocks (as defined in Data Sample) during the period 2003-2017.

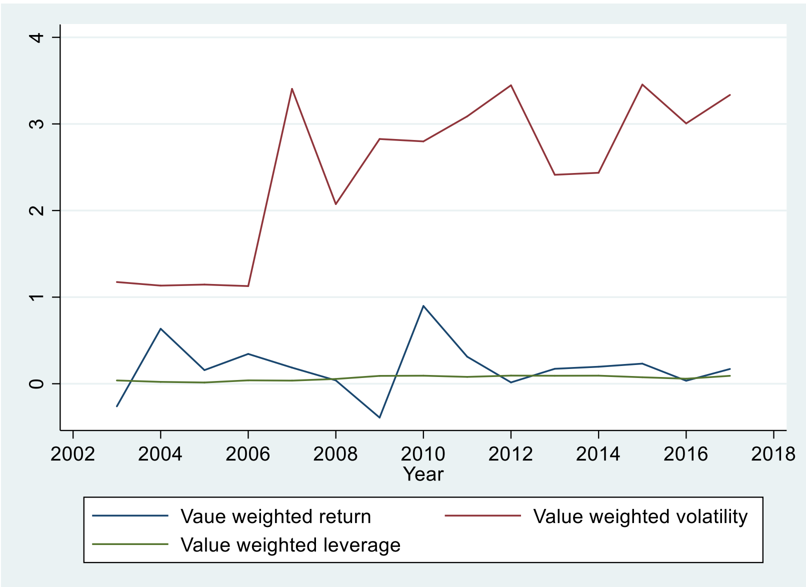

Figure 2. Value-weighted returns, volatility and leverage on Nordic stocks (as defined in Data Sample) during the period 2003-2017.

3.2.2. Variables

The following variables are included in the regressions. See Table 5 in Appendix for definition and construction of each variable.

Ln(Returns) Natural logarithms of yearly returns adjusted for dividends.

Return Quintile is a categorical variable representing the 5 return quintiles. Quintile 1 consists of stock with lowest yearly returns whereas quintile 5 comprises of highest return stocks.

Sharpe will be used as a proxy for yearly risk-adjusted returns and replaced with Ln (Returns) for the purpose of robustness test.

Volatility. Range-based volatility has been proven to be theoretically, numerically, and empirically superior to other measures of volatility in its efficiency. Compared to other measures of volatility, range-based volatility is distributed more normally and is robust to microstructure issues that are often a big issue in volatility estimation (Blau et al.,2017; Alizadeh, Brandt, Diebold; 2002). Hence, range-based volatility will be used throughout this thesis. For the sake of simplicity, the term volatility will be referred to as yearly range-based volatility in this thesis if nothing else is specified.

Volatility Quintile is a categorical variable representing the 5 volatility quintiles. Quintile 1 consists of stock with highest yearly volatility whereas quintile 5 comprises of lowest volatility stocks.

Leverage. Both *Debt/Assets* and *Debt/Equity* ratios are used as proxies for leverage to analyse the possible impact of leverage on return-volatility relationship. Using both ratios allows us to undertake robustness tests to make sure that the statistical results are robust to different measures of leverage. As mentioned, book values are used instead of market values due to lack of data.

Interaction. Interaction terms between the dummy of Leverage and Volatility. See Table 5 in Appendix for definition

Ln (CAPEX). Natural logarithm of the firm's CAPEX

Ln (Assets). Natural logarithm of the firm's total assets

EBIT/Assets ratio is used as an indicator for the firms' performance. For the purpose of robustness test, EBITDA/Assets ratio is used.

Below are the size, value and momentum portfolios that have been constructed in accordance with Blitz et al. (2013). See Table 5 for portfolio formations in details.

*Small Minus Big SMB (size factor)***.** The monthly stock returns spread between stocks in highest and lowest quintile in terms of market capitalization.

*High Minus Low HML (value factor)***.** The monthly stock returns spread between stocks in highest market-to-book quintile and the lowest market-to-book quintile.

Winner Minus Looser WML (momentum). The monthly stock returns spread between stocks in the lowest quintile and highest quintile in terms of past performance.

Country

Figure 3 shows the number of countries in which the stock exchanges are located. Swedish stocks account for nearly 40 % of the stock sample while the remaining stocks has an approximately equal proportion of 20 %. Unfortunately, all Icelandic stocks were excluded in the stock selection process due to lack of data. Country is a dummy variable which takes value of 1 if the stock exchange on which a stock is listed has its location in a certain country and equals 0 otherwise. Including Country allows us to account for possible differences between the stocks at country (stock exchange) level.

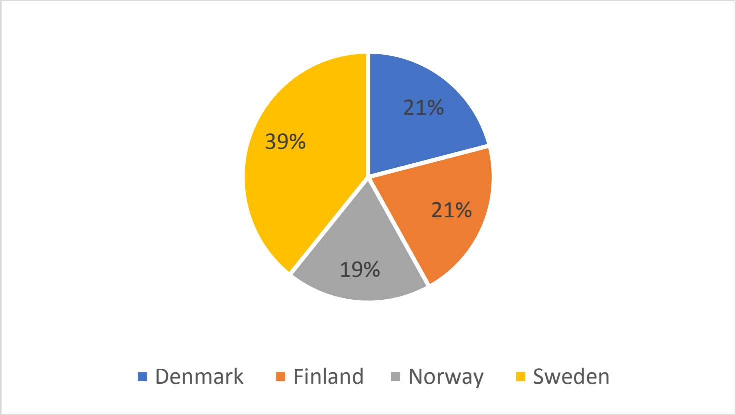

Figure 3. Country classification

Industry

Industry is a dummy variable which takes the value of 1 if a firm is in one of the industries below and 0 otherwise. The aim of including industry in the model is to account for possible variation between the stocks at industry level.

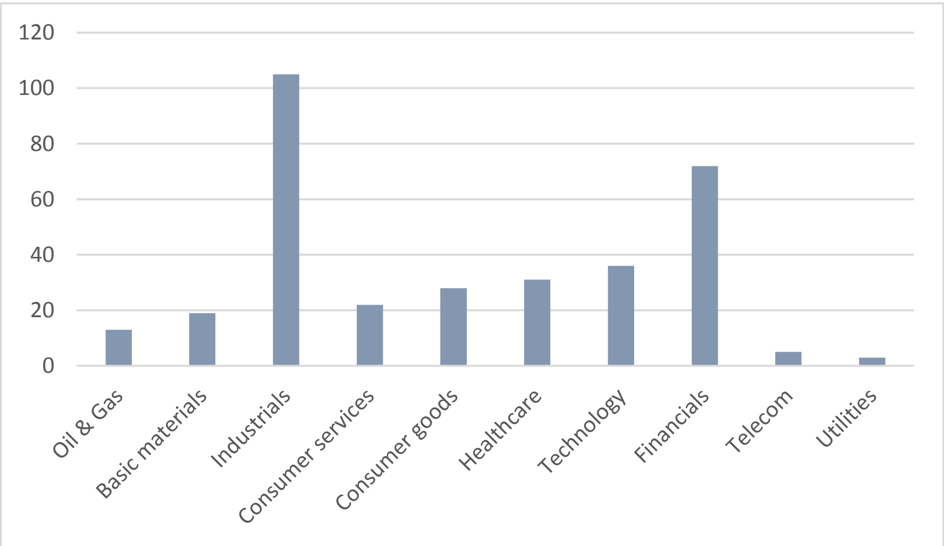

Figure 4. Industry classification

Year is a dummy variable which takes the value of 1 if the data is in a specific year and 0 otherwise.

3.3. Models

The econometric models used to explain the relationships between the variables of interest are specified in this section. The definitions on the variables can be found in Table 5 in the Appendix. For the discussion of the results, see Analysis section.

3.3.1. Leverage and volatility

The aim with the econometric models in this subsection is to investigate the relation between leverage and volatility as discussed in the literature review.

To analyse the possible effect leverage has on volatility, ordered logit model regressions are run on cross-sectional data for the years 2003 and 2007. In model (1a), the dependent variable is a categorical variable that comprises five volatility quintiles. The volatility quintiles range from 1 to 5 where quintile 1 contains stocks with lowest volatility and quintile 5 is made up by highest volatility stocks. The dependent variable Leverage, measured by both Debt/Assets and Debt/Equity ratios is the firms' Debt/Assets (Debt/Equity) from previous year (see Table 5 for clarification of each balance sheet item). The control variables include the firm's current natural log of CAPEX and Total Assets, along with first lagged yearly stock return and first lagged operating performance measured by EBIT/Assets ratio (or EBITDA/Assets ratio interchangeably). The idea is that if the coefficient on last year's leverage is statistically significant one might be able to say that leverage affects volatility. Model (1a) is specified as follows:

$$Volatility\ Quintile\ _{i,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_2 Ln(Return)_{i,t-1} + +\beta_3 Ln(Assets)_{i,t} \\ +\beta_4 Ln(CAPEX)_{i,t} + \beta_5 Operatingperformance_{i,t-1} + \beta_6 Industry_{i,t} + \beta_7 Country_{i,t} + \varepsilon_{i,t} \quad (1a)$$

Additionally, OLS time series and fixed effects regression of volatility against the firm's first lagged leverage are run to estimate model 1b. In this model, additional control variables such as year dummies, industry dummies and country (exchange) dummies are added to account for the variation across industries, countries and the variation over years in the data. Here, the dependent variable is yearly rang-based volatility. The independent variables include first lagged leverage expressed in both Debt/Assets and Debt/Equity, past operating performance (EBIT/Assets and EBITDA/Assets). Model 1b is specified as below:

$$Volatility\ _{i,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_2 Ln(Return)_{i,t-1} + +\beta_3 Operatingperformance_{i,t-1} + \\ \beta_4 Ln(Assets)_{i,t} + \beta_5 Ln(CAPEX)_{i,t} + \beta_6 Year_{i,t} + \beta_7 Industry_{i,t} + \beta_8 Country_{i,t} + \varepsilon_{i,t} \quad (1b)$$

where $i = 1, \ldots,$ is the number of firms, $k = 1, \ldots, N$, the number of control variables and t represents year. The control variables in this model include ln(CAPEX), ln (Total assets) and the dummies.

3.3.2. Leverage and stock returns

$$Return\ quintile\ _{i,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_2 Volatility_{i,t-1} + \beta_3 Ln(Assets)_{i,t} + \beta_4 Ln(CAPEX)_{i,t} + \beta_5 Operating performance_{i,t-1} + \beta_6 Industry_{i,t} + \beta_7 Country_{i,t} + \varepsilon_{i,t} \quad (2a)$$

Similarly, Model 2a and 2b examine the relation between leverage and stock returns. The prediction is that firms with higher leverage will more likely be in the low return quintile as postulated by the mechanical leverage effect discussed in Literature Review section.
Model 2a analyses cross sectional data for the year 2003 and 2017 and is estimated using ordered logit regression where dependent variable is the return quintile. Here, the dependent variable is the categorical variable that comprises of 5 return quintiles. Quintile 1 represents stocks with lowest yearly returns whereas quintile 5 consists of highest volatility stocks. Again, the dependent variable Leverage is expressed in both Debt/Assets and Debt/Equity ratio. The control variables are natural log of CAPEX and Total Assets as well as the lagged variables of Volatility, EBIT/Assets (EBITDA/Assets). Industry dummies and country dummies are also included.

$$Ln\ (Return)\ _{i,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_2 Volatility_{i,t-1} + \beta_3 Operating performance_{i,t-1} + \beta_4 Assets_{i,t} + \beta_5 CAPEX_{i,t} + \beta_6 Year_{i,t} + \beta_7 Industry_{i,t} + \beta_8 Country_{i,t} + \beta_9 SMB_{i,t} + \beta_{10} HML_{i,t} + \beta_{11} WML_{i,t} + \varepsilon_{i,t} \quad (2b)$$

On the other hand, model 2b is estimated using OLS regression on panel data. Unlike model 2a the control variables are expanded to include size, value and momentum factors, i.e. SMB, HML and WML, respectively. This is done in line with other studies (Ang et al.,2009; Blitz, et al.,2007,2013) to capture other effects that may also be determinants on stock return. Year dummies are included to account for variation over time in the panel data.

3.3.2. Stock returns, volatility and leverage

$$Ln(\ Return)\ _{i,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_2 Volatility_{i,t-1} + \beta_3 Interaction_{i,} + \beta_4 Operating performance_{i,t-1} + \beta_5 Ln(Assets)_{i,t} + \beta_6 Ln(CAPEX)_{i,t} + \beta_7 Year_{i,t} + \beta_8 Industry_{i,t} + \beta_9 Country_{i,t} + \beta_{10} SMB_{i,t} + \beta_{11} HML_{i,t} + \beta_{12} WML_{i,t} + \varepsilon_{i,t} \quad (3)$$

The specification of Model 3 is similar to Model 2b but with one exception: The interaction term between the dummy on Leverage and Volatility is included. The dummy variable on Leverage takes the value of 1 if Leverage is positive (larger than or equal to 0), and takes the value of 0 if Leverage is negative (smaller than 0). The ambition thereof is to examine the impact of leverage on the risk-return relationship by looking at the coefficient sign of the variable Interaction.

The purpose of including lagged volatility in Model 3 is to together with model 1a and 1b examine whether volatility drives stock return or vice versa, which existing studies have already touched upon. While the leverage effect predicts that negative returns make firms more levered, hence riskier, which in turn leads to higher volatility, the volatility effect reverses the causality by stating that increase in volatility results in negative future returns. Model 3 is estimated using OLS, FE and Quantile regressions. While FE accounts for possible unobserved microstructure at firm-level quantile regression eliminates the problems of outliers according to Blitz et al. (2013) and Dutt et al. (2013).

4. ANALYSIS

This section provides the interpretation and discussion of the regression results by comparing with the findings in prior studies. Additionally, stated research questions will be answered.

4.1. Findings

4.1.1. Do stocks with higher leverage have higher volatility?

The cross-sectional regressions in Table 6 (in Appendix) indicates a reverse relationship between leverage and volatility, which contradicts the theory of mechanical leverage effect and the empirical findings in Dutt et al. (2013). The coefficients on both Lagged Debt/Equity and Lagged Debt/Assets are negative, except for one coefficient on Debt/Equity in 2003 data. The interpretation is that highly leveraged firms are more likely to be in the lower volatility quintile. However, the coefficients are not statistically significant. The differences in results may depend on the fact that Black (1976), Christie (1982) and Dutt et al. (2013) use panel data when analysing the impact of leverage on stock return volatility. In addition, despite using a similar econometric approach as in Dutt et al. (2013), the ordered logit models in this thesis include industry dummies instead of year dummies. The intention was to account for the variation in volatility that might exist at the industry level, which seems to be true in cross-sectional data. The positive coefficients on Financials, Consumer goods and Telecom are positive and statistically significant at the 0.05 and 0.001 level showing that firms in these industries are more likely to be more volatile. The regression results also provide strong evidence that the Swedish stocks are more likely to be in the lower volatility quintile, followed by the Norwegian stocks.

In contrast with Dutt et al.'s (2013) findings, the coefficients on ln(CAPEX), ln(Assets) and the firm's operating performance proxy EBIT/Assets (as well as EBITDA/Assets) in Table 6 show mixed results. However, it is worth mentioning that the coefficient on ln (CAPEX) in 2017 cross-sectional data is positive and statistically significant at both 0.05 and 0.01 level, implying that CAPEX-heavy firms have higher volatility quintiles. This finding is inconsistent with Dutt et al. (2013) who examine a global stock sample including all Nordic countries except Iceland. For both 2003 and 2017 data, lagged returns seem to be negatively related to volatility although this result is not statistically significant in cross-section data.
The main result documented in Table 6 is that cross-sectional regressions imply a negative, however weak and statistically insignificant relation between volatility and the firm's prior year leverage. It should be emphasized that the coefficients on most of the independent variables in Table 6 change sign from year to year. The variation over time will be accounted for in the regressions reported in Table 2 below.

Table 2. OLS and FE regression on Volatility against Leverage

This table documents the regression model (as specified in equation 1b.) that examine the impact of leverage on volatility using panel data for the time period 2003-2017. The model is estimated using both OLS and Fixed Effects Regression. The dependent variable is the firm's yearly (range-based) volatility. The independent variable is the firm's last year leverage expressed in both Debt/Equity and Debt/Assets ratios. The control variables include the natural log of firms' CAPEX and so forth (See Table for variable definitions). All models include country dummies, industry dummies, year dummies and clustered standard errors by firm.

Dependent Variables	Volatility			
Models	OLS Firm Clustering		FE Firm Clustering	
	(1)	(2)	(3)	(4)
Lagged Debt/Assets	-0.101**		-0.124**	
	(0.0440)		(0.0485)	
Lagged EBIT/Assets	0.0382		-0.0401	
	(0.0401)		(0.0384)	
Ln (Lagged Returns)	0.0651***	0.0760***	0.0530***	0.0554***
	(0.0201)	(0.0190)	(0.0196)	(0.0182)
Ln (Assets)	-0.0185*	-0.0164	-0.0224*	-0.0255**
	(0.0108)	(0.0111)	(0.0117)	(0.0117)
Ln (CAPEX)	0.0185**	0.0136*	0.0258***	0.0232***
	(0.00762)	(0.00780)	(0.00792)	(0.00805)
Sweden	0.0378	-0.222***	-0.298***	-0.293***
	(0.0328)	(0.0320)	(0.0384)	(0.0383)
Finland	0.261***		-0.0762*	-0.0759*
	(0.0366)		(0.0416)	(0.0416)
Norway		-0.260***	-0.338***	-0.337***
		(0.0375)	(0.0411)	(0.0419)
Denmark	0.334***	0.0706*		
	(0.0411)	(0.0414)		
Consumer Service	0.101*	0.0937	0.104*	0.0887
	(0.0612)	(0.0615)	(0.0617)	(0.0615)
Consumer Goods	0.151***	0.135***	0.159***	0.136***
	(0.0442)	(0.0436)	(0.0453)	(0.0448)
Financials	0.260***	0.240***	0.274***	0.255***
	(0.0439)	(0.0429)	(0.0452)	(0.0447)
Telecom	0.317***	0.307***	0.310***	0.296***
	(0.0542)	(0.0541)	(0.0549)	(0.0544)
Lagged Debt/Equity		-0.00173		-0.00119
		(0.00139)		(0.00145)
Lagged EBITDA/Assets		0.0167		-0.00365
		(0.0111)		(0.0109)
Constant	1.483***	1.761***	1.798***	1.859***
	(0.107)	(0.1000)	(0.115)	(0.111)
Observations	4,904	4,903	4,904	4,903
R-squared	0.793	0.793		
Number of Stocks			334	334

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

The results in Table 2 show strong evidence of a negative relationship between leverage and volatility. The coefficient on Lagged Debt/Assets is -0.101 and -0.124, statistically significant at 0.01 and 0.05 level in the OLS and fixed effects regression model, respectively. This indicates that an increase of Debt/Assets by 1 unit is associated with a decrease in volatility by approximately 10 to 12 %, holding other things constant. When using Lagged Debt/Equity as measure of leverage this reversed relationship remains. However, the coefficients are not statistically significant. Despite a fairly large difference in the magnitude of the coefficients they indicate a negative relationship between leverage and volatility. This finding doesn't support the mechanical leverage effect that has been postulated in Black (1976), Christie (1982) and the recent research of Dutt et al. (2013). Dutt et al. (2013) use the same proxy for leverage, however the volatility in their study is estimated by the 500-day moving variance.

Nevertheless, the negative leverage-volatility relationship reported in this thesis is in line with the finding of Brandt et al. (2010) who suggest that firms with higher leverage appear to have lower idiosyncratic volatility. It is worth mentioning that Brandt et al. (2010) examine idiosyncratic volatility that has been adjusted for market variation and use the ratio book debt to the sum of book debt and market equity as a proxy for leverage. Both findings imply that Debt is negatively related to volatility whereas equity is positively associated with volatility. Since a firm is financed through either debt or equity, one could argue that lower debt leads to a higher degree of financing through equity, thus higher volatility. More specifically, equity (in the leverage ratio) drives volatility, possibly because firms become more exposed to market or industry risk through equity financing.

The coefficients on EBIT/Assets respective EBITDA/Assets have inconsistent signs in both models implying that whether strong performers have lower volatility is not so clear cut as documented in Dutt et al. (2013). Interestingly, Lagged Return when accounting for variation over time has positive impact on volatility in both OLS and fixed effects regression models with strong statistical significance, indicating that stocks with higher past return tend to be more volatile. This finding is inconsistent with those documented in Blau et al. (2017), which postulates that range-based volatility is negatively associated with expected stock returns. This thesis on the other hand focuses on historical returns. Once again, this supports the discussion in the literature review chapter, namely that the relation between return and volatility varies depending on how the two are estimated. This might also be an indication on simultaneous causality between risk and return, i.e. volatility drives return and vice versa.

Furthermore, firms with larger total assets have lower volatility as predicted in the study of Dutt et al. (2013). Conversely, CAPEX-heavy firms tend to be more volatile, likely because CAPEX is an expense, if maintained could reduce future earnings making a firm riskier. Similar to the results from the ordered logit regressions, Telecom and Financials are the most volatile industries, followed by Consumer goods. Some other variables are not reported in this table as they are not statistically significant or omitted due to multicollinearity and must be excluded to spare space. This procedure will be done for the rest of the thesis. Overall, both the OLS and FE regressions in Table 2 strengthens the results obtained in Table 6 by showing that the firm's past leverage has a statistically significantly negative impact on volatility. This result is robust to both measures of leverage, i.e. Debt/Assets and Debt/Equity.

4.1.2. Do stocks with higher leverage generate higher returns?

Table 7 in the Appendix reports the cross-sectional regression of Ln(returns) against leverage. The results show that the variable Lagged Debt/Assets in 2003 data has a coefficient of 1.064, statistically significant at the 5 percent level. For 2017 data, Lagged Debt/Assets consistently has a positive coefficient. However, the coefficient on Debt/Equity is negative and statistically insignificant in 2017 data implying that the positive leverage-return relationship is not robust to Debt/Equity. Overall, the cross-section regression results give an indication that Leverage (in terms of Debt/Assets) seem to be positively associated with stock returns. Table 3 is dedicated to a more thorough investigation on this subject.

The regression on 2017 cross-sectional data shows that large firms tend to generate higher stock return whereas CAPEX-heavy firms seem to have lower stock return. Both variables are statistically significant at the 0.01 level. Firms with higher lagged volatility are more like to be in the higher return quintile, indicating a positive relationship between the two. Sweden and Norway are two interesting cases. As discussed in section 4.1.1 Swedish and Norwegian stocks seem to be less volatile in relation to other Nordic counterparts. The regressions on 2013 cross-section data in this table show that these are also two stock subsamples that are more likely to be in the lower return quintile. Stocks in Financials, Consumer Service and Consumer Goods tend to have higher returns than other industries. What is notable in the cross-section regressions is that the coefficients on many variables change sign from year to year. Despite the statistical significance, the results discussed above serve as an indication rather than a conclusion since the variation over time must be first accounted for. The panel data analysis (Table 3) tackles this problem.

Table 3. OLS regression on Ln(Return) against Leverage

This table documents the regression model (as specified in equation 2b.) that examine the return-leverage relationship using panel data for the time period 2003-2017. The model is estimated using OLS Regression. The dependent variable is the firm's natural log of return. The independent variable is the firm's last year leverage expressed in both Debt/Equity and Debt/Assets ratios. The control variables include the natural log of firms' CAPEX and so forth (See Table for variable definitions). All models include Fama-French three factors, country dummies, industry dummies, year dummies and clustered standard errors by firm.

Dependent Variable	Ln (Return)	
MODDELS	OLS Regression Firm Clustering	
	(1)	(2)
Lagged Debt/Assets	-0.0480	
	(0.0292)	
Lagged EBIT/Assets	0.208***	
	(0.0511)	
Ln (Assets)	0.0122**	0.0164***
	(0.00491)	(0.00532)
Ln (CAPEX)	-0.00118	-0.00224
	(0.00453)	(0.00441)
Lagged Volatility	0.0346**	0.0351**
	(0.0141)	(0.0142)
WML	1.049***	1.046***
	(0.0909)	(0.0895)
Sweden	0.0158	0.0352*
	(0.0133)	(0.0194)
Telecom	-0.0129	-0.146***
	(0.0302)	(0.0492)
Lagged Debt/Equity		-0.00169*
		(0.000888)
Lagged EBITDA/Assets		0.0786
		(0.0636)
Constant	-1.493***	-1.564***
	(0.180)	(0.182)
Observations	4,911	4,910
R-squared	0.391	0.386
Number of stocks		

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

In contrast to the cross-section regression results, the leverage-return relationship becomes negative after controlling for variation over time by including year dummies. Since the coefficients on both Debt/Assets and Debt/Equity are negative, this is an indicator on a negative relation between stock returns and leverage. More specifically, the coefficient on Lagged Debt/Equity is -0.00169, statistically significant at 0.1 level, implying that one unit increase in the firm's last year Debt/Equity is associated with a decrease by approximately 0.69 % in stock return, holding other variables constant. This finding is in line with the studies of Penman et al. (2007), Dutt et al. (2013) and Acheampong et al. (2014) who use similar measures of leverage when examining the return-leverage relationship. However, one must be extremely cautious when predicting the stock return-leverage relation since the relation might vary depending on the time period and the proxy for leverage. Kallunki et al. (1997) find that there exists a positive relationship between return and leverage expressed in equity to capital in the late 1980s due to the liberalization of Finnish financial markets. As a result of the liberalization, firms have better access to equity market. However, prior to the 1980s this relationship was negative. Artikis et al. (2011) document a strong positive and statistically significant relationship between leverage (measured by Total Debts/Total Assets) and stock returns when examining stocks listed on Milan Stock Exchange. Similarly, Min et al. (2016) suggest positive and strong relation between the relative leverage (bank debts) and returns in the Japanese financial market. Most recent study of Hu et al. (2018) document a mixed relationship between leverage and return by comparing the firm's leverage to its target leverage. This comparison results in gain and loss domain for the firm. In particular, Hu et al. (2018) conclude that leverage and expected returns exhibit positive and negative relationships in gain and loss domains, respectively. The regression results in this section contribute to earlier research by showing a negative and statistically significant relationship between Debt/Equity and stock returns.

Furthermore, the regression results show a strong positive and statistically significant relation between the firm's operating performance (EBIT/Assets) likely because investors have higher expectation on firms with strong operating performance, which drives stock prices, therefore stock returns. The coefficient on EBITDA/Assets is also positive although it is not statistically significant. The coefficients on Ln (Assets) are positive and statistically significant indicating that larger firms seem to generate higher return. Possible explanations might be the advantages from economy of scale and a better access to capital market. CAPEX-heavy firms on the other hand seem to generate lower return possibly because CAPEX is an expense, which reduces EBIT and operating performance if maintained. These finding are consistent with Dutt et al's. (2013). The OLS regression results again show a positive and statistically significant relationship between lagged volatility and return. The coefficients on Lagged Volatility indicate that an increase in lagged volatility by 1 % may be associated with an increase by approximately 3.5. % in return.

4.1.3. Leverage – a possible explanation for return-volatility relation?

The results reported in Table 4 are to a large extent consistent with those documented in Table 2 and 3. The coefficient on Debt/Assets is negative in all 3 models and is statistically significant at 0.01 level in the quantile regression model. The quantile regression coefficient on Debt/Assets is identical with Dutt et al.'s (2013) in the regression of stock returns against leverage using the same econometric approach. The coefficient of -0.0617 indicates that an increase in the firm's Debt/Assets ratio by one unit could be associated with a decrease by 6.17 % in return on average.

When using Debt/Equity as a proxy for leverage, the coefficient on Debt/Equity (See Table 8 in Appendix) is statistically significant at the 0.05 in OLS regression with as small magnitude as -0.00216. However, this is still an indication of a negative return-leverage relation, which is consistent with previous results from Table 3.

Lagged Volatility has a positive and statistically significant relation with returns in both OLS and quantile regressions implying that low volatility effect does not exist in the Nordic stock market. This result is robust to current volatility. When using current volatility (See Table 9 in Appendix) the coefficient on volatility has even larger magnitude and is statistically significant in all models. This evidence supports many previous researches including Fu (2009), Rachwalski et al. (2016) and Tariq et al. (2017) by showing that high (lagged) volatility stocks seem to have higher return. Interestingly, Table 2 also documents that lagged return is positively related to volatility. The variable Lagged returns has positive coefficients and are statistically significant at 0.01 level in both OLS and FE regressions indicating that a 1 % increase in volatility would result in an approximate 5-7 % rise in returns, holding other things constant (See Table2). This provides additional evidence that stock return and volatility are simultaneously determined, i.e. volatility drives stock returns and vice versa. This result is robust to Sharpe ratio as a proxy for risk-adjusted return (see Table 10 & 11 in Appendix). The finding of this thesis supports the prediction made by many asset pricing models (e.g., Sharpe, 1964; Treynor, 1962; Lintner, 1965a, b; and Mossin, 1966; Merton, 1973) and the empirical findings reported in Fu (2009) and Rachwalski et al. (2016).

Rachwalski et al. (2016) suggest that the negative return-volatility relation is short-lived and only lasts for a few months after an idiosyncratic volatility shock. This is due to the investors' temporary underreaction to risk innovations and the fact that recent information is not yet fully incorporated into prices. However, returns become positive over time as the shock gradually settles. In the long-run idiosyncratic risk is positively priced which theory suggests. The finding of this thesis is also in line with Tariq et al. (2017) even after addressing the issue concerning the positive volatility-return effect among small stocks.

The positive return-volatility relation contradicts the findings of Ang et al. (2006,2009), Bali et al. (2008, 2011) and Dutt et al. (2013). Dutt et al. (2013) further clarify that the low volatility effect can be explained by the firm's operating performance. More specifically, they suggest that stocks with higher returns also belong to the firm category with stronger operating performance. Thus, operating performance is one of the explanatory factors of low volatility effect. Seemingly this does not apply to Nordic stocks, i.e. operating performance cannot be used to explain the return-volatility relationship. So far, it has been shown that firms with higher EBIT/Assets appear to have higher stock return. The coefficients on EBIT/Assets in Table 4 are 0.209 and 0.222 in OLS and Quantile regression, respectively. Both coefficients are statistically significant at 0.01 level showing a strongly positive relation between the firm's operating performance and stock return. However, whether the relationship between the firm's operating performance and volatility is ambiguous and statistically insignificant (See Table 2 and 6). Leverage seems to have some impact on the return-volatility relationship. Documented results from both panel and cross-sectional data show that leverage has a negative and statistically significant relationship with both volatility and returns. Although this relationship is not statistically significant in all models but the coefficients have consistent sign in all panel data regressions after controlling for variation across industry, time and at firm-level. The interaction terms between Debt/Assets and Lagged Volatility have negative coefficient in all models indicating that leverage impacts the return-volatility relationship negatively. To be more precise, the effect of having positive leverage is that it could reduce the impact of volatility on returns by 0.352 % according the OLS regression result, 0.538 % according to the quantile regression result and so forth. Despite the statistical insignificance it has consistent sign across the models indicating its negative impact on the risk-return relationship.

Again, Ln (CAPEX) has a negative coefficient but only statistically significant at 0.05 level in FE regression. Larger firms in terms of total assets tend to have higher stock return because of the same reasons discussed earlier. Consistent with the result in Table 3, Swedish stocks appear to generate highest return among Nordic counterparts. The coefficient on Sweden is 0.0360 in Table 5, statistically significant at 0.01 level indicating that Swedish stocks generate a return which is 3.6 % higher than others on average. The coefficients on the size, value and momentum factors are statistically significant on 0.01 level in all models. The differences between the figures in OLS, Quantile and FE regressions are likely because FE models control for the panel structure of data and thus for unobserved characteristics at firm-level whereas the quantile regressions accounts for possible outliers in the data, that might affect the estimates' accuracy.

Table 4. OLS, Quantile and FE Regression on Ln (Return) against Debt/Assets and Volatility

This table documents the regression models (as specified in equation 3) that examine the possible impact of leverage on the return-volatility relationship using panel data for the time period 2003-2017. The model is estimated using OLS, Fixed Effects and Quantile Regression. The dependent variable is the firm's natural log of returns. The independent variables are lagged (range-based) yearly volatility, the firm's last year leverage expressed in Debt/Assets ratios as well as the interaction term between the two. The control variables include the natural log of firms' CAPEX and so forth (See Table for variable definitions). All models include Fama-French three factors, country dummies, industry dummies, year dummies. Clustered standard errors by firm are used in OLS and FE models whereas robust standard errors are used in the quantile regression.

Dependent Variable		Ln (Return)	
MODELS	OLS Firm clustering	Quantile Regression Robust Std Errors	FE Firm Clustering
	(1)	(2)	(3)
Lagged Debt/Assets	-0.0610	-0.0617***	-0.00683
	(0.0386)	(0.0237)	(0.0826)
Lagged Volatility	0.0322**	0.0234***	0.0164
	(0.0144)	(0.00860)	(0.0162)
Interaction	-0.00352	-0.00538	-0.00206
	(0.00585)	(0.00390)	(0.00728)
Lagged EBIT/Assets	0.209***	0.222***	0.0805
	(0.0510)	(0.0364)	(0.0787)
Ln (CAPEX)	-0.00114	0.000534	-0.0173**
	(0.00454)	(0.00300)	(0.00796)
Ln (Assets)	0.0120**	0.00628**	-0.0337
	(0.00492)	(0.00311)	(0.0219)
SMB		-2.316***	
		(0.177)	
HML		1.108***	
		(0.119)	
WML	1.048***	2.533***	0.956***
	(0.0909)	(0.215)	(0.0958)
Basic Mats	-0.0341	-0.0555*	
	(0.0264)	(0.0296)	
Sweden	0.0160	0.0358***	
	(0.0133)	(0.0111)	
Constant	-1.487***	-2.387***	-0.591*
	(0.179)	(0.212)	(0.347)
Observations	4,911	4,911	4,911
R-squared	0.391		0.400
Number of Stocks			334

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

4.2. Robustness tests

The robustness of reported results in this thesis has been considered in several ways: First, clustered standard errors are used in all regressions apart from quantile regressions to ensure that the variation at firm-level is accounted for. Also, year, country and industry dummies are included in all regression models to control for variation over time, across countries/exchanges and industries. One concern addressed in the similar study of Dutt et al. (2013) is that different stock exchanges have different market microstructures, trading rules and different levels of direct market access. However, it could be argued that these dissimilarities might not be significant among Nordic exchanges/countries. Second, the variables are replaced by other comparable variables e.g. returns by risk-adjusted returns measured by Sharpe ratio, EBIT/Assets by EBITDA/Assets, Debt/Assets by Debts/Equity to ensure that the results are robust to different variable definitions.

5. CONCLUSION

This thesis provides evidence that low volatility effect does not exist in the Nordic stock market. The regression results point towards a positive and statistically significant relationship between yearly (range-based) volatility and yearly returns among Nordic stocks. This finding is robust to both lagged and current volatility as well as risk-adjusted returns measured by Sharpe ratio. Additionally, both fixed effects and OLS regressions result suggest that the firm's lagged leverage is negatively associated with volatility. This is statistically significant when using Debt/Assets as the proxy for leverage. Consistently, the coefficient on Debt/Equity is negative, however statistically insignificant. This finding is consistent with Brandt et al. (2010) who predict a negative relationship between idiosyncratic volatility and leverage with a slightly different measure of leverage (Debt to the sum of Debt and Market Equity). Both findings indicate that equity is positively related to volatility. One possible explanation could be that firms become more exposed to the market/industry risk through equity financing. There is evidence on a negative return-leverage relationship however with somewhat weaker statistical significance. While Dutt t al. (2013) argue that the low volatility effect that prevails in emerging markets and developed markets outside of North America including the European stock market can be explained by the firms' operating performance (measured by EBIT/Assets) the findings of this thesis indicate this does not apply for the Nordic equity market alone. The regression results indicate that leverage seems to have a negative impact on the risk-return relationship as there is evidence suggesting that leverage is negatively related to both volatility and stock returns. Again, this is likely because of the increased exposure to market risk through equity financing.

Furthermore, some evidence regarding the Nordic stock market are noteworthy: (a) Firms with strong operating performance (higher EBIT/Assets) generate higher returns with strong statistical significance in all models; (b) CAPEX heavy firms have lower returns possibly because CAPEX is an expense which impacts EBIT negatively; (c) Larger firms in terms of total assets appear to have higher equity returns which is in line with prior research; (d) SMB is negatively associated with returns confirming previous conclusion that larger firms generate higher stock return. On the other hand, WML portfolios seem to have outperformed SMB and HML portfolios during the period 2003-2017 in the context of Nordic equity market.

The regression results also indicate that there exists simultaneous causality between volatility and returns. Hence, a suggestion for future research would be to find a relevant instrument variable to address the issue of simultaneous causality and enhance robustness of the econometric estimates.

REFERENCES

Acheampong, P., Agalega, E., Shibu, A. K., 2014. The effect of Financial Leverage and Market Size on Stock Returns on the Ghana Stock Exchange: Evidence from Selected Stocks in the Manufacturing Sector. International Journal of Financial Research 5(1), 125-134.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 51, 259-299.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: international and further US evidence. Journal of Financial Economics 91, 1-23.

Artikis, P. G., Nifora, G., 2011. The industry effect on the relationship between leverage and returns. Eurasian Business Review 1(2), 125-145.

Aziz, T., Ansari, V. A., 2017. Idiosyncratic volatility and stock returns: Indian evidence. Cogent Economics & Finance 5 (1).

Baker, M., Bradly, B., Wurgler, J., 2011. Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly. Financial Analysts Journal 61, 40–54.

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

Bali, T. G., Whitelaw, R. F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics, 99, 427-446

Black, F., 1976. Studies of stock price volatility changes. Proceedings of the 1976 Meetings of the American Statistical Association. Business and Economics Statistics Section, 177-181.

Brandt, M. W., Brav, A., Graham, J. R., Kumar, A., 2010. The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Episodes? The Review of Financial Studies 23(2), 863–899.

Blau, B. M., Whitby, R. J., 2017. Range-based volatility, expected stock returns, and the low volatility anomaly. PLoS One 12 (11). https://doi.org/10.1371/journal.pone.0188517. Accessed [2018-03-04]

Blitz, D. C., Vliet, P., 2007. The volatility effect. Journal of Portfolio Management, 34(1), 102-113.

Blitz, D. C., Pang, J., Vliet, P., 2013. The volatility effect in emerging markets. Emerging Markets Review 16, 31-45.

Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected stock returns and variance risk premia. Review of Financial Studies 22, 4463–4492.

Christie, A. A., 1982. The stochastic behavior of common stock variances: Value, leverage and interest rate effects. Journal of Financial Economics 10, 407–432.

Dutt, T., Humphery-Jenner, M. 2012. Stock return volatility, operating performance and stock returns: International evidence on drivers of the 'low volatility' anomaly. Journal of Banking & Finance 37, 999-1017.

Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. Journal of Finance 47 (2), 427–465.

Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics 91, 24–37.

Haugen, R.A., Baker, N.L., 1996. Commonality in the determinants of expected stock returns. Journal of Financial Economics 41 (3), 401–439.

Hosmer, D., W., Stanley, L., 2000. Applied Logistic Regression. New Jersey: John Wiley & Sons, Inc., 2nd ed.

Hu, T., Gong, C., 2018. Does reference point matter in the leverage–return relationship? Evidence from the US stock market. Applied Economics 50 (21), 2339–2355.

Kallunki, J., Martikainen, T., 1997. Financial market liberalization and the relationship between stock returns and financial leverage in Finland. Applied Economics Letters 4 (1), 19-21.

Koenker, R., 2005. Quantile Regression. New York: Cambridge University Press.

Li, Q., Yang, J., Hsiao, C., Chang, Y., 2005. The relationship between stock returns and volatility in international stock markets. Journal of Empirical Finance 12, 650-665.

Li, X., Sullivan, R., Garcia-Feijoo, L., forthcoming. The limits to arbitrage revisited: The low-risk anomaly. Financial Analysts Journal.

Lintner, J., 1965a. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. Review of Economics and Statistics 47, 13–37.

Lintner, J., 1965b. Security Prices, Risk and Maximal Gains from Diversification. Journal of Finance, 20, 587–615.

Merton, R. C., 1973. An intertemporal capital asset pricing model. Econometrica 41, 768-783.

Min, T., Jiwen, S., Toyohiko, H., 2016. Banking relationship, relative leverage and stock returns in Japan. Pacific-Basin Finance Journal 40, 86-101.

Modigliani, F., Miller, M. H., 1958. The cost of capital, corporation finance and the theory of investment. American Economic Review 48 (3), 261-297.

Mossin, J., 1996. Equilibrium in a capital asset market. Econometrica 41, 485 - 512.

Penman, S., Richardson, S. A., Tuna, I., 2007. The Book-to-Price Effect in Stock Returns: Accounting for Leverage. Journal of Accounting Research 45 (2), 427-467.

Perold, A. F., 2004. The Capital Asset Pricing Model. Journal of Economic Perspective 18 (3), 2-24.

Rachwalski, M., Wen, Q., 2016. Idiosyncratic Risk Innovations and the Idiosyncratic Risk-Return Relation. The Review of Asset Pricing Studies 6 (2), 303–328.

Sharpe, W. F., 1966. Mutual Fund Performance. Journal of Business 39, 119–38.

Stock, J. H., Watson, M. W., 2015. Introduction to Econometrics. New Jersey: Pearson Education Inc, 3rd ed.

Treynor, J. L., 1965. How to Rate the Performance of Mutual Funds. Harvard Business Review 43, 63–75.

Tariq, A., Ahmad, V. A., 2017. Idiosyncratic volatility and stock returns: Indian evidence. Cogen Economics & Finance, 5 (1), 1-20.

Verbeek, M., 2004. A Guide to Modern Econometrics. Chichester: John Wiley & Son, Ltd, 2nd ed.

APPENDIX

Table 5. Variable Definitions

This table contains clarifications on the variables used in all regression models as well as Worldcope's definitions of the firms' balance sheet items.

Variable	Definitions
Ln(Return)	Yearly stock returns adjusted for dividends are calculated using the formula $R_{i,t} = ((S_{i,t} - S_{i,t-1}) + Div\ per\ share)/S_{i,t-1}$ where $R_{i,t}$ stands for return on stock i in period t. $S_{i,t}$ is the closing price of stock i in the last day of year t and $S_{i,t-1}$ is the closing price of stock i in the last day of the previous year.
Ln (Lagged Return)	Natural logarithm of the firm's first lagged returns
Return Quintile	Return quintiles are formed by sorting all stocks based on their yearly returns, more precisely for the year 2003 and 2017. Quintile 1 consists of stock with lowest yearly returns whereas quintile 5 comprises of highest return stocks.
Sharpe	is a proxy for yearly risk-adjusted returns and is calculated using Sharpe ratio for each stock: $$Sharpe_{\ M} = \frac{\bar{R}_i^e}{\sigma_{iM}^e}$$ The numerator $\bar{R}_i^e$ is the average monthly excess return of stock i : $$\bar{R}_i^e = \frac{1}{n}\sum_{M=1}^{n}(R_{iM} - R_{fM})$$ Where: R_{iM} = Return of stock i in month M. R_{fM} = Return of proxy for risk-free rate 1-month Euribor n = Number of months The denominator σ_{iM}^e is the monthly standard deviation of excess returns for stock i. The monthly Sharpe ratio $Sharpe_{\ M}$ is annualized by: $$Sharpe = Sharpe_M\sqrt{12}$$
Volatility	Is yearly range-based volatility estimated by taking the natural log of the difference between the highest ask price and the lowest bid price during a particular month, multiplied by $\sqrt{12}$.
Volatility Quintile	are formed by sorting all stocks based on their yearly (range-based) volatility for the year 2003 and 2017. Quintile 1 consists of stock with lowest yearly volatility whereas quintile 5 comprises of highest volatility stocks.

Lagged Volatility	The firm's first lagged volatility
Interaction	A dummy variable on lagged leverage is first created, which takes the value of 1 if first lagged leverage (expressed in Debt/Assets or Debt/Equity) is larger than or equals 0 and takes the value of 0 otherwise. The variable Interaction is the interaction term between the dummy variable on lagged leverage and lagged volatility.
Ln(CAPEX)	Natural logarithm of the firm's CAPEX. Capital Expenditures represent the funds used to acquire fixed assets other than those associated with acquisitions. It includes but is not restricted to: Additions to property, plant and equipment Investments in machinery and equipment.
Ln (Assets)	Natural logarithm of the firm's total assets. Total assets represent the sum of total current assets, long-term receivables, investment in unconsolidated subsidiaries, other investments, net property, plant and equipment and other assets.
Lagged Debt/Assets	The firm's first lagged Debt/Assets where Debt/Assets is the firm's net debts divided by its book total assets. Net debt represents Total Debt minus Cash. Cash consist of Cash & Due from banks for banks, cash for insurance companies and cash & short-term investments for all other industries.
Lagged Debt /Equity	The firm's first lagged Debt/Equity where Debt/Equity is the firm's net debt divided by shareholders' equity. Net debt represents Total Debt minus Cash. Cash consist of Cash & Due from banks for banks, cash for insurance companies and cash & short-term investments for all other industries. Shareholders' equity comprise of both common and preferred stocks.
Lagged EBIT/Assets	The firm's first lagged EBIT/Assets where EBIT/Assets is the firm's EBIT divided by total book assets. EBIT represent the earnings of a company before interest expense and income taxes. It is calculated by taking the pre-tax income and adding back interest expense on debt and subtracting interest capitalized
Lagged EBITDA/Assets	The firm's first lagged EBITDA/Assets where EBITDA/Assets is the firm's EBITDA divided by total book assets. EBITDA represents the earnings of a company before interest expense, income taxes and depreciation. It is calculated by taking the pre-tax income and adding back interest expense on debt and depreciation, depletion and amortization and subtracting interest capitalized.

Small Minus Big SMB	The monthly stock returns spread between stocks in highest and lowest quintile in terms of market capitalization. To construct SMB portfolio, the firm's market capitalization for the first day in January during the entire period 2003-2017 is obtained. For each year in the time period, the stocks are sorted based on market capitalization to create the quintiles. The equally weighted average of the stock returns is calculated for each quintile. The yearly SMB is computed by calculating the difference in average returns of the two quintiles: the quintile with smallest market cap quintile and the quintile with largest market cap. This calculation is repeated for each year during the time period 2003-2017.
High Minus Low HML	The monthly stock returns spread between stocks in highest market-to-book quintile and the lowest market-to-book quintile. The construction of HML portfolio is as follows: The market-to-book ratio for the first day in January during the entire period 2003-2017 is retrieved from Datastream. For each year, all stocks are sorted based on their market-to-book value ratio to create the quintiles. The equally weighted average return is calculated for each quintile. The yearly HML is computed by calculating the difference in average return of the two quintiles: quintile with lowest market-to-book ratio and the one with highest market-to-book ratio. This calculation is repeated for each year during the time period 2003-2017.
Winner Minus Looser WML	The monthly stock returns spread between stocks in the lowest quintile and highest quintile in terms of past performance. To construct an UMD portfolio, each stock's total return for the past 12-months minus 1-month is calculated starting in January of each year in the period 2003-2017. Later on, all stocks are sorted based on their total returns for past12-months minus 1-month and divided into quintiles. The equally weighted average of the returns are calculated for each quintile. The yearly UMD is computed by calculating the difference in average returns of the two quintiles: the quintile with lowest total return for past 12-months minus 1-month and the quintile with highest total return for past 12-months minus 1-month. This calculation is repeated for each year during the time period 2003-2017.

Table 6. Ordered Logit Regression on Volatility Quintile against Leverage

This table documents the ordered logit models (as specified in equation 1a.) that examine the possible impact of leverage on volatility using cross-sectional data for the year 2003 and 2017. The dependent variable is a categorical variable that contains the volatility quintiles, ranking from 1 to 5 where quintile 1 represents stocks with lowest volatility and quintile 5 consists of stocks with highest volatility. The independent variable is the firm's last year leverage expressed in both Debt/Equity and Debt/Assets ratios. The control variables include the natural log of the firms' CAPEX and so forth (See Table for variable definitions). The models include country dummies, industry dummies and clustered standard errors by firm.

Dependent Variable	Volatility Quintile			
Models	Ordered Logit Regression on 2003 data		Ordered Logit Regression on 2007 data	
Ln (CAPEX)	-0.0836	-0.0537	0.213^{*}	0.232^{**}
	(-0.94)	(-0.61)	(2.57)	(2.77)
Ln (Assets)	-0.0776	-0.0785	0.0651	0.0735
	(-0.80)	(-0.82)	(0.70)	(0.81)
Lagged Return	-0.157	-0.134	-0.149	-0.257
	(-0.57)	(-0.47)	(-0.88)	(-1.70)
Lagged EBITDA/Assets	-0.446		1.915	
	(-0.61)		(0.98)	
Lagged Debt/Equity	-0.000866		0.0354	
	(-0.31)		(1.23)	
Sweden	-1.630^{***}	-1.699^{***}	-1.467^{***}	-1.421^{***}
	(-5.89)	(-6.21)	(-4.55)	(-4.33)
Finland	-0.653^{*}	-0.736^{*}	-0.199	-0.168
	(-1.97)	(-2.19)	(-0.59)	(-0.50)
Norway	-1.155^{**}	-1.179^{***}	-2.132^{***}	-0.592
	(-3.17)	(-3.31)	(-5.79)	(-1.05)
Industrials	0.317	0.418	0.511	0.691^{*}
	(0.97)	(1.24)	(1.56)	(2.03)
Consumer Service	-0.134	-0.0447	1.104	1.230^{*}
	(-0.25)	(-0.08)	(1.95)	(2.24)
Consumer Goods	0.0103	0.154	1.225^{**}	1.370^{**}
	(0.02)	(0.31)	(2.77)	(3.00)
Financials	0.713	0.935^{*}	1.901^{***}	2.160^{***}
	(1.74)	(2.11)	(4.86)	(5.01)
Telecom	0.326	0.337	3.000^{*}	3.318^{**}
	(0.88)	(0.90)	(2.20)	(2.58)
Lagged EBIT/Assets		-0.559		1.981
		(-0.85)		(1.11)
Lagged Debt/Assets		-0.457		-0.988
		(-1.23)		(-1.78)
cut1	-4.054^{***}	-3.788^{***}	0.769	1.017
	(-5.13)	(-4.74)	(0.91)	(1.31)
cut2	-2.910^{***}	-2.640^{***}	2.198^{*}	2.478^{**}
	(-3.77)	(-3.38)	(2.56)	(3.10)
cut3	-1.969^{**}	-1.691^{*}	3.389^{***}	3.675^{***}
	(-2.58)	(-2.19)	(3.91)	(4.55)
cut4	-0.853	-0.570	4.647^{***}	4.932^{***}
	(-1.12)	(-0.74)	(5.35)	(6.08)
N	310	310	323	323

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$

Table 7. Ordered Logit Regression on Return Quintile against Leverage

This table reports the ordered logit models (as specified in equation 2a.) that examine the possible impact of leverage on yearly return using cross-sectional data for the year 2003 and 2017. The dependent variable is a categorical variable that contains the return quintiles, ranking from 1 to 5 where quintile 1 represents stocks with lowest return and quintile 5 consists of stocks with highest return. The independent variable is the firm's last year leverage expressed in both Debt/Equity and Debt/Assets ratios. The control variables include the natural log of the firms' CAPEX and so forth (See Table for variable definitions). The models include country dummies, industry dummies and clustered standard errors by firm.

Dependent Variable	Return Quintile			
	Ordered Logit Regression on 2003 data		Ordered Logit Regression on 2007 data	
Ln (CAPEX)	0.0333	-0.00870	-0.303***	-0.291***
	(0.37)	(-0.10)	(-3.89)	(-3.92)
Ln (Assets)	-0.0178	-0.0288	0.347***	0.325***
	(-0.16)	(-0.27)	(3.70)	(3.77)
Lagged Volatility	0.193*	0.202*	-0.185	-0.192
	(2.33)	(2.53)	(-0.64)	(-0.65)
Lagged EBITDA/Assets	1.166		-0.0367	
	(0.84)		(-0.05)	
Lagged Debt/ Equity	0.00349		-0.0209	
	(0.87)		(-1.04)	
Sweden	-1.009***	-0.938**	0.00717	-0.0244
	(-3.37)	(-3.09)	(0.03)	(-0.09)
Finland	-0.481	-0.388	0.0412	0.00841
	(-1.41)	(-1.13)	(0.12)	(0.03)
Norway	-1.400***	-1.437***	0.634	0.544
	(-4.06)	(-4.24)	(1.78)	(1.62)
Basic Mats	1.167*	0.782	1.209*	1.182*
	(2.26)	(1.48)	(2.24)	(2.14)
Industrials	0.958*	0.742	0.238	0.211
	(2.36)	(1.78)	(0.68)	(0.59)
Consumer Service	1.886***	1.725***	-0.338	-0.368
	(3.80)	(3.40)	(-0.65)	(-0.71)
Consumer Goods	1.504**	1.181*	0.316	0.265
	(2.87)	(2.16)	(0.70)	(0.58)
Financials	1.931***	1.549**	-0.411	-0.459
	(3.64)	(2.93)	(-1.09)	(-1.13)
Lagged EBIT/Assets		1.317		-0.0738
		(1.00)		(-0.09)
Lagged Debt/Assets		1.064*		0.0858
		(2.38)		(0.19)
cut1	0.0323	-0.581	-0.0912	-0.328
	(0.02)	(-0.43)	(-0.07)	(-0.25)
cut2	1.283	0.705	0.969	0.730
	(0.98)	(0.53)	(0.70)	(0.55)
cut3	2.304	1.752	1.847	1.605
	(1.75)	(1.30)	(1.33)	(1.22)
cut4	3.443**	2.944*	2.860*	2.617*
	(2.62)	(2.20)	(2.06)	(1.98)
N	317	317	323	323

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. OLS, Quantile and FE Regression on Ln(Return) against Debt/Equity, Lagged Volatility and Interaction
This table documents the regression models (as specified in equation 3) that examine the possible impact of leverage on the return-volatility relationship using panel data for the time period 2003-2017. The model is estimated using OLS, Fixed Effects and Quantile Regression. The dependent variable is the firm's natural log of returns. The independent variables are lagged (range-based) yearly volatility and the firm's last year leverage expressed in Debt/Equity ratios as well as the interaction term between the two. The control variables include the natural log of firms' CAPEX and so forth (See Table for variable definitions). All models include Fama-French three factors, country dummies, industry dummies, year dummies. Clustered standard errors by firm are used in OLS and FE models whereas robust standard errors are used in the quantile regression.

	Ln (Return)		
MODELS	OLS Firm clustering	Quantile Robust Std Errors	FE Firm Clustering
Lagged Debt/Equity	-0.00216**	-0.00102	-0.00270
	(0.00109)	(0.000918)	(0.00191)
Lagged Volatility	0.0365**	0.0270***	0.0129
	(0.0142)	(0.00868)	(0.0157)
Interaction	-0.00207	-0.000877	0.00323
	(0.00429)	(0.00334)	(0.00595)
Lagged EBITDA/Assets	0.0506	0.101	0.0124
	(0.0430)	(0.0748)	(0.0195)
Ln (CAPEX)	-0.00194	-0.00241	-0.0181**
	(0.00445)	(0.00381)	(0.00794)
Ln (Assets)	0.0165***	0.00998***	-0.0272
	(0.00534)	(0.00386)	(0.0242)
SMB		-2.332***	
		(0.181)	
HML		1.135***	
		(0.122)	
WML	1.046***	2.591***	0.939***
	(0.0894)	(0.221)	(0.0938)
Basic Mats	-0.0401	-0.0666**	
	(0.0294)	(0.0271)	
Sweden	0.0348*	0.0353***	
	(0.0193)	(0.0117)	
Finland	0.0235	5.57e-05	
	(0.0203)	(0.0137)	
Denmark	0.00928		
	(0.0196)		
Constant	-1.569***	-2.452***	-0.632*
	(0.182)	(0.217)	(0.373)
Observations	4,910	4,910	4,910
R-squared	0.386		0.399
Number of stocks			334

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

Table 9. OLS, Quantile and FE Regression on Ln(Return) against Debt/Assets, current Volatility and Interaction

This table documents the regression model that examines the possible impact of leverage on the return-volatility relationship using panel data for the time period 2003-2017 and current volatility instead of lagged volatility as in Tale 5. The model is estimated using OLS, Fixed Effects and Quantile Regression. The dependent variable is the firm's natural log of return. The independent variables are current (range-based) volatility and the firm's last year leverage expressed in both Debt/Assets ratio as well as the interaction between the two. The control variables include the natural log of firms' CAPEX and so forth (See Table for variable definitions). All models include Fama-French three factors, country dummies, industry dummies, year dummies. Clustered standard errors by firm are used in OLS and FE models whereas robust standard errors are used in the quantile regression.

Dependent Variable		Ln (Returns)	
VARIABLES	OLS Firm clustering	Quantile Regression Robust Std Errors	FE Firm Clustering
Lagged Debt/Assets	-0.0144	-0.0452**	-0.0533
	(0.0383)	(0.0221)	(0.0801)
Volatility	0.0566***	0.0306***	0.0515**
	(0.0177)	(0.0101)	(0.0207)
Interaction	-0.00897	-0.00358	-0.0147**
	(0.00576)	(0.00369)	(0.00724)
Lagged EBIT/Assets	0.207***	0.215***	0.0795
	(0.0515)	(0.0380)	(0.0771)
Ln(CAPEX)	-0.00135	0.000243	-0.0184**
	(0.00449)	(0.00225)	(0.00796)
Ln (Assets)	0.0117**	0.00582**	-0.0328
	(0.00492)	(0.00274)	(0.0218)
SMB		-1.623***	
		(0.161)	
HML		0.685***	
		(0.116)	
WML	0.876***	1.950***	0.869***
	(0.0455)	(0.208)	(0.0443)
Basic Mats	-0.0275	-0.0502*	
	(0.0270)	(0.0296)	
Sweden	0.0198	0.0342***	
	(0.0134)	(0.0124)	
Norway	-0.0178	0.00134	
	(0.0199)	(0.0152)	
Denmark	-0.0119		
	(0.0137)		
Constant	-1.216***	-1.812***	-0.485*
	(0.0770)	(0.165)	(0.278)
Observations	4,911	4,911	4,911
R-squared	0.391		0.401
Number of stocks			334

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10. OLS, Quantile and FE Regression on Sharpe against Debt/Equity, Lagged Volatility and Interaction

This table documents the regression models (as specified in equation 3) that examine the possible impact of leverage on the return-volatility relationship using panel data for the time period 2003-2017. The model is estimated using OLS, Fixed Effects and Quantile Regression. The dependent variable is the firm's yearly risk-adjusted returns proxied by Sharpe ratio. The independent variables are lagged (range-based) yearly volatility and the firm's last year leverage expressed in both Debt/Equity as well as the interaction term between the two. The control variables include the natural log of firms' CAPEX and so forth (See Table for variable definitions). All models include Fama-French three factors, country dummies, industry dummies, year dummies. Clustered standard errors by firm are used in OLS and FE models whereas robust standard errors are used in the quantile regression.

Dependent Variable		Sharpe	
MODELS	OLS Firm clustering	Quantile Regression Robust Std. Errors	FE Firm Clustering
Lagged Debt/Equity	0.00512	0.00693*	0.00681*
	(0.00316)	(0.00375)	(0.00412)
Lagged Volatility	0.116***	0.103***	0.0535
	(0.0340)	(0.0236)	(0.0361)
Interaction	-0.00419	-0.00549	-0.000213
	(0.0154)	(0.00639)	(0.0161)
Lagged EBIT/Assets	1.244***	1.164***	1.117***
	(0.141)	(0.0877)	(0.127)
Ln (CAPEX)	-0.0373**	-0.0316***	-0.0449
	(0.0165)	(0.00815)	(0.0286)
Ln (Assets)	0.0916***	0.0670***	-0.195***
	(0.0204)	(0.00938)	(0.0740)
HML		-10.47***	
		(0.475)	
WML	-0.126	0.523	-0.466**
	(0.181)	(1.037)	(0.192)
Industrials	0.227***	0.133***	
	(0.0804)	(0.0262)	
Consumer Service	0.242*	0.113**	
	(0.135)	(0.0479)	
Consumer Goods	0.282***	0.127***	
	(0.0981)	(0.0363)	
Financials	0.500***	0.185***	
	(0.103)	(0.0427)	
Telecom	0.562***	0.409***	
	(0.205)	(0.0658)	
Sweden	-0.311***	0.257***	
	(0.0739)	(0.0190)	
Norway	-0.145	0.314***	
	(0.0944)	(0.0305)	
Denmark	-0.576***		
	(0.0795)		
Constant	1.797***	1.741*	6.083***
	(0.388)	(0.891)	(1.009)
Observations	4,911	4,911	4,911
R-squared	0.670		0.701
Number of stocks			334

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

Table 11. OLS, Quantile and FE Regression on Sharpe against Debt/Assets, Lagged Volatility and Interaction
This table documents the regression models (as specified in equation 3) that examine the possible impact of leverage on the return-volatility relationship using panel data for the time period 2003-2017. The model is estimated using OLS, Fixed Effects and Quantile Regression. The dependent variable is the firm's yearly risk-adjusted returns proxied by Sharpe ratio. The independent variables are lagged (range-based) yearly volatility and the firm's last year leverage expressed in Debt/Assets as well as the interaction term between the two. The control variables include the natural log of firms' CAPEX and so forth (See Table for variable definitions). All models include Fama-French three factors, country dummies, industry dummies, year dummies. Clustered standard errors by firm are used in OLS and FE models whereas robust standard errors are used in the quantile regression.

Dependent Variable		Sharpe	
MODELS	OLS Firm clustering	Quantile Regression Robust Std. Errors	FE Firm Clustering
Lagged Debt/Assets	-0.00889	-0.00450	-0.128
	(0.112)	(0.0629)	(0.164)
Lagged Volatility	0.113***	0.102***	0.0549
	(0.0347)	(0.0253)	(0.0371)
Interaction	-0.00379	-0.00447	0.000970
	(0.0190)	(0.0113)	(0.0181)
Lagged EBIT/Assets	1.240***	1.146***	1.106***
	(0.140)	(0.104)	(0.127)
Ln (CAPEX)	-0.0406**	-0.0352***	-0.0444
	(0.0168)	(0.00840)	(0.0287)
Ln (Assets)	0.0968***	0.0722***	-0.191**
	(0.0201)	(0.00961)	(0.0745)
HML		-10.41***	
		(0.470)	
WML	-0.142	0.542	-0.451**
	(0.179)	(0.945)	(0.192)
Industrials	0.234***	0.137***	
	(0.0799)	(0.0286)	
Consumer Service	0.249*	0.112**	
	(0.135)	(0.0492)	
Consumer Goods	0.289***	0.119***	
	(0.0977)	(0.0385)	
Financials	0.519***	0.207***	
	(0.103)	(0.0432)	
Telecom	0.567***	0.414***	
	(0.207)	(0.0411)	
Sweden	-0.314***	0.261***	
	(0.0738)	(0.0235)	
Denmark	-0.580***		
	(0.0798)		
Constant	1.790***	1.672**	6.002***
	(0.387)	(0.844)	(1.016)
Observations	4,911	4,911	4,911
R-squared	0.669		0.700
Number of stocks			334

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