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School of Economics and Management

Asymmetric Volatility:
Testing Firm-specific Factors as a Cause for the "Leverage Effect" Using GARCH-modeling

By

Joos Jacob Maarten de Voogd & Thijs Geschiere

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Supervisor: Anders Vilhelmsson

Abstract

This thesis aims to investigate the dynamics of the so-called "leverage-effect". This asymmetry in volatility after negative shocks, relative to positive shocks has been documented extensively before. However, except for findings that it is not due to leverage, the underlying or enhancing factors that cause it have not been investigated. This thesis aims to do so, by testing for the influence of firm-specific variables on this volatility asymmetry size. The methods that are used are both GJR-GARCH(1,1)-modeling and the use of panel-data. The results show, except for the leverage variable, that firm-specific variables do indeed have their own characteristic effect on the size of the volatility asymmetry. The combined R-squared of the firm specific variables shows a good fit; hence they do form a considerable part of the contributing factors to the size of volatility asymmetries.

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Keywords: Volatility forecasts; leverage effect; GARCH; GJR-GARCH

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1 Introduction

The introduction will, in several stages, outline why this thesis has been written and which methods are employed to do so. It will do so by first giving a background, based on empirical evidence and previous research. The reasoning behind the topic will then follow and eventually it will briefly outline the structure of this thesis.

1.1 Background

``A drop in the value of the firm will cause a negative return on its stock, and will usually increase the leverage of the stock. [...] That rise in the debt-equity ratio will surely mean a rise in the volatility of the stock''.

- *Fletcher Black (1976)*

With these words Fletcher Black laid the foundation for the phenomenon of the *leverage effect*. Black observed that the volatility of stock prices is inversely correlated to the actual stock prices. What he meant by this is that a negative return on a stock will cause an increase in volatility that is greater than what it would have been, had the return on the stock been positive and of equal size. This observation has been confirmed and disputed by many other investigations into the matter. For example (Har, Sunderam, & Ong, 2008) conclude that the leverage effect does not exist in Kuala Lumpur, for the period 2004 to 2007. However, many papers, such as (Schwert, 1989), (Bekaert & Wu, 2000) and (Braun, Nelson, & Sunier, 1995) come to the conclusion that it does exist.

The academic society therefore generally assumes that the leverage effect substantially influences levels of volatility. How this happens is, however, strongly debated. According to (Black, 1976) the larger increase in volatility after a negative return is due to the change in leverage of the underlying asset, the firm. (Christie, 1982) comes to a similar conclusion and intuitively one might say that this is valid, as a drop in equity value will increase the degree to which a firm is levered. This

increase in leverage will consequently cause the firm to be closer to default, as the decline in equity value will be of equal size as the change in the present value of the assets. This will in turn cause the firm to incur distress costs and this will result in investors being increasingly skeptic towards the firm.

This notion has, however, been contested numerous times since then. (French, Schwert, & Stambaugh, 1987), (Figlewski & Wang, 2000) and (Hasanhodzic & Lo, 2011) for instance, come to the conclusion that the effect may exist, but probably not (solely) due to a change in leverage. Even more compelling is that (Hasanhodzic & Lo, 2011) finds that the effect seems to be more severe for all-equity firms. The leading thought nowadays then is that the leverage effect may in fact not be due to financial leverage. What does cause it then, has barely been investigated.

1.2 Aim and Objective

This thesis then, will examine what has not been examined before: the underlying factors causing the "leverage" effect. We aim to fill in this blank spot in academic research to volatility asymmetries and to further explain this anomaly. This should be a valuable contribution to previous research and the financial profession as a whole, as volatility is one of the pillars of financial research and lies at the heart of risk modeling and valuation.

Since leverage does not seem to cause the volatility asymmetry we make another assumption, which is that other firm specific variables may enhance this asymmetry. For this reason several other factors, which differ in size per firm, are chosen and then regressed on the size of their respective leverage effect.

The research question that is deducted from the introduction above is the following:

"*Which firm specific attributes, if any, enhance the "leverage" effect?*"

1.3 Thesis Outline

This research question will be examined in depth throughout the coming chapters. The remainder of the thesis is organized as follows:

The next chapter will address the theoretical background and has two parts. In the first part the concept of volatility will be reviewed and special attention is paid to the way it has been modeled through time. To do so various volatility forecasting models that have been used over time will be discussed, which will eventually lead up to the now most commonly used model: the GARCH(1,1)-model. The other part will then discuss the various firm specific factors that will be regressed on the size of the volatility asymmetry. This chapter will briefly outline why and how certain variables are expected to affect the size of the volatility asymmetry.

Chapter three will discuss the data that is used for the tests, as well as the methods that are employed to do so. This entails the dataset, its requirements and the models that are used to estimate the size of the volatility asymmetry and the regression used afterwards to test for firm specific influences.

Chapter four presents the results of the tests that are run on the data using the previously discussed models. It will furthermore give additional insights and discuss the findings.

Chapter five will summarize the results and present the conclusions. It will also relate them to previous research and make recommendations for further research on this matter or related subjects.

2 Literature and Theoretical Review

This chapter will first address volatility in Finance and how it is measured and ends up with the GJR-GARCH(1,1)-model to model volatility asymmetries. Then various firm-specific variables, which will be used in the tests, are explained using empirical evidence both in favor and against the idea of volatility asymmetries.

2.1 Volatility Modeling in Finance

2.1.1 Uses for Volatility

Volatility is measured extensively in finance and is considered to be one of its most important concepts. The primary reason being that volatility is an important input to determine risk. For this reason volatility is used both for risk management purposes and for asset pricing. Both will briefly be discussed in 2.1.1.1 and 2.1.1.2.

2.1.1.1 Asset Pricing

The Modern Portfolio Theory (MPT), introduced by Markowitz, illustrates how volatility is used for asset pricing (Markowitz, 1952). The theory states that the variance of a portfolio can be obtained with the following formula:

$$\sigma_P^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_i \sigma_j \rho_{ij} \tag{1}$$

Where w_i and w_j stand for the weight of the investments in respectively asset *i* and *j*. σ_i and σ_j represent the volatility of these assets and ρ_{ij} the correlation between them. According to the formula, the variance of a portfolio containing two assets can be estimated as follows:

$$\sigma_P^2 = w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\rho_{12}\sigma_1\sigma_2 \tag{2}$$

From this formula it follows that an investor can reduce his risk by investing in assets that are not perfectly correlated. This inspired (Sharpe, 1964), (Lintner, The Valuation of Risk Assets and the Selection of Risky Investments, 1965a), (Lintner, 1965b), (Treynor, 1962) and (Mossin, 1966) to develop the model that we now

know as the Capital Asset Pricing Model (CAPM). This model can be formulated as follows:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) \tag{3}$$

In which:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} \tag{4}$$

Where R_i is the expected return of asset *i* and R_m the expected return of the market. As formulated in equation (4), β_i is the correlation of the market returns and the asset returns. The idea of the CAPM is that correlation between the volatility of the assets and the volatility of the market is priced, because the risk cannot be diversified away. This pushes the demanded return for investors upwards.

What is evident here is that volatility is the connecting and determining factor in asset pricing.

2.1.1.2 Risk Management

Another important field of finance, in which volatility is also the corner stone, is risk management. A simple representation of the formula to calculate the portfolio's Value at Risk (VaR) is formulated below, using a normal distribution:

$$VaR_{\alpha}^{p} = V_p(-\mu_p - \sigma_p z_{1-\alpha}) \tag{5}$$

Where V_p is the value of the investment in the portfolio and μ_p the average return. $z_{1-\alpha}$ Is the z-score, given a normal distribution. The presence of σ_p in this formula shows once again the essence of a good framework for volatility estimation.

In another risk management model, the Merton model, one also finds that the calculation of the Probability of Default (PD) relies heavily on the volatility of the underlying asset (Merton, 1974). Even more so, the Distance to Default (DD), which is used to calculate the PD, is expressed as the number of standard deviations the underlying asset is from default.

2.1.2 Unconditional Volatility

At the origination of the Merton model, but also at the origination of for instance the Black-Scholes model the assumption is that volatility is constant (Merton, 1974). However, looking at historical data on any kind of security or asset, it is clear that this is not the case. Volatility is not a constant factor, but is conditional on time (Andersen & Bollerslev, 1997) and comes in clusters, as is noted by (Mandelbrot, 1963): "Large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes."

This is interesting information, as this undermines, in part, the validity of a lot of models. When one looks, for example, at the Value at Risk formula in equation (5) it can be seen that it relies heavily on the standard deviation. However, this risk measure may not be as accurate as one would ideally like it to be, when unconditional volatility is applied. It is therefore useful to know the conditional volatility and preferably the forward-looking version of it, as anticipating an increase or decrease in riskiness presents the possibility to act accordingly, before it has actually become reality (Kuester, Mittnik, & Paolella, 2006). In short then, it is crucial to estimate volatility correctly. For this reason it is interesting to go into more detail how volatility works and on what factors it is dependent.

To start off, unconditional volatility will be explained for a time series of stock returns, r_t. This begins with calculating the error term, u_t, of the returns. Starting off with a regression for the individual price forming and returns of a series:

$$p_t = c + \sum_{i=1}^{N} \kappa_i x_{i,t} + \varepsilon_t \tag{6}$$

Where:

p_t	=	price of an asset at time t
c	=	constant term of the returns
κ_i	=	parameter for explanatory variable x_i
$x_{i,t}$	=	explanatory variable i
ε_t	=	residual term at time t

The returns of an asset then are as follows:

$$r_t = p_t - p_{t-1} \tag{7}$$

It then depends on the state of the dataset what follows. Assuming a dataset with a fixed beginning and ending, the average (expected) return, μ_i, can be calculated by simply taking the sum of the returns and dividing this by the number of observations:

$$E[r_t] = \mu = \frac{1}{T}\sum_{t=1}^{T} r_t \tag{8}$$

The residual term for each observation can then be calculated as:

$$u_{i,t} = r_{i,t} - E\left[r_{i,t}\right] \tag{9}$$

Note that this assumes a fixed mean that does not change through time, as it would when for instance a Moving Average-model (MA(q)) would be used. If that were the case the mean would obviously differ through time, but the calculation of the error term would be the same.

Repeating this process from equation (9) for every observation in the series and calculating the average of all observations, will yield the average error, $E[u_{i,t}] = 0$. Squaring the error term for each observation and taking the average of it will in turn result in the unconditional sample variance.

$$\hat{\sigma_i}^2 = \frac{1}{T-1}\sum_{i=1}^{T} \hat{u}_{i,t}^2 \tag{10}$$

Taking the square root of the unconditional sample variance will then yield the standard deviation. For the remainder of this thesis this will not be done, as the variance in this sense merely imposes a non-negativity constraint on volatility[1].

Taking a closer look at equation (10) above, it is clear that the variance in this scenario is unconditional. It is therefore considered to be constant throughout the sample. As stated before, this may be theoretically accurate, but in practice the

[1] For more information on this constraint: (Brooks, 2008).

variance differs from time to time and comes in clusters. This presents a challenge: backward looking variances may not sufficiently cover the risks that one faces. For this reason various models have been created to forecast volatility, based on historical data. One of the first modern models to do so is the ARCH(q)-model, presented by Engle in 1982.

2.1.3 The ARCH(q) Model

In 1982 Engle presented his ARCH(q) model (Engle, 1982). This model let go of the assumption of homoskedasticity[2]. As stated before, this provides a much more realistic perspective on things. The model is still not able to predict variance out of nowhere, but this does mean that an ARCH(q) model will change its predictions regarding the variance when a spike in variance has occurred in the observation preceding the lag to be forecasted. Hence also the name of the model; the model is conditional on the heteroskedastic nature of the sample.

The ARCH(q) model can be written as follows:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} a_i u_{t-i}^2 \tag{11}$$

Where: $a_0 > 0$,

$a_i \geq 0$

H_0: There are *no* ARCH effects, that is, there is no heteroskedasticity

H_a: There *are* ARCH effects, that is, there *is* heteroskedasticity

Looking at this model, it can be seen that it requires several arbitrary inputs. The first to look at is the number of lags, q, to take into account. (Engle, 1982) uses four lags, but this choice was mostly arbitrary. The second thing to take into account is the estimation of the error term. This term is now conditional on time, and as such it

[2] Homoskedasticity assumes constant variance: $E[\sigma_t^2] = \sigma^2 < \infty$.

may be counter intuitive to use a constant mean. Engle himself advocates the use of the conditional mean and gives the example of an AR(1)-process:

$$y_t = \Phi y_{t-1} + u_t \tag{12}$$

The conditional mean, Φy_{t-1}, then is in part dependent on the preceding lag, which is given by:

$$y_t | \psi_{t-1} \sim N(0, \sigma_t^2) \tag{13}$$

In this formula ψ_{t-1} is the information set that determines the conditional mean. The unconditional mean is assumed to equal zero.

On the other hand, he also points out that for instance (Klein, 1977) uses moving averages. An alternative view is proposed by (Figlewski, 1997), who gives the example that traders often use three months of daily data. But then adds that around one out of three times these estimates could be as much as 85% off the real volatility value on an annual basis. Consequently he proposes the use of either a zero-mean or the use of the risk-free rate as the mean.

Eventually the mean is not the biggest worry there is, as long as extreme sample mean returns are not used (Figlewski, 1997). This does, however, not solve the problem of the number of lags, q, that are required. This problem was no longer relevant when (Bollerslev, 1986) came along.

2.1.4 The GARCH(p,q) Model

In 1986 Tim Bollerslev adjusted the ARCH(q) model to become the GARCH(p,q) model. The most common version of this model is the GARCH(1,1) model, as it takes all previous lags of variance into account by construction. To show this, consider the general form of the GARCH(p,q) model:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{14}$$

Transform this into a GARCH(1,1) model, which can be written as equation (15):

$$\sigma_t^2 = \omega + a_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{15}$$

Where: $\omega > 0$,

$a_1 > 0$,

$\beta > 0$ and

$\alpha + \beta < 1$.

Remember however, that the variance of the previous lag is also included:

$$\sigma_{t-1}^2 = \omega + a_1 u_{t-2}^2 + \beta \sigma_{t-2}^2 \tag{16}$$

This in turn leads to:

$$\sigma_t^2 = \omega + a_1 u_{t-1}^2 + \beta (a_0 + a_1 u_{t-2}^2 + \beta \sigma_{t-2}^2) \tag{17}$$

$$\sigma_t^2 = \omega + a_1 u_{t-1}^2 + \beta a_0 + \beta a_1 u_{t-2}^2 + \beta^2 \sigma_{t-2}^2 \tag{18}$$

Consequently this process would theoretically go on till infinity and therefore more than one lag for both the variance and error terms is unnecessary.

Now there are several extensions to this model. All of which are aimed at modeling some anomaly or another. The one this thesis will focus on is that after a negative shock the variance will increase more than after a positive shock of equal size.

2.1.5 Asymmetric Volatility and Applicable Models

As mentioned before, volatility asymmetries are considered common finance theory and therefore several models have been created to model them. Two GARCH-models have been further specified to take those asymmetries into account. The first one is the E-GARCH, as published in (Nelson, 1991). Nelson finds that negative returns result in a bigger volatility rise than positive returns of the same magnitude do. Furthermore he finds that standard GARCH models inadequately measure this effect. Assuming normality, (Nelson, 1991) used the following E-GARCH model:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \tag{19}$$

Using this equation the volatility asymmetry effect is observed when $\gamma > 0$.

Furthermore, no restrictions have to be applied on the parameters, since the log of the variance is modeled. So even if the parameters are negative, the estimated variance will be positive. This can be considered a benefit of the E-GARCH model.

Two years later (Glosten, Jagannathan, & Runkle, 1993) created another asymmetric GARCH model, which is known under the name GJR-GARCH. This latter model forecasts the volatility slightly more accurate than the E-GARCH model (Liu & Hung, 2010). The GJR-GARCH(1,1)-model relies on the following formula:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \qquad (20)$$

Where I_{t-1} = 1 for all $u_{t-1} < 0$

= 0 for all $u_{t-1} \geq 0$

Furthermore we apply the following restrictions:

$\omega > 0$,

$\alpha > 0$,

$\beta \geq 0$ and

$\alpha + \gamma \geq 0$.

The use of both models gives rise to certain expectations. Given the explicit way that negative returns are more aggressively modeled than the standard GARCH(1,1) model, one can expect a higher volatility after a negative shock. This is exactly what one would expect to see and by default is due to the rise in leverage of the underlying firm. However, a "higher" volatility in itself is a bad measure. Therefore the focus is on the gamma, which is expected to be positive, should the solely *negative* stock returns prove to significantly influence the forecasted variance. Which factors may have an influence on this gamma (γ) will be discussed in the next part of this chapter.

2.2 Firm Specific Variables

Offered explanations for the aforementioned volatility asymmetry do exist. (Hasanhodzic & Lo, 2011) reason that the cause of the leverage effect may be psychological in nature. Other research like (French, Schwert, & Stambaugh, 1987) and (Campbell & Hentschel, 1992) suggests that the cause of the leverage effect may be related to the fact that increased volatility would increase the required risk premium. A higher risk premium would drive the stock price down. However, the problem is that this suggests a reverse causal relationship; the increased volatility drives the stock price down instead of the causal relationship suggested by (Black, 1976), that a downward movement of the stock price increases the volatility. However, no research has been conducted thus far as to the influence of firm specifics on the size of volatility asymmetries.

The following sub-chapters will describe why certain ratios and values that are unique for each firm may influence the size of a possible volatility asymmetry.

2.2.1 Debt-Equity Ratio

The first possible contributor is the ratio of the Debt level as opposed to the level Equity that a firm holds. This heavily relates to what (Black, 1976) originally assumed to cause the "leverage effect". Black assumed that a negative shock in stock prices, and thus equity, increase the leverage and therefore increase the risk of equity. The cost of equity then goes up and the value drops accordingly.

A deduction that could follow then is that firms with already high debt levels will have a steeper increase in the riskiness of equity (and debt), as they are closer to incurring costs of financial distress. One would therefore expect that firms with high debt levels are more prone to volatility asymmetries, than firms with lower debt levels. As mentioned in the introduction, (Hasanhodzic & Lo, 2011) have found this to be unfounded, as they found that all-equity firms seem to have a larger volatility asymmetry.

On the other hand (Andrade & Kaplan, 1998) documents that companies that become highly levered due to takeovers seem to be distressed rather quickly. This could be used to underwrite the phenomenon of the "leverage effect".

2.2.2 Price-Earnings Ratio

The second possible contributor to volatility asymmetries is the Price-Earnings ratio. A high P/E-ratio might indicate overvaluation (Basu, 1977) and high P/E-ratios are often associated with high growth expectations. Empirical evidence has shown that these expectations are often overestimated (Malkiel, 1963). However, the market will gradually correct this overestimation and return the stock price to its correct level (Lakonishok, Shleifer, & Vishny, 1994).

The theory is that the market is aware of this overvaluation and will therefore respond more heavily to a negative shock as it would to stocks they assess to be correctly valued or undervalued. For this reason it could be expected that overvalued stocks, stocks with a high P/E-ratio, would react heavier to negative shocks than stocks with a lower P/E-ratio. This was evident during the collapse of the dot-com bubble in the period of 1999-2001. Overvaluation led to an extreme increase in volatility. This may also be deducted when regressing the P/E ratio on the size of the volatility asymmetry.

Opposing this theory is (La Porta, Lakonishok, Schleifer, & Vishny, 1997), which finds that stocks with high P/E-ratios are often considered to be so called "glamour stocks". In this sense investors keep these stocks in their portfolio because of their name and general allure. As a result these stocks are often overvalued for extended periods of time. Investors though, hold on to them regardless. From this perspective one would expect no real causal effect between the P/E-ratio and the size of the leverage effect.

2.2.3 Firm Size

The third possible contributing factor is firm size. This factor has been used in several models and is widely assumed to influence stock returns, both for the better and for the worse. Should size prove to be of significant influence on the size of volatility asymmetries there are two scenarios to be expected.

The first scenario is that size negatively influences the size of volatility asymmetries; smaller firms would then be more prone to the asymmetry. There are several reasons to believe this; one of the reasons is mentioned in the article of the three-factor model of Fama and French. This article describes how smaller firms tend to recover slower from economic downturns than bigger firms (Fama & French, 1992). This argument is supported by (Chan & Chen, 1991), who argue that bigger firms are more stable than smaller firms. They assess that this is due to the less efficient way that smaller firms are, on average, run. As a consequence smaller firms are overleveraged and tend to be easily distressed after a big downturn. This explanation then, essentially boils down to the perception that smaller firms, for various reasons, have a higher risk on their assets than bigger firms. This translates directly to the risk of levered equity (LE), as equation (21) below shows:

$$\beta_{LE} = \beta_{Assets}\left[1 + \frac{D}{E_L}\right] \tag{21}$$

A contradicting view is that larger firms are more sensitive to this volatility asymmetry. A cause for this is presented by (Piotroski & Roulstone, 2004), who find that larger firms get more coverage and that the information asymmetry between the firms and the market is therefore smaller. A consequence of this is presented by (Ciner, 2003), which finds that smaller firms over all experience lower trade volumes than larger firms. One may therefore wonder if the idea of a volatility asymmetry is even feasible for smaller firms.

2.2.4 Net Margin Level

The fourth possible contributing factor is the net margin. This factor tells us about the efficiency of a company. A higher net margin entails that a company is able to turn its investments efficiently into sales, thus a high revenue stream, relative to the incurred costs in achieving them.

One could assume two scenarios here as well, as there are different theories about it. For instance, (Qualls, 1974) states that companies that have high profit margins will not be able to sustain those for the long term. In this sense the same reasoning as overvaluation for the P/E-ratio works. Essentially the high profit (net) margin cannot stay at the high current level and is bound to go down at some point, the exceptions being monopolies and oligopolies. In markets with perfect competition the margin will theoretically converge to zero, where markets with high market concentration and entrance barriers will be positive and the persistence of high margins will be stronger. In this scenario the net margin will therefore be positively correlated to the size of the volatility asymmetry.

On the other hand, one could assume the opposite to materialize. Companies with low net margins have trouble turning their invested capital into value. These companies cannot maintain this state of affairs for too long, for the economic distress will eventually turn into financial distress. This can have all sorts of unfavorable consequences and put the state of the company under further duress (Andrade & Kaplan, 1998). One can be sure that the market will take note and will put this company under the loop. This could translate into a more severe response should negative news come out. In this scenario the net margin would be negatively correlated to the size of the volatility asymmetry.

3 Data and Methodology

In this section the data and employed methods will be discussed. First we will address the assumptions we make and the reasoning behind the selected data. Subsequently we will describe our methodology. This embodies an estimation of the leverage parameter using a GJR-GARCH model, followed by panel data methodology to obtain the parameters of the firm-specific variables.

3.1 Data

For the data we have several criteria, since the aim is to measure the influence of a certain firm specific variable on the conditional variance, we need a sample with enough variety, both in the time dimension and in the cross-sectional dimension.

3.1.1 Gathering and Screening of Data

To conduct this research, data is used from a variety of economies in Europe. The three biggest economies are chosen and are assumed to accurately represent the whole European economy. These economies are Germany, The United Kingdom and France (Eurostat, 2014). We start off with every listed company of these countries as given by DataStream and come to a dataset of 1117 listed companies.

The data is retrieved on a daily basis, as volatility is best measured using high frequency data. Furthermore the data is obtained over a period of sixteen years, starting in 1999 and ending in 2014. The reason for this is that we have several volatility clusters in this time interval. First, the build up to the bubble of 2000 and the drop after, second the cluster of drop between 2007 and 2009 due to the financial crisis and then drop in 2011 as a result of the European debt crisis. These are interesting phenomena in terms of volatility clustering and should provide us with valuable insights into the markets' behavior.

The data is consequently screened on several factors. The first is that we want our panel data to be as balanced as possible. This means that we want all companies to

show their price levels for every observation, from 1999 to 2014. All companies that do not adhere to this requirement are removed. After this is done, the returns of the remaining companies are calculated. Doing so exposes the quality of the data in a very obvious way. DataStream is not consistent when it comes to the accuracy of the stock prices. Some are as accurate as three decimals, whereas some have none. As a result we observed many *zero* stock returns, which in some cases is likely due to the accuracy of the data. Because these zero stock returns are likely to distort our returns in an unfair way, we have removed series that have more than 10% of zero stock returns.

All of these measures have a tremendous impact on the quantity of the companies that are employed to conduct our research on. From the initial 1117 companies, 290 are eventually left to be used. This is still a quite large number of stocks, but significantly less than the original number. This obviously could question the validity of the research, which will be addressed later on in this chapter.

3.1.2 Firm Specific Variables and Panel Data

In order to test for firm specific variable influences, we make an important observation; the variables have the ability to vary heavily over the course of time. This implies that a certain value may accurately depict the situation of a company at one time, but may be completely off point several years later. For this reason we employ panel data, in order to compensate for this. To do so, we divide the sixteen years of data into eight branches of two years. We do so for both the returns (from 3.1.1) and for the firm specific variables.

The consequence is that we need to retrieve the firm specific variables for each firm eight times. It is worth noting that the variables are collected in the middle of each sample of two years. As an example: for the first branch of two years (1999 – 2000), the values for the firm specific variables are collected on December 31st of 1999. The reason for this is that we make the assumption that the characteristics of the firm

are best resembled by the value the firm specific variables taken at this point in time.

The firm specific variables are retrieved for all 290 firms using DataStream and are for the most part complete. The variables that are used are those mentioned in chapter 2.2; Debt-Equity, Net margin levels, Price-Earnings and Firm size. Furthermore we would like to mention that the first two variables are a percentage, Price-Earnings is obviously a ratio and Firm size is given in thousands. Table 1 gives brief descriptive statistics of the retrieved values and shows that the data has quite a high variance (as depicted by *Std. Dev.*). This is important, as the odds of retrieving meaningful observations are positively correlated to the spread of the explanatory variables. Furthermore, Appendix I graphically shows that the observations of our firm specific variables are highly spread out across the spectre.

Table 1 (as well as Appendix I) shows that the values are not evenly distributed. This is clear from the difference between the mean and the median in all variables. This is not a problem, as the standard deviation is at an acceptable level for each variable.

Table 1: Descriptive Statistics Firm Specific Variables

	Debt Level	Price-Earnings	Enterprise Value[3]	Net Margin
Mean	112.71	23.20	21.188	9.91
Median	57.30	16.40	3.839	5.66
Std. Dev.	242.96	23.00	53.183	19.79
Observations	2286	1980	2264	2194

[3] In billions of Euros

3.1.3 Representativeness of the Data

An important point of attention is the representativeness of the results as they follow from the data that is used. As the data is reduced significantly in quantity one might question this representativeness.

Once again looking at Table 1 and Appendix I, it is clear that there is a wide variance (as portrayed by *Std. Dev.*), which is to the further benefit of the measurability of variable specific influences on the main variable of interest: the size of volatility asymmetries. This also makes a case for the representativeness of the data, as a large variance in the data suggests that the companies come from great variety of the economy as a whole. Furthermore the number of observations is well beyond what is an acceptable number of companies (>200 as a rule of thumb).
On top of this it is interesting that, when looking at Appendix I, the distribution of the dataset in terms of firm specific variables largely remains the same through time.

As a preliminary conclusion then we find that the dataset is not perfect, but that the available data in combination with the requirements forms a stable basis for this research.

3.2 Methodology

To find the effect of certain firm specific effects on the conditional volatility of a firm we employ two models: the first is a GJR-GARCH(1,1)-model and the second is panel data.

3.2.1 The GJR-GARCH(1,1) Model

There are two different types of asymmetric GARCH-models: the E-GARCH and the GJR-GARCH. The models are basically the same, but empirical results show that the

GJR-GARCH achieves the most accurate forecasts (Liu & Hung, 2010), so we choose it to be our asymmetric volatility forecasting model.

The GJR-GARCH(1,1)-model (22) with a basic mean (23) is specified as follows:

$$\sigma_{i,t}^2 = \omega_i + \alpha_i u_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 + \gamma_i u_{i,t-1}^2 I_{i,t-1} \tag{22}$$

$$u_{i,t} = r_{i,t} - E[r_{i,t}] \tag{23}$$

For stock *i* in this model

$\sigma_{i,t}^2$ represents the conditional forecasted variance,

ω_i the mean variance,

α_i variance dependence on previous lag error terms,

$u_{i,t-1}^2$ previous lag error term,

β_i variance dependence on previous lag variance terms,

γ_i the magnitude of the leverage effect and

$I_{i,t-1}$ the dummy variable:

$I_{i,t-1} = 1 \; \forall \; u_{i,t-1} < 0$

$I_{i,t-1} = 0 \; \forall \; u_{i,t-1} \geq 0$.

Furthermore the following restrictions are applied: $\omega_i > 0$, $\alpha_i > 0$, $\beta_i \geq 0$ and $\alpha_i + \gamma_i > 0$.

3.2.1.1 Assumptions

To be able to put this model into work we make several assumptions. The first is that we assume that the returns of a stock are, on average, zero. This implies that, referring to equation (23); every return there is on a stock automatically equals the error term for that observation. In this sense we go along with (Figlewski, 1997). The second assumption we make is about the distribution of the errors. The distribution we use is the Normal distribution, because this is paramount for the specification of the likelihood function. More on this assumption follows.

3.2.1.2 The Estimation of the GJR-GARCH(1,1) Model

Estimating GARCH-models brings with it a challenge. The usual OLS estimation cannot be used, since the errors, which are being modeled, are non-linear. We therefore turn to Maximum Likelihood Estimation (MLE). MLE aims to maximize a set Log Likelihood (LLH) function by finding the optimal values for the parameters used in the GARCH model. The LLH is given by the following equation:

$$L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}\frac{(r_t - E[r_t])^2}{\sigma_t^2} \tag{24}$$

Given that we assume that $E[r_t] = \mu = 0$ and that the error term therefore equals the returns, we get the following:

$$L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}\frac{{r_t}^2}{\sigma_t^2} \tag{25}$$

Where σ_t^2 is provided by the GJR-GARCH(1,1)-model.

Essential in this LLH-function is the assumption of the distribution of the errors. By default the errors are assumed to be normally distributed, however it has been proven that this is generally not the case. The distribution of returns, and thus the distribution of the errors, tends to be more heavily tailed, so a student distribution would be more appropriate (Officer, 1972). Using the Student t-distribution could however lead to inconsistent parameter estimations. However, supposing that the returns of a series are not normally distributed, but in fact do have fatter tails, will still result in consistent parameters (Brooks, 2008).

We will therefore employ the probability density function (PDF) that assumes a log-normal distribution. This PDF will be used for every observation in every series and consequently the sum of the individual PDFs will be maximized by MS Excel's Solver function. Solver will do this by changing the parameters used for the GJR-GARCH(1,1)-model, until an optimum has been reached. The PDF used is shown in equation (26).

$$L_t = ln\left(\frac{1}{\sqrt{2\pi\sigma_t}} EXP\left[-\frac{r_t^2}{\sigma_t^2}\right]\right) \tag{26}$$

The maximization of the sum of all PDFs will then eventually lead to the MLE of the individual parameters of the GJR-GARCH(1,1)-model.

3.2.2 Panel Data

The estimation of the GJR-GARCH(1,1)-model has eventually yielded four parameters; ω, α, β and γ. It is the last one, γ, which we are interested in, as it portrays the dependence of the forecasted volatility on the leverage effect. To check if firm specific variables have an influence on the size of this dependence, we will use panel data. We do this, because we assess that firm specific variables vary heavily over time. In the cross-section this means regressing the firm specific variables as independent variables to find their relation with the size of the leverage effect. In terms of a panel data regression then, this can be portrayed as follows:

$$\gamma_{i,t} = c_{i,t} + \theta_{i,t}(EV)_{i,t} + \tau_{i,t}NM_{i,t} + \varphi_{i,t}\left({}^{P}/_{E}\right)_{i,t} + \rho_{i,t}\left({}^{D}/_{E}\right)_{i,t} + \nu_{i,t} \tag{27}$$

To estimate this equation we have a choice of two models: either the random effects model or the fixed effects model. In order to make a choice for either, we employ the Hausman test. With the results of this test we employ one of them and regress the various firm specific variables on the size of the leverage effect and will find out whether or not these variables have a significant influence.

3.2.2.1 Fixed Effects Model

To see how the fixed effects model works we have to consider the following equation:

$$y_{it} = \alpha + \beta x_{it} + u_{it} \tag{28}$$

This is the standard equation for panel data. y_{it} and βx_{it} are, respectively, our dependent variable and explanatory variable, both in cross-sectional dimension *i*, as in time-series dimension, *t*. α Is the intercept and ν_{it} is the disturbance term, which

is of particular interest in the fixed effects model. Since in the fixed effects model the disturbance term is decomposed into two separate terms:

$$u_{it} = \mu_i + \varrho_{it} \tag{29}$$

Where μ_i is the individual specific effect and ϱ_{it} is the remainder disturbance term. So we can re-specify to equation (30):

$$y_{it} = \alpha + \beta x_{it} + \mu_i + \varrho_{it} \tag{30}$$

As mentioned before, μ_i is the individual specific effect. When we have N different variables in the cross-section, we can use dummy variables for every firm specific effect. The formula for the fixed effect model will then look like this:

$$y_{it} = \beta x_{it} + \mu_1 D1_i + \mu_2 D2_i + \mu_3 D3_i \ldots + \mu_N DN_i + v_{it} \tag{31}$$

3.2.2.2 Random Effects Model

As an alternative for the fixed effects model we can use the random effects model. The random effects model suggests the use a separate term for the individual specific effect, which is constant over time and is the same as with the fixed effects model.

The difference, however, is that the random effects model assumes that the individual specific intercepts of each cross-sectional unit are dependent on a common intercept α, which is the same for every cross-sectional unit as over time. The other term is the error $\in_i$ that varies in the cross-section and measures the deviation of the individual intercept term around the common intercept α. The equations are as follows:

$$y_{it} = \alpha + \beta x_{it} + \omega_{it} \tag{32}$$

$$\omega_{it} = \in_i + \varrho_{it} \tag{33}$$

y_{it} And βx_{it} are still the same as in the random effects model. But instead of using dummy variables, the firm specific effect is captured by the individual error term $\in_i$. For this term we have the assumptions of a zero mean, independent of the error ϱ_{it} and the explanatory variable x_{it} and the assumption of constant variance.

Because ordinary least squares (OLS) estimates the parameters inefficiently, the generalized least squares method (GLS) is recommended to estimate the parameters.

3.2.2.3 Hausman Test

To decide if we should use the random effects model or the fixed effects model, we have to compare the two. The random effects model should in general be more efficient than the fixed effects model. It saves degrees of freedom and fewer parameters have to be estimated. The random effects model, however, has more restrictions that the fixed effects model. Because it assumes that $\in_i$ and ϱ_{it} are uncorrelated with x_{it}, ω_{it} is also required to be independent.

To see whether we can apply the random effects model or the fixed effects model, we can test if the error term ω_{it} is independent with the x-variables. A common test for this is the Hausman test, named after the founder of the methodology (Hausman, 1978). Under the null hypothesis the Hausman test assumes that both models are consistent, but one (in this case the random effects model) is more efficient. Under the alternative hypothesis the assumption is that the more efficient model is inconsistent, so the fixed effects model would be preferred.

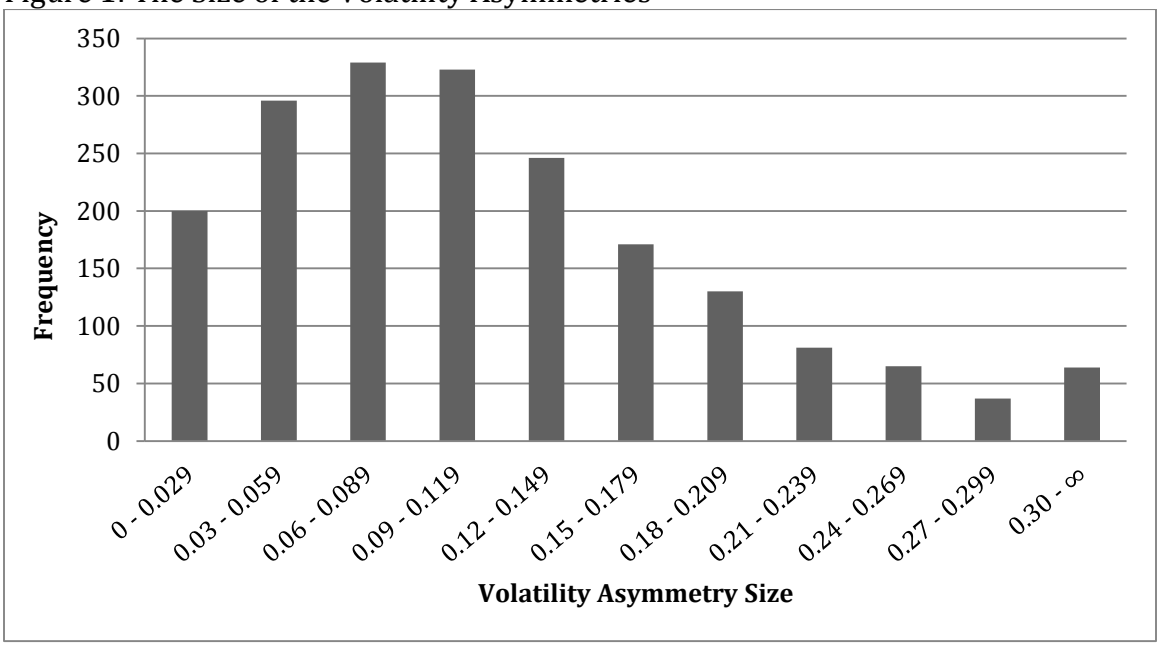
4 Results and Discussion

In this chapter the results from the various tests will be presented and discussed as they follow from the data that is used. This chapter will start off with the results from the GJR-GARCH(1,1) and will then put them in further context using the panel-data with firm-specific variables.

4.1 Results from the GJR-GARCH(1,1) Model

Figure 1 shows the size of the volatility asymmetry throughout this sample of sixteen years. The same, but more elaborate figure is shown in Appendix II. As is immediately clear is that the size of the volatility asymmetries is not normally distributed. The Jarque-Bera test yields a p-value of 0.000 for normality, which follows from a kurtosis of 3.724. The null-hypothesis of normality is clearly rejected[4]. Furthermore the mean of the leverage effect parameter, γ, is about 0.12 and the median about 0.10. The standard deviation is 0.078, which means the spread is moderately high.

Figure 1: The Size of the Volatility Asymmetries



[4] Henceforth: Significance levels are at 5%, unless stated otherwise.

Furthermore we have looked at the development of the size of the volatility asymmetry through time. This is graphically shown in Figure 2. The figure roughly shows the same distribution as the total sample in Figure 1. But it also shows that the size of the volatility asymmetry is not stable through time, as is also apparent from table 2. This observation then gives rise to the idea that volatility asymmetry is not just due to, for instance, firm specific variables, but may also be influenced by market situations or other global developments. Striking is that the asymmetry is relatively larger in the sub-periods of 2001 – 2002 and 2007 – 2008. This could mean that investor sentiment, which is generally negative after a bubble or crisis, plays a substantial role in stock volatility. The answer to this anomaly may very well be in the irrational or sentimental nature of investors.

Figure 2: The Size of the Volatility Asymmetries through Time

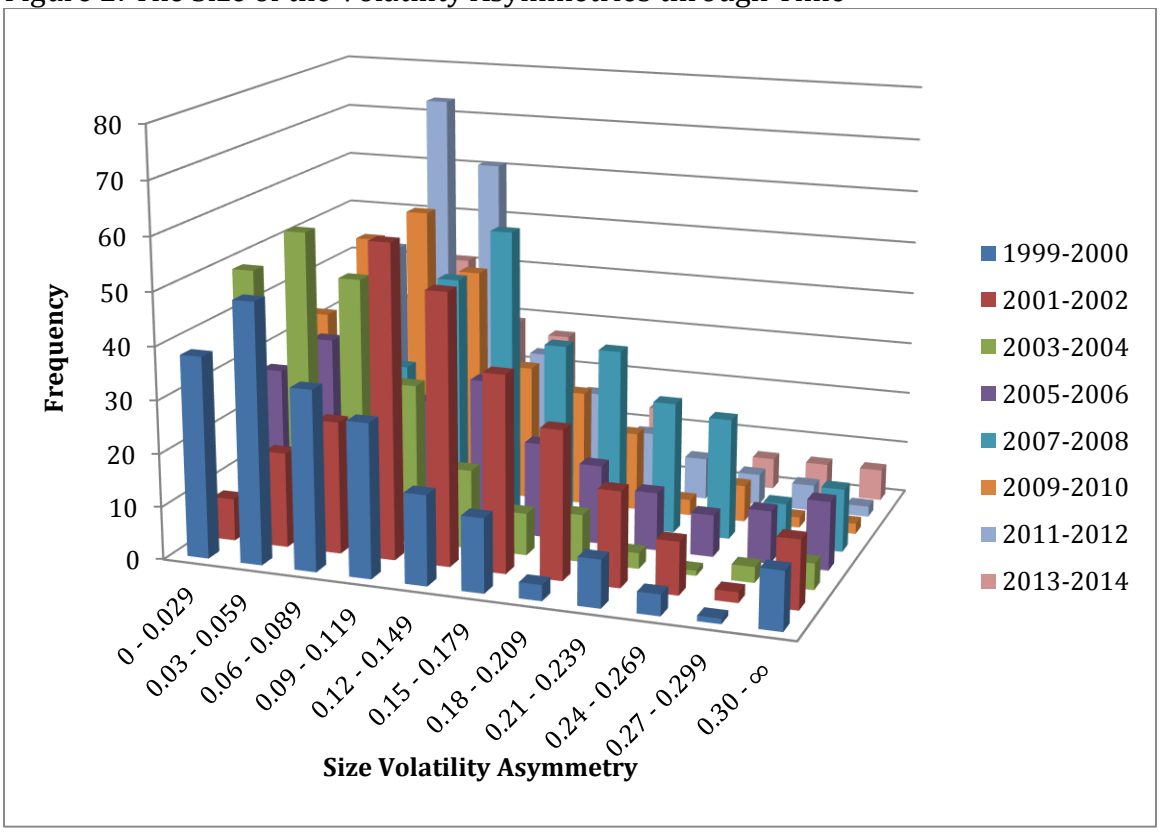


Table 2: Average Size Volatility Asymmetry throughout the Years

Period	1999-2000	2001-2002	2003-2004	2005-2006	2007-2008	2009-2010	2011-2012	2013-2014
γ	0.098	0.145	0.083	0.130	0.161	0.097	0.107	0.110

4.2 Results from the Panel Data Tests

4.2.1 Hausman Test

After the GJR-GARCH(1,1)-model estimation to obtain the size of the leverage effect, we have to estimate the effect of firm specific variables by use of the panel data technique. The first step for panel data is to perform the Hausman test, to ensure that the appropriate model is used for the respective data. As a reminder, under the null-hypothesis the Hausman test states that the random effects model is the appropriate model for the panel data set. Rejecting this null-hypothesis means that the fixed effects model is to be used. The comprehensive results for this test are shown in Appendix III. With a test statistic of 0.0026, the null-hypothesis is clearly rejected and the fixed effects model will be adopted in the cross-section to test for firm specific influences on the size of the volatility asymmetry.

4.2.2 Panel data results

Using the fixed effects model, Appendix IV shows the comprehensive results for the estimated relationship between the firm specific variables and the size of the volatility asymmetry. A short summary of this estimation is provided in Table 3 below. What immediately becomes clear is that there are numerous effects that seem to influence the size of the volatility asymmetry.

Table 3: Output Panel Data

$$\gamma_{i,t} = c_{i,t} + \theta_{i,t}(EV)_{i,t} + \tau_{i,t}NM_{i,t} + \varphi_{i,t}\left(P/E\right)_{i,t} + \rho_{i,t}\left(D/E\right)_{i,t} + \varepsilon_{i,t}$$

Parameter	Coefficient	Std. Error	t-Statistic
$c_{i,t}$	0.0991	0.0047	21.1780***
$EV_{i,t}$	3.63E-10	8.42E-11	4.3152***
$NM_{i,t}$	0.0006	0.0002	3.0406***
$P/E_{i,t}$	0.0003	0.0001	2.8670***
$D/E_{i,t}$	-2.61E-05	1.61E-05	-1.6234

Significant at the * 10% level; ** 5% level; *** 1% level

It is hard to give an interpretation to the size of these coefficients and how big the effects actually are. Therefore, graphs of the effect of the significant firm specific variables on the leverage effect are shown in Appendix V. These graphs will show how the leverage effect changes, under various values of the variables.

4.2.2.1 Firm Size

Starting with the proxy for size, the Enterprise Value (EV), has a significant influence on the size of volatility asymmetries. This proxy boasts a t-statistic of 4.315, resulting in a p-value of 0.0000, which makes it significant. The sign here is positive, but seems to be very small (3.63E-10). This, however, is deceiving. The enterprise value is measured in thousands of Euros, while most of the companies have an enterprise value of billions. Still, a ten billion Euro change in size would result in an increase of 0,00363 in the size of the volatility asymmetry, which has an average of 0,12. This is not that much. This leads to a first conclusion that the size of a firm has a slight positive influence on the size of volatility asymmetries, whereof the effect should not be underestimated. The t-statistic confirms this, as the influence of size appears to be very significant.

The sign, however, is a surprise, as common theory would expect larger firms to be more stable, so have a smaller coefficient of the leverage effect parameter. Instead, the size of firms seems to be positively correlated with the size of volatility asymmetries. This would suggest that firms that are smaller tend to be less affected by a downward turn in their stock price. The market then, apparently perceives less risk when this happens to small firms than when it happens to larger firms. This, however, would contradict theory about bigger firms being more stable.

A more plausible explanation would be, that there is simply less activity on the market when it comes to stocks of smaller firms, as (Ciner, 2003) suggests. Also, a downturn of a “big” stock would get more attention, which can result in

overreaction of the market; hence, more volatility. Regardless of why, the relationship between the volatility asymmetry and firm size is significantly positive.

4.2.2.2 Net Margin

The second estimated parameter is that of the Net Margin (NM). This also shows a significant t-statistic of 3.041, leading to a p-value of 0.0024. This is a little less than the EV, but a very strong sign nonetheless. Interesting is that the sign is positive, with a coefficient value of 0.000556. This means that an increase in the NM of 1% will lead to an increase of the volatility asymmetry of 0.00056. This is a minor increase. As stated before, the sign is positive. This would mean that a higher efficiency leads to a higher sensibility to negative shocks, in terms of volatility.

This is along the lines of the idea that higher margins tend to temporary in nature and cannot be sustained over longer periods of time. In this sense the market perceives the company to be in a state that it cannot maintain for a long time and will correct this. This theory is weak at best, as NMs are usually quite sturdy and tend to remain the same for extended periods of time, at the least for the medium term. Nonetheless, higher margins do seem to cause the market to respond more heavily to negative shocks.

4.2.2.3 Price-Earnings Ratio

The third estimated parameter is that of the Price-Earnings ratio. This ratio also shows a significant result, with a t-statistic of 2.867 and an accompanying p-value of 0.0042. The sign here is positive again, which may confirm the earlier suspected theory of overvaluation, which could also be in play for the NM. A higher P/E-ratio leads to an increase in the size of the volatility asymmetry and as a consequence the volatility of the stock price spikes relatively heavily when the stock price drops.

This is in sync with overreaction –and correction theories, that state that the market suspects a stock to be overvalued and consequently results in a correction. Contrary

to the NM, P/E-ratios are not usually that sturdy, but have the ability to fluctuate a lot more. This is of course due to the fact that companies are dependent on more factors to create value, than just the NM. The behavioral explanation is therefore quite likely to hold here.

4.2.2.4 Leverage

The last, but not least interesting parameter to be estimated is that of the level of debt relative to equity. Interesting is that this parameter is the only of the tested four that yields an insignificant result, with a t-statistic of -1.623 and accompanying p-value of 0.1048. This means that this variable is not significant, not even at a 10% level. For completeness the sign of this parameter is also mentioned and surprisingly this value is negative (-2.61E-05).

To entertain this thought more, this would mean that a higher level of debt would lead to reduced sensitivity to negative shocks, in terms of volatility. This is a remarkable observation, as it contradicts the original thought of the leverage effect. However, it is also in sync with what other research has found since (Black, 1976), that the leverage effect is not due to financial leverage. Even though theory on this factor is quite strong this factor does not seem to significantly increase or decrease the size of the "leverage effect".

4.2.2.5 The Model as a Whole

Looking then at the model as a whole, more specifically the R-squared value of 0.216, we find that this model appears to have a fair fit. Taking into account that this model only uses four firm specific variables as explanatory variables, it quickly follows that firm specific variables have an extensive impact on volatility asymmetries. Using more of those could be a valuable addition.

Compelling in this test is the fact that three out of the four used explanatory variables show a significant effect on the size of the volatility asymmetry. What

makes it even more compelling is that the one variable that is not significant is the leverage effect. So our findings do not contradict findings in previous research.

Furthermore the nature of the outcomes is interesting. The variables all have a more theoretical and behavioral side to them. In every case the behavioral case seems to have the upper hand. This thesis does not go into the specific detailed theory behind every variable, but presents the obvious underlying theories as possible explanations. These behavioral arguments however, seem to provide the explanation in every variable that was tested. Market rationality, as one would also expect with the original leverage explanation, does not appear to explain anything in this sense. This is also not totally unexpected, as an explanation for any asymmetry is usually easily found in the behavioral corner of finance.

5 Summary, Conclusions and Recommendations

This chapter will summarize the thesis and briefly discuss the results that are obtained. Furthermore the findings are placed in a broader perspective, both with regard to previous research, but also with regard to possible future research.

5.1 Summary

Looking at the results from the tests one can conclude that several firm specific variables significantly influence the size of volatility asymmetries. Out of the four firm specific variables that were test, three have a significant impact. Striking is that leverage is the one exception that does not have this significant relationship. Furthermore the model has an R-squared value of 0.216, which is relatively high. The conclusion then is that firm specific variables and maybe other factors, such as market- or global factors, have a definite relation to the size of volatility asymmetries.

5.2 Conclusion

With these observations it is clear that the main research question can be answered in a certain fashion. The question asked in the introduction was the following:

"*Which firm specific attributes, if any, enhance the "leverage" effect?"*

The leverage effect seems to be determined at least in part by firm specific variables, but not as (Black, 1976) states, by leverage itself. As far as this thesis can judge, by the use of firm-specific variables that were deemed fit, there are several firm specific factors that at least enhance the "leverage effect". These variables are the *firm size, operating efficiency and overpricing*. The proxies for these variables all yield significant positive results.

5.3 In Context of Previous Research

As stated several times before, the findings directly contradict those of (Black, 1976), but only in the sense that the results find that financial leverage does not affect the volatility asymmetries. Furthermore continued support for market irrationality is found. Looking at the parameter from the P/E-ratio, the same conclusion as (Lakonishok, Shleifer, & Vishny, 1994) is found, that the market seems to correct overvalued stocks. On the other hand the results contradict the work of (Chan & Chen, 1991), that larger firms are more stable.

However, in the end we must plainly face the fact that research into this area of volatility forecasting has not been done yet.

5.4 Recommendations for Further Research and Final Remarks

This particular niche of volatility forecasting has hardly been delved into before and as such this thesis is the first to do so. This thesis is merely a start, so based on our findings we have several recommendations. The first being the obvious, that more research should be conducted into the effect of firm specific variables. As no research has been performed with firm specific variables and we only use four of them, a lot is yet to be gained by more extensive research. A higher quality of the data would help immensely in this sense. Furthermore we recommend research on other factors that might cause volatility asymmetries and then in particular market conditions. This is based on our finding that the size of the leverage effect was higher during times of crisis, so market conditions may very well have their own specific influencing aspect. The last recommendation is that research has to be done to the underlying causes of the factors that seem to contribute to the size of volatility asymmetries. Anticipating these underlying factors may prove to be as least as helpful as having knowledge of the existence of their impact.

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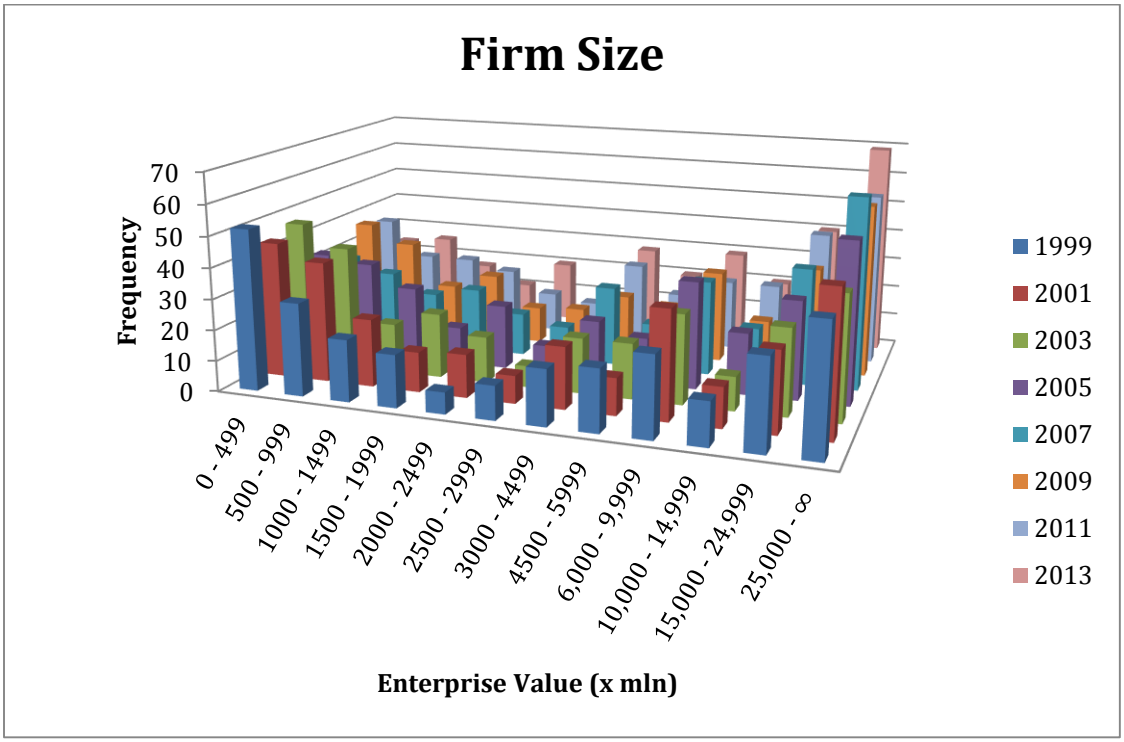
7 Appendices

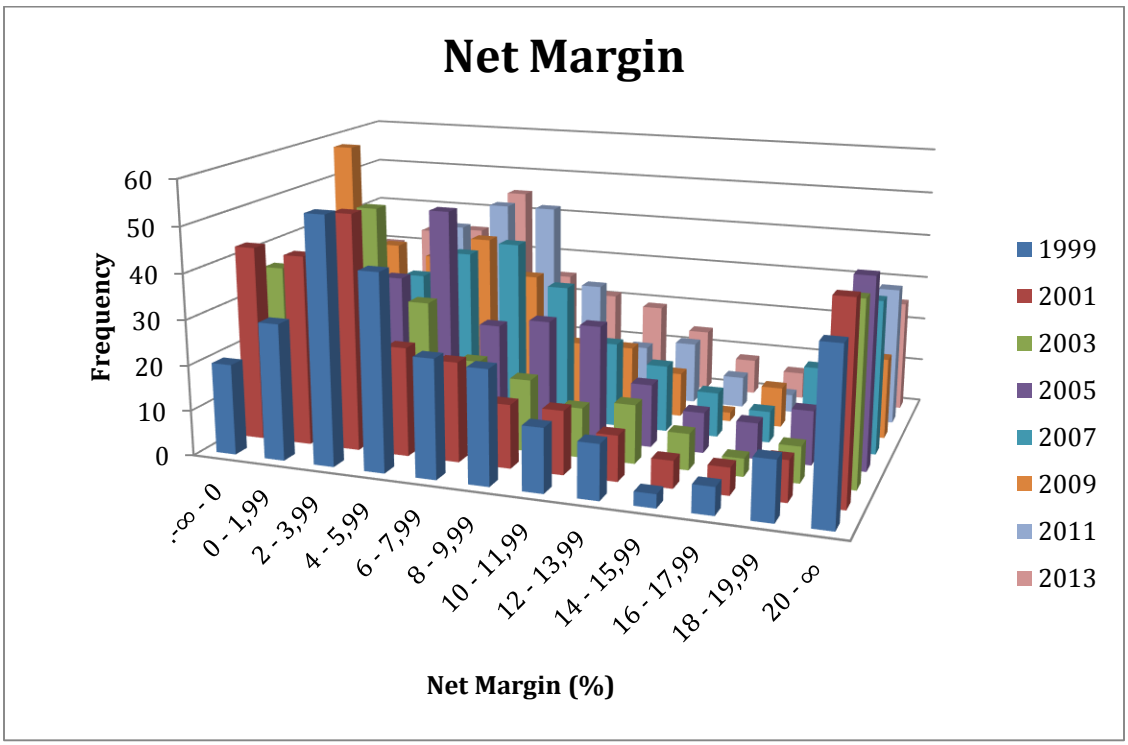
7.1 Appendix I: Firm Specific Variables through Time

This appendix shows, in four parts, the spread of the various firm specific variables. It does this for both the cross section and the time dimension. Note that for every figure the right most observation spikes due to the cumulative frequency of the more extreme observations.

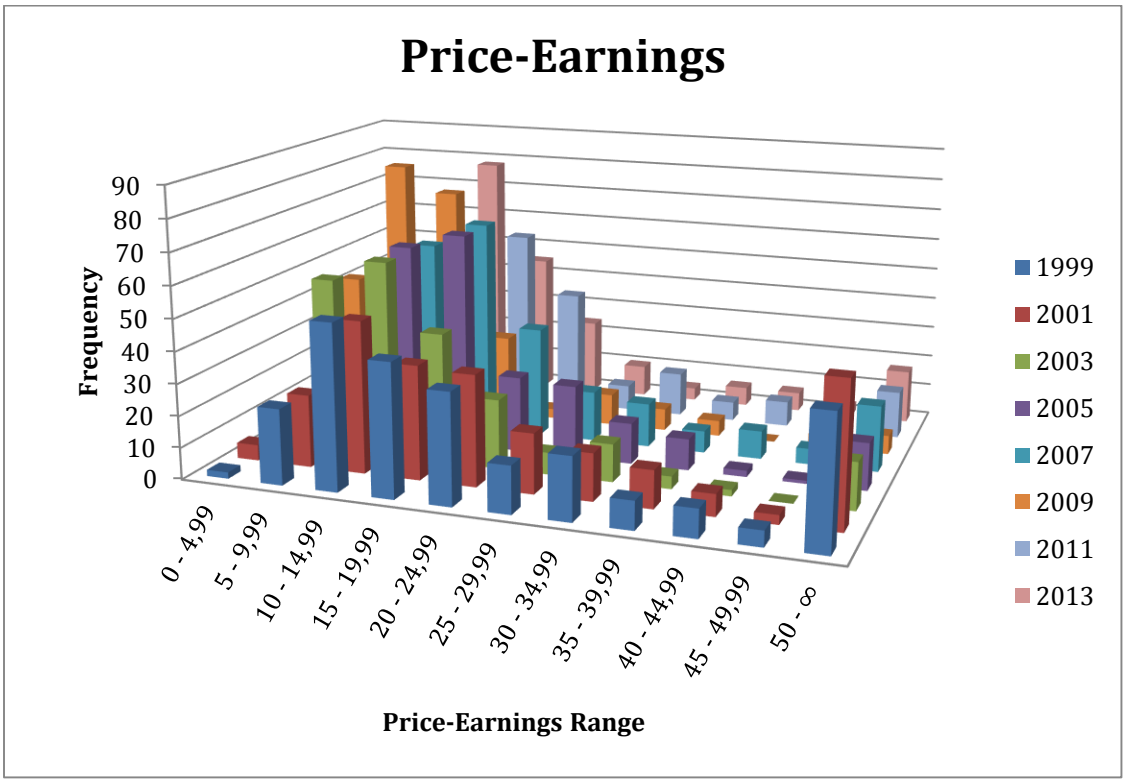
7.1.1 Firm Size



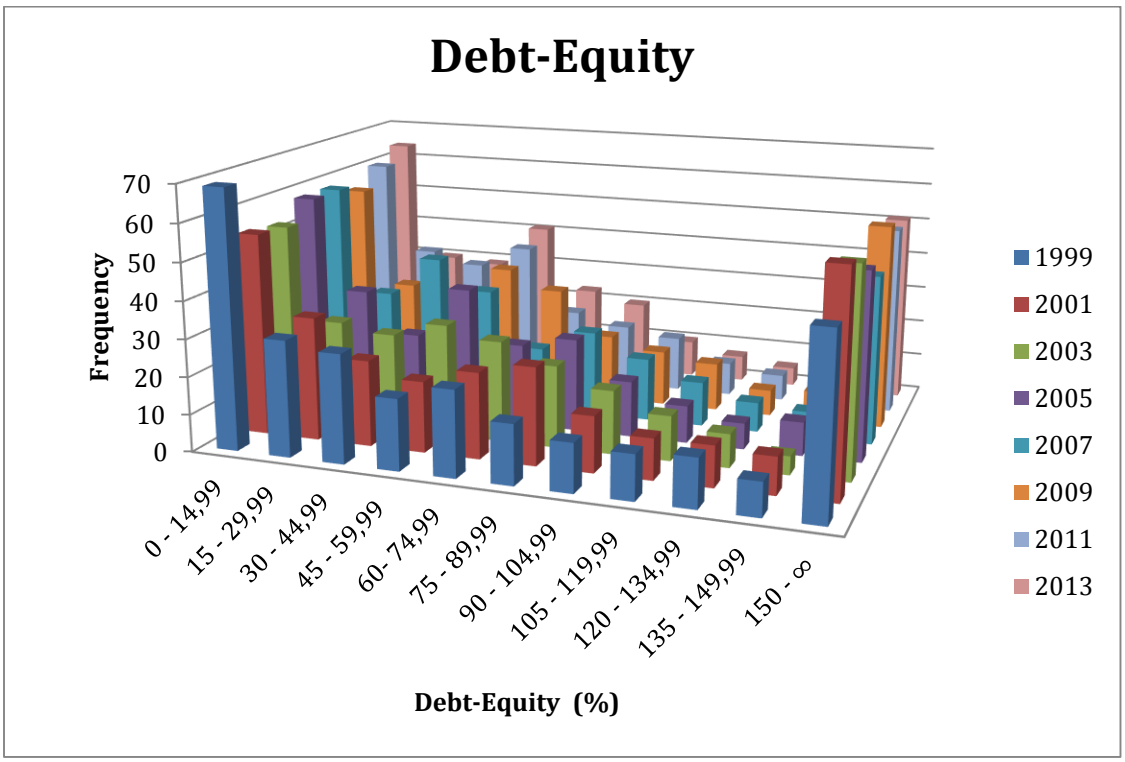
7.1.2 Net Margin



7.1.3 Price-Earnings ratio

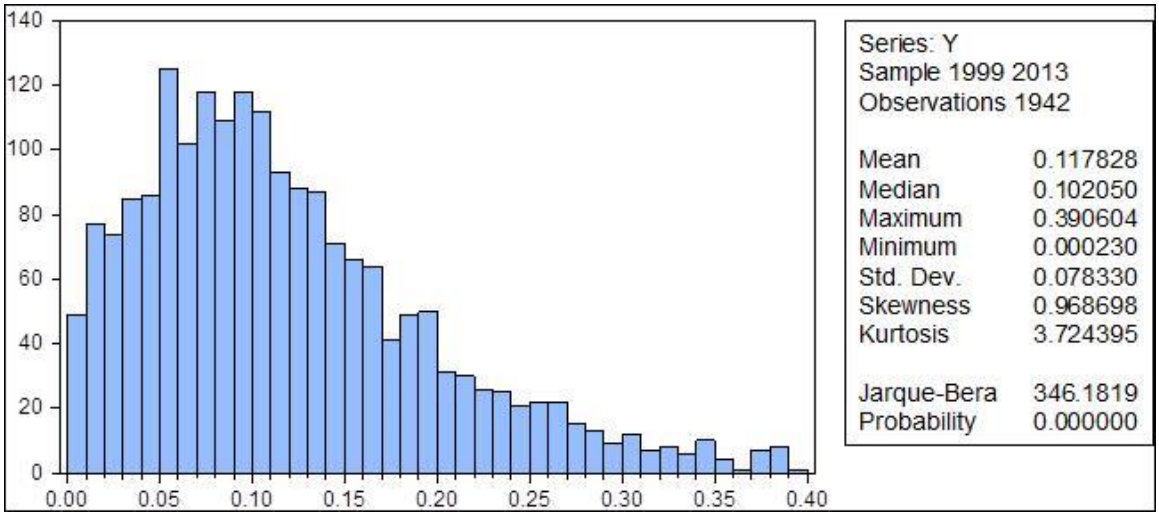


7.1.4 Debt-Equity



7.2 Appendix II: Size of the Volatility Asymmetry

Below the more comprehensive statistics of the volatility asymmetries can be found. This output is directly taken from Eviews.



7.3 Appendix III: Hausman Test

The table below shows the (visually altered) Eviews output on the Hausman test for the panel dataset. The actual test is shown on the top of the table. Note that we use a 5% significance level to determine whether or not to reject the Random Effects Model.

Correlated Random Effects - Hausman Test

Test cross-section random effects

Test Summary	**Chi-Sq. Statistic**	**Chi-Sq. d.f.**	**Prob.**
Cross-section random	**16,318425**	**4**	**0,0026**

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
EV	0,0000	0,0000	0,0000	0,0009
NM	0,0006	0,0004	0,0000	0,2726
PE	0,0003	0,0002	0,0000	0,1409
DE	0,0000	0,0000	0,0000	0,0858

Cross-section random effects test equation:
Dependent Variable: Y
Sample (adjusted): 1999 2013
Periods included: 8
Cross-sections included: 272
Total panel (unbalanced) observations: 1535

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.099130	0.004681	21.17801	0.0000
EV	3.63E-10	8.42E-11	4.315152	0.0000
NM	0.000556	0.000183	3.040599	0.0024
PE	0.000326	0.000114	2.866956	0.0042
DE	-2.61E-05	1.61E-05	-1.623383	0.1048

R-squared	0.215838	Mean dependent var	0.118560
Adjusted R-squared	0.044555	S.D. dependent var	0.079362
S.E. of regression	0.077574	Akaike info criterion	-2.113767
Sum squared resid	7.576353	Schwarz criterion	-1.154279
Log likelihood	1898.317	Hannan-Quinn criter.	-1.756736
F-statistic	1.260126	Durbin-Watson stat	2.358190
Prob(F-statistic)	0.005611		

7.4 Appendix IV: Panel Data Output

The table below depicts the output from the estimation of the panel data set

Panel Data Estimations

Dependent Variable: Y
Method: Panel Least Squares
Sample (adjusted): 1999 2013
Periods included: 8
Cross-sections included: 272
Total panel (unbalanced) observations: 1535

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.099130	0.004681	21.17801	0.0000
EV	3.63E-10	8.42E-11	4.315152	0.0000
NM	0.000556	0.000183	3.040599	0.0024
PE	0.000326	0.000114	2.866956	0.0042
DE	-2.61E-05	1.61E-05	-1.623383	0.1048

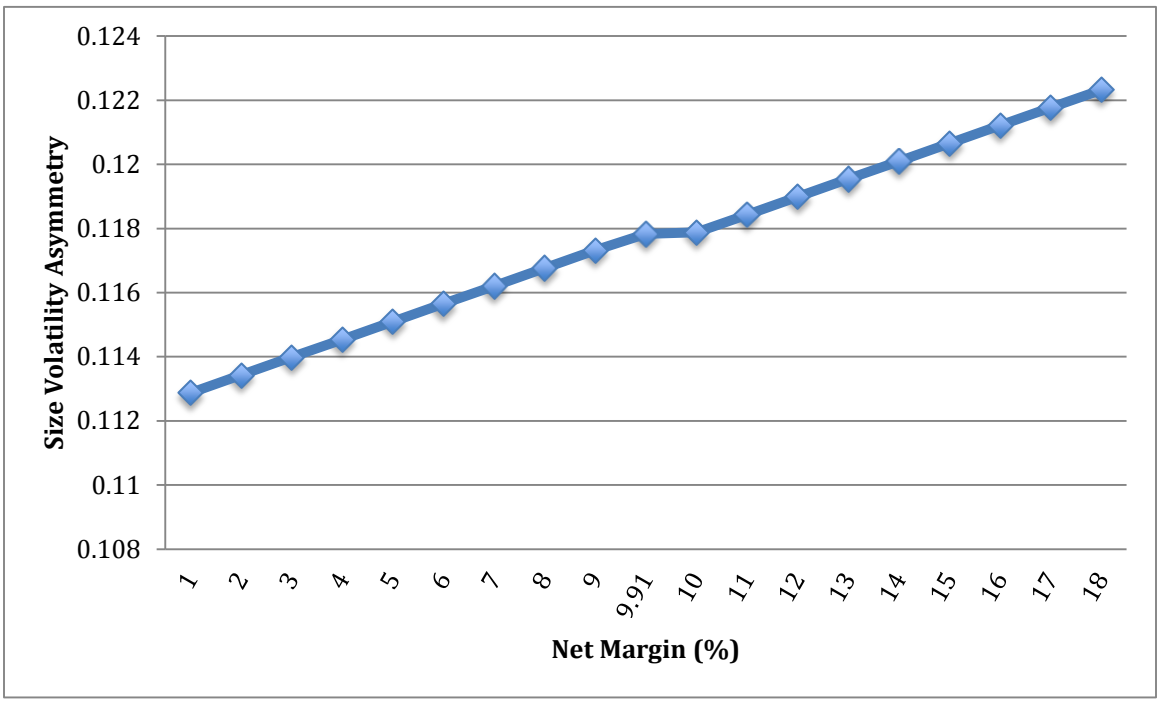
R-squared	0.215838	Mean dependent var	0.118560
Adjusted R-squared	0.044555	S.D. dependent var	0.079362
S.E. of regression	0.077574	Akaike info criterion	-2.113767
Sum squared resid	7.576353	Schwarz criterion	-1.154279
Log likelihood	1898.317	Hannan-Quinn criter.	-1.756736
F-statistic	1.260126	Durbin-Watson stat	2.358190
Prob(F-statistic)	0.005611		

7.5 Appendix V: Graphic Interpretation Panel Data Results

This appendix shows graphically, in three parts, the effect of the significant firm specific variables on the leverage effect. It does so to give a better understanding of the size of the coefficients, which we obtained from our panel data test. Note that this is just a simple graphic explanation of our results. It shows how the size of the volatility asymmetry, found on the y-axis, changes when the x-variable differs from the mean, which is shown on the middle of the x-axis.

7.5.1 Firm Size

7.5.2 Net Margin



7.5.3 Price-Earnings ratio