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The Idiosyncratic Volatility Puzzle: Further Evidence from the European Equity Market

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Abstract

Title: The Idiosyncratic Volatility Puzzle: Further Evidence from the European Equity Market

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Key words: Market anomaly, idiosyncratic volatility, asymmetric volatility, asset pricing, panel data

Purpose: Our purpose is to shed more light on the idiosyncratic volatility puzzle and more explicitly to examine if idiosyncratic volatility can predict future equity returns. Furthermore, we aim to examine if the relation between idiosyncratic volatility and return is different in bear and bull markets and can be explained by shocks to market volatility

Theoretical perspectives: Mean-Variance (Markowitz), CAPM (Sharpe), Factor models for asset pricing (Fama and French) The idiosyncratic volatility puzzle (Ang et al., Fu)

Empirical foundation: The thesis investigates the German, French and Dutch equity markets for the time period 1999 to 2009

Methodology: The idiosyncratic volatility is estimated as the standard deviation of the residuals from a Fama and French factor model. Regressions are run, both using time series data and panel data, to test various hypotheses regarding idiosyncratic volatility and equity returns

Conclusions: We do not find clear evidence of an idiosyncratic volatility puzzle on the three markets. Our models are inconclusive with a negative risk premium for the time series portfolio based regression model while the premium is positive in the panel data model. However, the parameter estimates are insignificant, therefore we accept the predictions of modern portfolio theories and conclude that idiosyncratic risk is not priced. We cannot find support that the "idiosyncratic volatility – future return"-relation is different over bear and bull markets. Neither do market volatility shocks seem to explain the difference in return between stocks with high and low idiosyncratic volatility

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Lund 2011-01-07

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1. Introduction

The introductory chapter provides a background to and discussion of market anomalies and especially our subject of interest, the "idiosyncratic volatility puzzle". We motivate our research questions and purpose and finally we present the limitations of the study as well as an outline for the thesis.

1.1 Background

Market anomalies have for long been a hot topic for research scholars. Examples of such anomalies include the "turn-of-the-year effect" and the "weekend effect" (Schwert 2003, pp.943-945). These are examples of "calendar anomalies" yielding abnormal returns not expected by traditional asset pricing theory. The "turn-of-the-year effect" is linked to another anomaly, the "size effect". The "size effect" relates to the finding that small capitalization stocks on average generate higher returns than large capitalization stocks. Research has shown that the "turn-of-the-year effect" largely explains the "size effect" as abnormal positive returns in January each year accounts for much of the difference between the average returns of small versus large capitalization stocks (Keim 1983, p.13). The "weekend effect" relates to the finding that one-day stock returns on the S&P 500 were significantly lower on Mondays than on other days of the week (French 1980, p.55). If stock returns are expected to be continuous over time, the one-day Monday return ought to be three times higher than other trading days as the holding period is three times longer[1]. On the other hand, if stock returns are measured only for trading days there should be no difference in returns for Mondays compared to other days of the week (Ibid.). Although strong statistical evidence was provided for both these anomalies they seem to have diminished or disappeared over time (Schwert 2003, pp.943-944).

Market anomalies can be labelled as "empirical results that seem to be inconsistent with maintained theories of asset-pricing behaviour. They indicate either market inefficiency (profit opportunities) or inadequacies in the underlying asset-pricing model" (Schwert 2003, p.940). Either way, if market anomalies occur due to true market inefficiency or if they exist as a result of poorly designed asset pricing models, they are of importance for many actors in the finance area.

[1] Friday to Monday as compared to e.g. Thursday to Friday.

Arbitrage opportunities can occur as a result of market anomalies and they can also have implications on the estimation of the cost of capital for projects and firms etc.

This thesis focuses on one of the more debated market anomalies of the last couple of years, the so called "idiosyncratic volatility puzzle". Research has shown that stocks with low past idiosyncratic volatility[2] have higher future returns than stocks with high past idiosyncratic volatility (Ang et al. 2006, Ang et al. 2009, Frieder & Jiang 2007). Interestingly, as modern portfolio theory predicts that idiosyncratic volatility is not priced at all, a wide range of studies have also found the reverse to be true, stocks with high idiosyncratic volatility gain higher returns than stocks with low idiosyncratic volatility (Fu 2009, Brookman et. al. 2009). These inconclusive findings leave room for further research as discussed in section 1.2 below.

1.2 Problem discussion and research questions

Fundamental to the relation between risk and expected return is that an increased exposure to risk ought to pay off in an increased expected return, ceteris paribus. Thus, the results found by e.g. Ang et al. are highly unexpected. A zero-investment portfolio long on stocks with low risk and short on stocks with high risk should intuitively not earn a positive expected return. On the other hand, the reverse should also not be true if modern portfolio theories, MPT, like Markowitz Mean-Variance criteria hold. The return differential should be non-existing or at least non-significant as investors are expected to diversify their portfolios in such a way that only market, non-idiosyncratic, risk is left. Although the assumptions behind MPT-models and theories like the Mean-Variance-criteria and the Capital Asset Pricing Model, CAPM, have been criticised and questioned[3], more recent models, such as Ross' Arbitrage Pricing Theory, APT, cannot explain the peculiar finding that stocks with low (high) past idiosyncratic volatility earn higher (lower) returns than stocks with high (low) past idiosyncratic volatility. Although MPT does not predict the reverse relation, these findings stand on more solid theoretical, or rather empirical, ground. Due to under-diversification and the cost of acquiring and digesting information investors might be compensated for idiosyncratic risk, as they do not have the ability to diversify their portfolios enough to carry only systematic risk (Merton 1987, p.496).

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[2] Idiosyncratic volatility refers to non systematic, i.e. firm specific risk i.e. not the market wide risk inherent in a company's stock.

[3] See for example Roll (1977)

The above reasoning highlights the ambiguity in the subject, not only between the different empirical findings regarding idiosyncratic volatility and return but also the ambiguity between asset pricing theories. Before presenting our research questions a short summary of some of the more important studies on the subject is presented below[4] as well as a motivation for our thesis vis-à-vis previous research.

The first study to find the unexpected relation between idiosyncratic volatility and return was conducted on data for all stocks on the AMEX, NASDAQ and NYSE, finding a monthly return differential of minus 1,06 percent between the average return of the quintile portfolio of stocks with the highest- and the quintile portfolio with the lowest past idiosyncratic volatility (Ang et al. 2006, pp.261-266). The results were robust to testing for characteristics such as size, book-to-market-ratio and liquidity etc. In a subsequent study, the data set used was extended to include 23 markets still with the same results; thus, highlighting the "idiosyncratic volatility-return" anomaly (Ang et al. 2009, p.1). The results of Ang et al. have been confirmed by a range of studies but they have also been contradicted. In his 2009 article, Fangjian Fu propagates that the relation between idiosyncratic volatility and equity returns is positive (Fu 2009, p.24). Fu's methodology differs from that of Ang et al. as Fu uses expected[5] idiosyncratic volatility (Ibid., p.1) instead of realised (past) idiosyncratic volatility (Ang et al. 2006, p.283). Fu's findings are validated on international data in a 2009 working paper examining the expected-"idiosyncratic-volatility-return"-relation for 58 thousand stocks across 44 markets (Brockman et al. 2009, p.1).

The dispersed findings by Ang et al. and Fu motivate this thesis and have formed our interest in the subject[6]. We aim to further examine the idiosyncratic risk-return relation by using a twofold method where we adapt both the methods of Ang et al. and also an intuitive approach using panel data on the same dataset. Further, we intend to examine if or how the market state[7] is a predictive factor for the relation between idiosyncratic volatility and stock returns. Ang et al. ruled out the predictive power of the market state in their 2006 article (Ang et al. 2006, p.297).

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[4] For further review of the previous work see section 2.2

[5] Using an exponential general autoregressive conditional heteroskedacity (EGARCH) regression methodology

[6] Also, one of the authors has previously conducted a study on the same theme for the Swedish equity market, see Bonthron & Rostedt (2010)

[7] As in bull and bear markets

We consider their approach to be somewhat too trivial as their sample was broken down into very long (seven to nine years) sub-periods. As our time period of interest includes the turbulent financial markets of two crisis periods, the dotcom bubble and the credit crunch, we also aim to test how market volatility shocks affect the idiosyncratic volatility return relation. In summary, our primary contribution to this narrow field of research is a more thorough investigation of the impact of the market state and volatility shocks as well as a twofold methodology on the same dataset.

Following the above paragraphs we have formulated the following research questions that we aim to answer and analyse:

1. What is the relation between idiosyncratic volatility and future equity returns using different methods of analysis?
2. What impact do the market state and volatility shocks have on the relation between idiosyncratic volatility and equity returns?

1.3 Purpose

Our purpose is to shed more light on the idiosyncratic volatility puzzle and more explicitly to examine if idiosyncratic volatility can predict future equity returns. Further we aim to examine if the relation between idiosyncratic volatility and return is different in bear and bull markets and can be explained by shocks to market volatility.

1.4 Limitations

We limit our dataset to include stocks from the German, French and Dutch stock exchanges for the time period 1999-01-01 to 2010-01-01. Furthermore, we limit our sample to include stocks that are actively traded as of the 15th of November 2010; thus, excluding so called dead securities. Our factor model used to estimate the idiosyncratic volatility of each stock in our sample is limited to three factors following the Fama and French 1993 model (Fama & French 1993, p.3). We limit the estimation of idiosyncratic volatility to the most commonly used methodology regarding the time frame of estimation as we use daily data over one month. Further, we do not estimate expected idiosyncratic volatility by e.g. using a more sophisticated regression methodology such as an autoregressive conditional heteroskedacity model. We do not use more than one definition for market state and volatility shock.

1.5 Outline

The thesis proceeds as follows: in chapter two we present the theoretical perspectives including MPT and previous research on the idiosyncratic volatility puzzle. Chapter three provides a description of the methodology applied. In chapter four we present descriptive- and regression statistics as well as analysis of the results. Finally, in chapter five we conclude and provide suggestions for further research.

2. Theory

The chapter outlines the foundations of the Modern Portfolio Theory approach to asset pricing including Markowitz's Mean-Variance analysis and Sharpe's Capital Asset Pricing Model. Further, we present more sophisticated asset pricing models such as the three-factor model proposed by Fama and French. We proceed with a discussion of the market state importance for financial research and end the chapter with a review of previous research in the idiosyncratic volatility puzzle.

2.1 Asset pricing theory

During the 20th century theories on the pricing of securities have developed. However, an ultimate asset pricing model is today still to be found as models that were established more than 50 years ago are still used although they have been heavily criticised. Below we provide a brief introduction to some of the most recognized models used for the pricing of equities.

2.1.1 The Mean-Variance approach

In 1952 Harry Markowitz presented his theory behind portfolio selection. Markowitz found that by investing in a certain combination of several risky assets, i.e. diversifying, an investor could lower the risk while keeping the same expected rate of return of his portfolio of assets. This is today known as the Mean-Variance criteria. The approach is based on the idea of finding the securities with the highest relation between expected return and risk. The best possible portfolio of securities will have the same expected return (mean return) as the second best but lower risk (variance) or the same level of risk as the second best but higher expected return (Markowitz 1952, pp.77-78). Given that it is the relation between risk and expected return that is the cornerstone of the model the best possible portfolio of securities is not necessarily the one with highest expected return (Ibid., p.79).

2.1.2 The Capital Asset Pricing Model

When William Sharpe in 1964 further investigated the phenomena of diversification he proposed that the risk of a security could be divided into different types, idiosyncratic and systematic risk. Systematic volatility can be defined as the market risk whereas idiosyncratic, company specific, risk only is related to one single security (Sharpe 1964, p.438). The market risk can never be avoided by diversification; however, it is possible to eliminate the idiosyncratic volatility of a portfolio by combining a large range of securities. With this finding Sharpe developed the Capital

Asset Pricing Model, CAPM. The model explains how the expected return of a security is correlated with the risk of the market portfolio, measured by the beta-coefficient. Due to the possibility of diversification, the price of an asset will be adjusted until only the risk of the market is priced (Ibid., pp.441-442). The expected return of an asset according to the CAPM is the risk-free interest rate plus the market risk premium, expected return of the market minus the risk-free interest rate, multiplied with the company specific beta-coefficient (Elton et al. 2007, pp.287-288). Consequently, Sharpe argues that an investor will only be compensated for market risk exposure. Therefore the level of company specific risk in a stock will not be reflected in the expected return (Sharpe 1964, pp.441-442). Another implication of the CAPM is the linear relation between market risk and expected return. According to the CAPM the expected return of any portfolio, or individual security, is directly related to its beta-value and follows the logic that an increase in beta will lead to a proportional increase in the expected return (Elton et al. 2007, pp.296-297) as illustrated in figure 1 below.

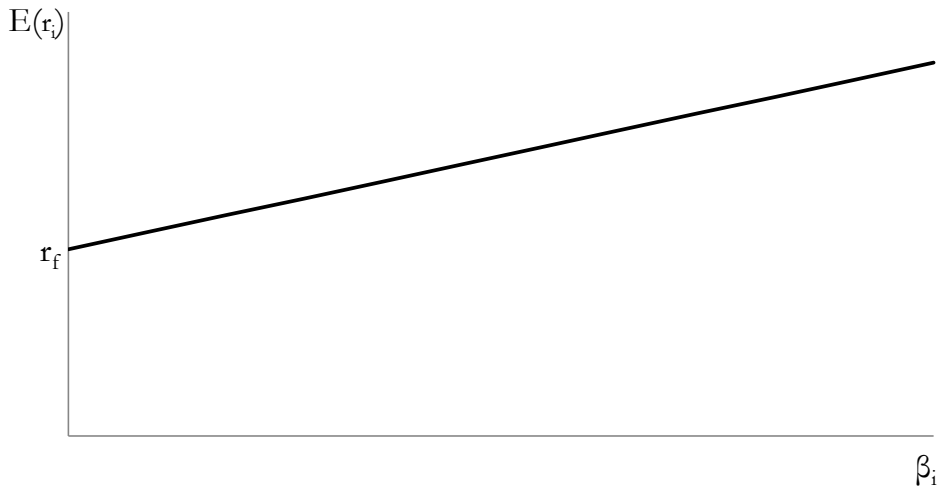


Figure 1 - The security market line, Source: Own

The figure illustrates how the expected return, $E(r_i)$, of a security is equal to the risk-free interest rate, r_f, for a zero beta asset. As beta increases the expected return of the security increases linearly.

2.1.3 Multi factor models

In 1976 Stephen A. Ross developed a more advanced model for estimating the expected return of an asset, the Arbitrage Pricing Theory, APT. Whereas CAPM only explains the expected

return with one variable, the APT model contains several different factors each with individual beta-coefficients (Ross 1976, p.353).

Eugen Fama and Kenneth French developed another multi factor model in 1993. Fama and French had shown that expected return depends on a company's size and book-to-market equity. Their findings showed that returns for companies with small market capitalization exceeded the returns of companies with big market capitalization. Furthermore, stocks with high book-to-market equity proved to have higher returns than stocks with low book-to-market equity. With these findings Fama and French developed a three-factor model including:

1. A market factor reflecting the market risk premium, MKT, which is the difference between the return of the market portfolio and the risk-free interest rate.
2. SMB, the difference in return of small minus big capitalization stocks.
3. HML, the difference in return of stocks with high- minus stocks with low book-to-market equity (Fama & French 1993, pp.52-53).

Nonetheless, the three-factor model is in many cases complemented with a fourth and sometimes even a fifth factor. Although size and book-to-market factors can seem arbitrary and not theoretically established the model has gained popularity and is today widely used as a complement to, or substitute for, the single-factor model CAPM.

2.1.4 Idiosyncratic volatility and asset pricing

Robert C. Merton belongs to those who are not convinced that idiosyncratic volatility is not reflected in the expected return of a security. In an article from 1987 Merton discuss the price of information from a time perspective. According to the CAPM investors understands and acts on new information uniformly. This might be true for earnings reports and similar information that is readily accessible and relatively easy to interpret for all investors. However, for information that is more difficult to interpret it might not be that all investors have the time and financial strength to analyse the information and act on it instantly in a correct manner. Therefore, Merton argues that investors will be compensated for idiosyncratic risk and not only market risk exposure (Merton 1987, pp.485-486). Consequently Merton's theories suggest that securities with high idiosyncratic volatility are expected to earn greater returns in comparison to securities with low idiosyncratic volatility.

2.2 The idiosyncratic volatility puzzle

Higher risk will intuitively give rise to higher expected returns; however, the idiosyncratic volatility puzzle indicates the opposite. In such findings stocks with low idiosyncratic volatility appear to have higher returns than stocks with high idiosyncratic risk. This inverted relation between idiosyncratic volatility and expected return is more or less contradictive to all previously recognized asset pricing theories. However, other studies have also found the opposite result that is more theoretically feasible, at least if Merton's theory regarding the cost of information is a relevant cause for a positive risk premium for idiosyncratic risk. Below we provide a review of some of the more important articles published on the idiosyncratic volatility puzzle.

2.2.1 The negative relation

According to classic asset pricing theory such as the CAPM investors are not compensated for company specific risk. Intuitively, if they were to be compensated, you would expect higher returns from stocks with higher company specific risk. In 2006 Ang et al. found the contra-intuitive phenomena that portfolios of stocks with low idiosyncratic risk outperform portfolios containing stocks with high idiosyncratic risk (Ang et al. 2006, p.261). According to Ang et al. the main reason for the difference between their result and previous studies proving the opposite is that they examine the idiosyncratic risk at firm-level. Ang et al. divides companies into portfolios ranked on idiosyncratic risk whereas previous studies first sort the portfolios on for example market size (Ibid., pp.261-262).

In a subsequent article Ang et al. verify the results of their 2006 paper. The same methodology is used to test the "idiosyncratic volatility-return"-relation in an international setting over 23 markets to prove that their previous results were not an effect of datasnooping (Ang et al. 2009, p.2). In the article Ang et al. suggest that the relation between idiosyncratic volatility and future return is a worldwide phenomenon as it is strongly statistically significant in the G7 countries and also observed in the remaining 16 countries (Ibid.). A second finding of the article is that the international return differential between stocks with high and low idiosyncratic volatility has a high degree of co-movement with the spread between stocks with high and low idiosyncratic volatility in the US. Ang et al. suggest that some broad risk factor, or factors, that is hard to diversify lie behind their finding of a negative premium for idiosyncratic risk (Ibid.). Finally, a range of control variables, such as analyst coverage, institutional ownership and transaction costs, are tested but none of these explain the idiosyncratic volatility puzzle (Ibid.).

Ang et al. (2009) also comment on Fu's findings that if expected idiosyncratic volatility is used, the risk premium is the opposite. Ang et al. mean that expected volatility "is unobservable and must be estimated. In contrast, past idiosyncratic volatility is an observable, easily calculated stock characteristic. Since idiosyncratic volatility is persistent, we expect that our lagged measure is correlated with future idiosyncratic volatility that agents might assess in determining expected returns" (Ibid.). Ang et al. test whether the historical idiosyncratic risk can explain the future idiosyncratic risk and after this control the anomaly still exists.

2.2.2 The positive relation

In an article from 2009 Fangjian Fu argues that historic idiosyncratic volatility cannot be used to estimate the future idiosyncratic volatility. Fu applies an EGARCH model to estimate the future idiosyncratic volatility. According to him the reason for the negative relation, found by Ang et al., is that the majority of the stocks with high idiosyncratic volatility are small cap stocks. Small capitalization stocks tend to have higher transaction costs, which disables any profit opportunities from the strategy and therefore it should not be profitable to exploit the findings by Ang et al. Furthermore, the return reversal of stocks can also be used to explain the negative relation according to Fu. This means that stocks with high idiosyncratic volatility normally have high returns for the same period. These returns then reverse to negative returns the following period (Fu 2009, p.25).

Brockman et al. confirm Fu's findings regarding a positive relation between idiosyncratic risk and future return in a later study from 2009, where they also use an EGARCH model. In 36 of the 44 countries they examine they find this positive relation to be significant. They show how investor characteristics can explain the magnitude of the company specific risk premium, more specifically how low GDP per capita and high share turnover result in higher idiosyncratic risk premiums. Moreover, their study supports Merton's theories about how investors are compensated for idiosyncratic volatility exposure due to information costs (Brockman et al. 2009, pp.3-4).

2.3 Market state and asymmetric volatility

During history many researchers have modified regressions depending on the market state. For example different betas for bull and bear markets have been used in an attempt to investigate whether the market risk premium can vary over time and if it depends on the market state. Thus, a definition of the market state is needed to investigate the phenomena. In an article from 1977

where Frank J. Fabozzi and Jack Clark Francis try to map out whether regression statistics for NYSE stocks differ between bull and bear market states they define the two. Since there were no previous recognized definitions they used three different approaches defined as follows:

1. "It places most months when the market rises in the bullish category. But, months when the market rose amidst adjacent bearish months were classified as part of the bearish subset. That is, the BB categorization is based on market trends".
2. "Months in which r_{mt} (a/n, market return) was non-negative are defined as Up months. And, months when r_{mt} was negative were placed in the Down category. This procedure yields a mutually exclusive and exhaustive division of the total sample into two subsets. But, the UD partitioning procedure ignores trends in the market and views every month independently".
3. "Substantial Up and Down (SUD) Months. The SUD procedure partitioned the sample into three subsets-(3a) months when the market moved Up- Substantially, (3b) months when the market moved Down-Substantially, and, (3c) months when the market moved neither Up- nor Down-Substantially" (Fabozzi & Francis 1977, pp. 1093-1095).

In the third definition they leave out months where the market did not move so that only two thirds of the observations are used (Ibid.).

In their 1976 article Cox and Ross discuss the pricing of options and especially whether one of the assumptions behind the Black and Scholes model for option pricing is reasonable. In the Black and Scholes option pricing model stock prices are expected to follow a random walk process where the stock price process are log-normally distributed (Black & Scholes 1973, p.640). However, Cox and Ross suggest some more flexible price processes that imply that the relation between stock prices and volatility does not need to follow a symmetric pattern. Rather they allow for an inverse relation between equity returns and volatility where volatility declines as the stock returns are positive (Cox & Ross 1976, p.150). The important implication for our thesis is that stock returns can be inversely related to volatility.

Christie further investigates a possible asymmetric volatility property of equity return and find an inverted relation between volatility and equity value. According to Christie this can largely be explained by the effects financial leverage has on volatility. Christie means that "Volatility is an

increasing function of financial leverage", this phenomenon is called leverage effects and demonstrates how a high level of debt can cause the negative relation (Christie 1982, pp. 427-428). The debt-to-equity-ratio increases when a stock shows negative return due to the fact that the equity value drops while the debt remains unchanged. Higher financial leverage makes the security riskier which intuitively increases its volatility.

2.4 Idiosyncratic volatility and equity returns – a summary

The previous sections on asset pricing, the idiosyncratic volatility puzzle, market state and asymmetric volatility all pose important restrictions and opportunities for our study. Below we summarize the most important implications for our thesis.

First of all, MPT does not predict idiosyncratic risk to be priced as investors are expected to diversify their portfolios to only carry market risk. However, both Ang et al. and Fu have found the reverse to be true, that idiosyncratic risk is priced. Fu's research is in line with Merton's theory regarding the cost of information as a cause for a positive risk premium for idiosyncratic volatility. Ang et al. on the other hand find a negative premium for idiosyncratic volatility exposure. Thus, there are three different possible relations between idiosyncratic volatility, a positive or a negative risk premium as well as no premium at all. Further, according to the CAPM the relation between expected return and market risk is linear as illustrated in figure 1. As theory does not predict idiosyncratic risk to be priced, an analogous return profile for idiosyncratic risk does not exist. Consequently, theory does not necessarily predict a linear relation between expected return and idiosyncratic risk. The possibility of e.g. a log-linear or any other return profile is possible and cannot be ruled out. Finally, the sections on market state and asymmetric volatility explain the logic and relevance to test whether the factors can give further guidance to the properties of the "idiosyncratic risk-return"-relation. As it has not been firmly established, the risk premium for idiosyncratic risk might differ between bear and bull markets. Also, as market volatility seems to be inversely related to equity returns, it might be that market volatility shocks can explain a potential risk premium for idiosyncratic volatility.

3. Methodology

The chapter starts with a summary of the data selection process. Thereafter we describe the data handling process, our approach to estimate idiosyncratic volatility and hypothesis testing using regression analysis.

3.1 Research approach

We use a quantitative approach with similar methods as previous research to be able to compare our work with past research on the area. As an overall method for analysis and conclusions we use regression analyses in different forms. The data processing has mainly been conducted using Microsoft Excel 2007 and most of the regressions are run in Eviews 7.0. We have used Thomson Datastream Advance to collect all data.

3.2 Data

3.2.1 Data selection

As our research questions differ from previous research we have had the opportunity to select a relevant data set. First of all we have aimed at a broad set of equities from more than one market. Secondly, to get rid of currency discrepancies and the impact of exchange rates on equity returns we have chosen to study only Euro-zone markets. Third of all, to be able to compare our results with previous research, we have chosen markets that have previously been studied. With these three criteria we have chosen the German, French and Dutch stock exchanges. These three markets provide what we believe is a large enough sample of stocks without the problem of different trading currencies as all our quotes are in Euro. As we only use Euro-zone equities the time frame is limited historically to the first of January 1999 when the Euro was introduced as the official currency in these three countries. The upper bound of our time frame is set to the first of January 2010. The sample could have been expanded to include more equities and a longer time frame possibly making the results more general but due to data availability and the data processing capabilities of the hardware and software used we have left the sample size at the three mentioned markets.

The dataset includes all actively traded stocks of the three exchanges on the 15th of November 2010[8]. We collect price quotes[9] for all equities constituent in the France CAC All Shares, Amsterdam SE All Share and the Prime All Share (Xetra) for France, the Netherlands and Germany respectively. To build our factor model we use the MSCI Euro[10] as a proxy for the market portfolio and the one-month EURIBOR[11] as a proxy for the risk-free rate of interest. The Fama-French factors are built using market value as well as book-to-market-ratio quotes for all the firms in the sample[12]. To create variables for the market state and volatility shocks we have used the MSCI Euro index. Table 1 below summarizes our dataset.

Country	Exchange	# of securities	# of daily observations	# of monthly observations
Netherlands	AEX	119	341 649	15 827
France	CAC	354	1 016 334	47 082
Germany	Xetra	354	1 016 334	47 082
Total		**827**	**2 374 317**	**109 991**
MSCI Euro			2 871	133
EURIBOR 1 M			2 871	133

Table 1 - Data overview, Source: Own

3.2.2 Data processing

We start our data handling by excluding stocks that have adverse characteristics from the data set. Firms with negative book-to-market-ratios and market values close to zero are removed from the sample. After the data set has been adjusted we proceed by calculating the daily and monthly excess return of each stock. The excess return of each stock, $r_{i,t}$, is defined as:

[8] For a complete list of all securities in the sample please see appendix 1.

[9] Data type "P", price- default, adjusted for dividends, stock splits etc.

[10] MSCI Euro is a market capitalization weighted equity index comprising stocks from the European Monetary Union. The data type used is "PI", price index.

[11] EURIBOR is an abbreviation of Euro Interbank Offered Rate, an average of the interest paid on interbank loans in the European Union. We set the data type to default which provides the annualized interest rate.

[12] The market value data type used is "MV", daily quotes of the number of shares outstanding times the closing share price. For the book-to-market-ratio we inverted the daily "MTBV", market-to-book-value, for each stock.

$$r_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} - \frac{r_{f,t}}{T} \tag{1}$$

where $P_{i,t}$ is the price of stock *i* at time *t*. $r_{f,t}$ is the risk-free rate of interest, i.e. the one-month EURIBOR at time *t* and *T* is the time period, 365 (days) for the daily return and 12 (months) for the monthly return series. The excess return of the market portfolio factor MKT has also been calculated using (1) with the MSCI Euro as *i*.

Following Ang et al. we use the Fama-French three-factor model to calculate the idiosyncratic volatility of each stock (Ang et al. 2006, p.283). We create factors mimicking the size- and book-to-market-ratio risks of equities, SMB and HML. To define a market wide risk factor for firm size we first sort all firms in the sample based on market capitalization at the end of each year. Thereafter we define two portfolios of stocks, one containing the stocks with above median market capitalization and one with below median market capitalization. The daily value weighted return of each portfolio is then calculated and the risk factor, SMB, is defined as a zero-investment portfolio long on the 50 percent stocks with below median market capitalization and short on the remaining 50 percent of stocks. Hence, the SMB-factor is calculated according to:

$$SMB_t = \sum_{i=1, i \in Small}^{I} w_i r_{i,t} - \sum_{j=1, j \in Big}^{J} w_j r_{j,t} \qquad i \neq j \tag{2}$$

where w_i is the weight of security *i* in the portfolio and $r_{i,t}$ is the return of security *i* at time *t*. The stocks in the small group, *i-I*, have below median market capitalization and *j-J* above median market capitalization.

The return of the factor is calculated on a daily basis and the composition of the two portfolios is updated at the end of each year. The risk factor relating to a firm's book value of equity to market value of equity, HML, is calculated analogously.

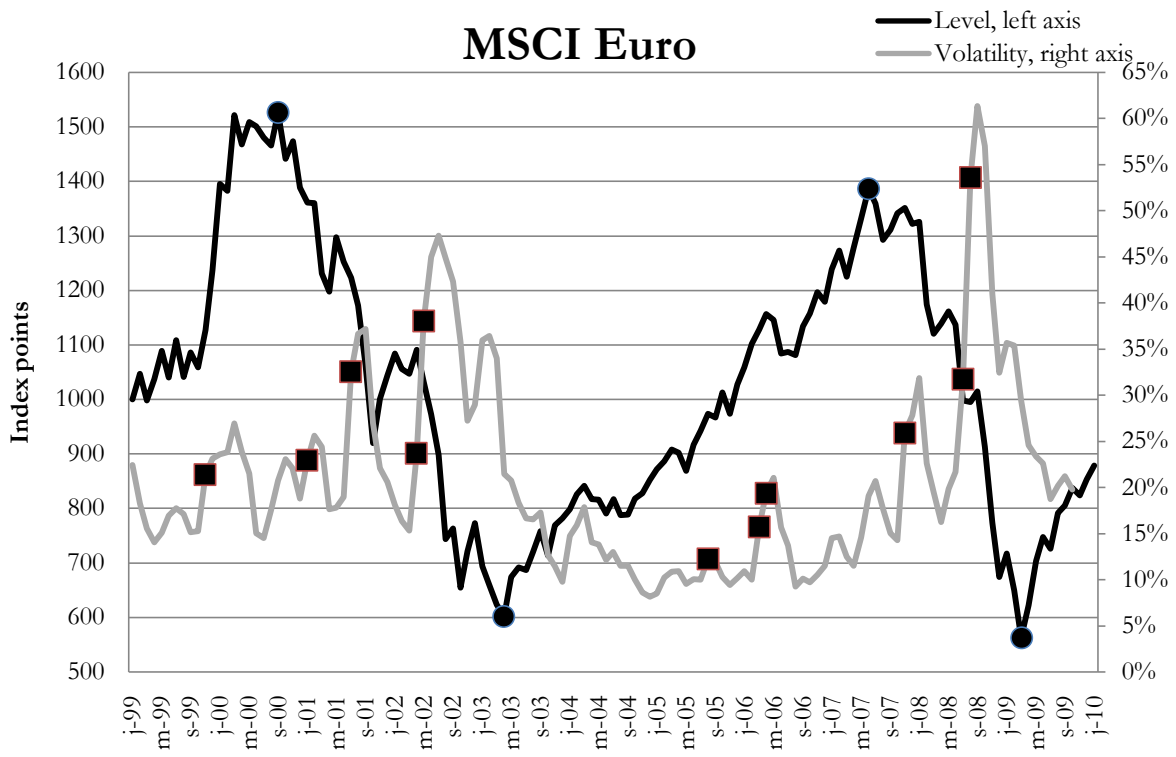
We have used a somewhat simplified approach when constructing the risk factors SMB and HML. Fama and French divide stocks sorted on book-to-market-ratio into three groups, high-, medium- and low containing 30, 40 and 30 percent of the stocks respectively (Fama & French 1993, p.8). Thus, our methodology differs as we divide the stocks into two groups. We do not

consider this simplification crucial as the risk factor relating to book-to-market equity should be insensitive to the splits (Fama & French 1993, p.9). Further, the Fama and French approach to capture the sole risk factor of size and book-to-market-ratio is more thorough as the market value effect is averaged out in the book-to-market-factor and vice versa. For the SMB-factor, the return of stocks with small market capitalization is calculated for an average book-to-market-ratio by combining the three book-to-market portfolios (Ibid.). However, we do not consider this to be problem as the correlation between our SMB and HML time series is close to zero (0,05), indicating that the risk factors are independent. Apart from these simplifications our factor model follows the Fama and French methodology and should potentially have a larger explanatory power for cross sectional differences in equity returns than a single index model like the CAPM.

To investigate the impact of the market state on the idiosyncratic volatility future return relation we follow Fabozzi and Francis' first definition of the market state and define it as a general trend of bear or bull market (Fabozzi & Francis 1977, p.1094). We identify five separate trends in the market for our time period measured by the development of the MSCI Euro. We define the time period until September 2000 as a bull market. This time period was characterised by sharply rising prices of internet-related equities and has later been called the "dotcom mania" (Ofek & Richardson 2003, p.1113) or the "dotcom bubble". The post dotcom bubble period of declining equity markets ending April 2003 is defined as a bear market. The following four years of rising levels in the MSCI Euro is defined as a bull market, ending in June 2007. Thereafter we identify a distinct bear market in the sub-prime crisis and the following credit crunch as the market falls from a peak of 1380 to a through of 560 index points in March 2009. We label the recovery from the all time low of the index as a period of bull market.

Identifying bull and bear markets is no precise art and as mentioned in section 2.3 there are no precise definitions. Our aim has been to label the different market states in accordance to some kind of common perception of whether a bull or bear market has been present for our time period of interest. We believe that our definitions follow this logic with five distinct market states as follows: dotcom bubble, dotcom crisis, bull market, sub-prime crisis/credit crunch and finally the post credit crunch recovery. For our sample time period, the market state definitions could hardly been made with lower frequency. Possibly, shorter trends like bear market rallies could have been incorporated in the definitions but as we want to test whether the *general market trend*

has predictive power for the idiosyncratic volatility future return relation we find our definitions to be the most suitable. Graph 1 below illustrates the MSCI Euro for the time period of interest:



Graph 1 - Volatility shocks, bear and bull markets of the MSCI Euro, Source: Own

The black dots on the level series represent the end of the market state; thus, we have five different periods of either bear or bull markets. For our regression analysis we define a dummy variable, M, for the market state where M equals 1 if the market is in a bull state and equals 0 if the market is in a bear state.

As volatility and equity returns are expected to be inversely related (Cox & Ross 1976, p. 150, Christie 1982, p.427) we have also constructed a dummy variable representing a volatility shock. If the volatility at month *t* is greater than the volatility of month t-1 plus the volatility of volatility of the past two months we consider this to be a volatility shock. We calculate the volatility of the MSCI Euro using 60 daily observations and annualize by multiplying with the square root of 250 as this is the standard procedure. The volatility of volatility is defined as the standard deviation of the last 12 months' volatility observations. In graph 3.1 above months with a volatility shock are marked with black squares on the volatility series. We define the dummy variable as V equals 1 if

the MSCI Euro experiences a volatility shock and 0 otherwise. The logic behind the inclusion of a volatility shock variable in our regression analysis follows the expected inverse relation between stock market volatility and equity returns. Even though theory does not predict an asymmetric relation between market volatility and equity returns it has been found in empiric investigations. Hence, investigating the effect of volatility shocks for the idiosyncratic volatility puzzle is motivated.

3.3 Idiosyncratic volatility

To calculate the idiosyncratic volatility of each stock at each point of time we have used the method of Ang et al. where the idiosyncratic risk is calculated as the standard deviation of the residuals from a three-factor model (Ang et al. 2006, p.283). Following this methodology we calculate the idiosyncratic volatility using daily data over one month (Ibid.). Thus the idiosyncratic volatility, $\sigma_{\varepsilon,i,t}$, of each stock at time *t* is defined as:

$$\sigma_{\varepsilon,i,t} = \sqrt{\frac{\sum_{t=1}^{T}(\varepsilon_{i,t} - \overline{\varepsilon_i})^2}{(T-1)}} \tag{3}$$

where $\varepsilon_{i,t}$ is the residual for stock *i* at time *t* from the factor model (4), $\overline{\varepsilon_i}$ is the mean residual from *t*=1 to *t*=*T*. *T* is equal to the last trading day of the month where 20 days are used as a proxy for one month of trading days.

The factor model is defined as:

$$r_{i,t} = \alpha + \beta_{i,t,MKT} MKT_t + \beta_{i,t,SMB} SMB_t + \beta_{i,t,HML} HML_t + \varepsilon_{i,t} \tag{4}$$

where $r_{i,t}$ is the excess return of stock *i* at time *t* and α is the regression intercept coefficient. $\beta_{i,t,MKT}$ is the coefficient of slope for stock *i* at time *t* against the market-factor, MKT, and the same goes for the SMB- and HML-factor. MKT_t , SMB_t and HML_t are the Fama French factors at time *t*. Finally $\varepsilon_{i,t}$ is the regression error term for stock *i* at time *t*.

To test whether the quintile of stocks with the lowest idiosyncratic volatility gains higher, or lower, future returns than the quintile portfolio of stocks with the highest idiosyncratic risk, we

sort all stocks based on their idiosyncratic risk each month. Then we calculate the value weighted return of each portfolio for the forthcoming month. Each month the composition of stocks in the five portfolios is updated according to the level of idiosyncratic volatility in each stock. The return of the portfolios, $r_{P,t}$, can be defined as:

$$r_{P,t} = \sum_{i=1, i \in P}^{I} w_i r_{i,t} \tag{5}$$

where w_i is the weight of stock *i* in portfolio *P* and $r_{i,t}$ is the return of stock *i* at time *t*. All stocks from *i* to *I* are part of portfolio *P*. The determination of the stocks in the portfolios is based on a ranking of all stocks idiosyncratic volatility at time *t*-1. The ranking from high to low idiosyncratic volatility is divided into five groups (portfolios): High, Medium High, Medium, Medium Low and Low. To test whether equities with high past idiosyncratic volatility gain higher or lower future return we create a zero-investment portfolio long on stocks with high past idiosyncratic volatility and short on stocks with low past idiosyncratic volatility according to:

$$HML_t^{\sigma_{\varepsilon,i}} = r_{High,t} - r_{Low,t} \tag{6}$$

where $r_{High,t}$ is the return of the portfolio containing the quintile of stocks in the sample with the highest idiosyncratic volatility and vice versa for $r_{Low,t}$.

The sample of stocks is as mentioned based on the constituents of the three indices as of the 15th of November 2010; hence, there are a lot of securities that have been listed after the first day of our sample period. To include as many observations as possible we have decided to work with an expanding dataset where stocks are included into the ranking when there are enough observations to calculate past idiosyncratic volatility. In the beginning of February 1999, after the first set of idiosyncratic volatilities in the sample has been calculated, there are 436 stocks and at the last month of calculation there are 864 stocks. Consequently, there are 87 stocks in each of the quintile portfolios on the first observation and 172 stocks at the last observation. We do not consider this fact to be problematic as we find it better to include as many observations as possible at any given observation in the time series.

3.4 Regression analysis

We have used both time series and panel data sets to test whether past idiosyncratic volatility has predictive power for future returns. The time series portfolio based analysis is described first followed by a description of the panel data methodology.

3.4.1 Time series regressions

We follow the methodology used by Ang et al. where quintile portfolios are formed based on the stocks' idiosyncratic volatility as described in section 3.3. To test whether the quintile portfolio of stocks with the highest idiosyncratic volatility has higher or lower, future return than the quintile portfolio of stocks with the lowest idiosyncratic volatility we run an OLS[13]-regression on the following form:

$$HML_t^{\sigma_{\varepsilon,i}} = \beta_0 + \beta_{M,t}M_t + \beta_{V,t}V_t + \varepsilon_t \tag{7}$$

where $HML_t^{\sigma_{\varepsilon,i}}$ is the one-month return of the quintile portfolios of stocks with the highest and lowest idiosyncratic volatility respectively at each month *t*. β_0 is the regression intercept, and $\beta_{M,t}$ is the coefficient of slope against the dummy variable M_t and vice versa for the volatility shock variable. Finally, ε_t is the standard error term of the regression. We run double sided hypothesis test for the parameters according to H_0: $\beta_i = 0$ against H_1: $\beta_i \neq 0$. If MPT's predictions that idiosyncratic volatility is not priced β_0 is not significantly different from zero.

To minimize the risks of making incorrect inference of the test statistics and coefficients we run a set of residual test for (7). The OLS regression methodology rests on a couple of assumptions that need to be fulfilled in order to assure that the regression is BLUE, best linear unbiased estimator. The assumptions are (Brooks 2008, pp.129-130):

1. $E(\varepsilon_t) = 0$
2. $Var(\varepsilon_t) = \sigma^2 < \infty$
3. $Cov(\varepsilon_t, \varepsilon_{t-1}) = 0$

[13] Ordinary Least Squares

4. $Cov(\varepsilon_t, X_t) = 0$
5. $\varepsilon_t \sim N(0, \sigma^2)$

The first necessary assumption is that the expected value of the residual is zero which is not a problem in (7) as the model has an intercept (Brooks 2008, p.131) The second assumption requires that the variance of the residuals is constant, i.e. homoskedastic and not heteroskedastic residuals. The third assumption needed is that the residuals are time independent and not auto correlated. The fourth assumption dictates that the independent variables are non-stochastic. This assumption relies on an implicit assumption of the OLS-regression methodology, that the independent variables are not correlated (Ibid., p 170). The fifth assumption demands that the residuals are normally distributed with a mean of zero and a constant variance of σ^2. However, this assumption can be relaxed if the sample size is large enough (Westerlund 2005, p.74, p.134). Since our sample can be considered as large enough we do not test for normality. A final implicit assumption that needs to be fulfilled is that the regression model is linear in the parameters (Brooks 2008, p.174).

A general test for heteroskedacity that does not depend on assumptions about the likely form of heteroskedacity is White's (1980) heteroskedacity test (Brooks 2008, p.134). We run Eviews' featured White heteroskedacity test where the squared residuals of (7) are regressed against the parameters and the cross term of the parameters as follows:

$$\hat{\varepsilon}_{i,t}^2 = \alpha + \beta_{M,t} M_t + \beta_{V,t} V_t + \beta_{VM,t} V_t M_t + u_t \tag{8}$$

where $\hat{\varepsilon}_{i,t}^2$ is the squared residual of (7) and α is the regression intercept. The β-values are the coefficients of slope against the respective variables and the cross-term. u_t is the regression residual. The test statistics has an F-distribution where H_0: $\beta_M = \beta_V = \beta_{MV} = 0$ is tested against H_1: at least one $\beta_i \neq 0$. If the p-value for the test is smaller than the chosen significance level the null hypothesis is rejected and heteroskedacity is present. We use the cross term specification of the test as this is recommended when the model have relatively few independent variables (Ibid., p.137)

To test for serial correlation we use the Durbin Watson (1951) test. The Durbin Watson test tests whether the residual at time *t* is dependent on the residual of time t-1 (Brooks 2008, p.144). The residual series of (7) is used as the dependent variable in the following auxiliary regression:

$$\hat{\varepsilon}_t = \rho\hat{\varepsilon}_{t-1} + u_t \tag{9}$$

where $\hat{\varepsilon}_t$ is the regression error term from (7) at time *t*. ρ is the coefficient of slope against the prior periods' residuals and can be interpreted as the correlation between the residuals at time *t* and time *t*-1. Finally, u_t is the regression error term. The null hypothesis H_0: $\rho = 0$ is tested against H_1: $\rho \neq 0$. Thus, if the alternative hypothesis is accepted the regression model is impaired by auto correlation. The test statistic, DW, is calculated as follows (Brooks 2008, p.146):

$$DW = 2(1 - \rho) \tag{10}$$

where ρ is the coefficient of slope from (9). The DW-statistic is compared against the critical DW-values, d_U (upper bound) and d_L (lower bound). If DW > d_U the null hypothesis is accepted and if DW < d_L the null hypothesis is rejected and the residuals are positively auto correlated. If DW>4-d_U the null hypothesis is rejected and the model is impaired by negative auto correlation. If d_L < DW < d_U the test is indecisive and no conclusions regarding autocorrelation can be drawn (Brooks 2008, p.147).

To detect multicollinearity between the independent variables we use the variance inflation factor, VIF. The VIF is calculated as follows (Westerlund 2005, p.160):

$$VIF = \frac{1}{1 - R^2} \tag{11}$$

where R^2 is the coefficient of determination of (7). A large value of VIF indicates that the model might suffer from multicollinearity (Ibid.).

To test whether the model is linear and thus correctly specified we use the Ramsey RESET test in Eviews. The RESET test is run with an auxiliary regression where the higher powers of the original explanatory variables in (7) are regressed against the dependent variable. The test statistic

follows a χ^2 distribution where H_0: correct functional form is tested against H_1: wrong functional form (Brooks 2008, pp.174-175).

A further test that does not involve the properties of the residuals is the F-test. In a multiple linear regression model the F-test tests whether any of the parameters except the intercept is significantly different from zero. We run the enclosed F-test in Eviews where H_0: $\beta_{M,t} = \beta_{V,t} = 0$ and H_1: at least one of $\beta_{M\ or\ V,t} \neq 0$. If H_0 is accepted there simply is no regression (Westerlund 2005, pp.151-152). The test statistic has an F-distribution.

3.4.2 Panel data regressions

A natural advantage of panel data is that it often includes more observations than traditional cross-sectional or time series data sets. This property increases the degrees of freedom which potentially lead to more accurate inference of parameters (Hsiao 2006, p.5). A problem with the portfolio based time series regressions described in the section above is the absence of firm specific analysis. Time series analysis does not take heterogeneity into account, i.e. differences between individual units of observations. As panel data incorporates a cross sectional dimension to the time series, problems with heterogeneity are obstructed. Further, panel data alleviate multicollinearity problems (Kennedy 2003, p.302).

A problem with using a panel data approach to investigate the idiosyncratic volatility puzzle is that our approach does not directly test whether *differences* in idiosyncratic volatility yield *differences* in future return, be it higher or lower. Another negative feature compared to our portfolio based time series regressions is that the portfolio regressions clear for much of firm specific characteristics as the return series are value weighted and include at least 87 different securities, hopefully providing a quite high diversification. Nevertheless, intuitively the panel approach ought to provide further knowledge about the relation between idiosyncratic volatility and future returns as we can test directly whether past idiosyncratic risk has explanatory power for future returns using our fairly large panel data set.

A range of different estimators can be used for panel data but for financial research the fixed effects and random effects models are the most common (Brooks 2008, p.490). The fixed effects model is to prefer when the entities of interest constitute the whole population (Ibid., p.500) as is

the case for our study where we have not made a selection of a limited number of securities from the three exchanges but instead included all stocks. One can argue that the theoretical entire population constitutes all equities traded worldwide but we find it more plausible to consider our subset of equities as the entire population of the three markets of interest. The fixed effects model allows the intercept of the regression to differ cross-sectionally, in the time series or in both the cross-section and time series dimension, diagonally. In the random effects model the intercept can still vary but it is assumed to arise from a common intercept. Thus, the intercept for each entity constitutes the global intercept plus a random error term (Ibid., pp.490-498).

To create a panel data set of our observations we exclude all securities that do not have return observations for the entire time frame. If a security's return is absent for any given date it does not have observations for market value, book-to-market-ratio and idiosyncratic volatility as all these variables, like the return variable, need a price to be calculated. Simply put, we exclude all stocks that are not actively traded on the first day of our time period in the panel data set. This narrows the number of cross-sections, i.e. stocks, in the panel dramatically but generates a balanced panel. We still consider the amount of stocks to be sufficient as we have 347 stocks with quotes for all the necessary variables over the 131 periods from February 1999 to December 2010.

To test whether past idiosyncratic volatility has predictive power for future stock returns we run the panel data regression:

$$r_{i,t} = \alpha + \beta_1 \sigma_{\varepsilon,i,t-1} + \beta_2 MV_{i,t} + \beta_3 BTMV_{i,t} + \beta_4 M_t + \beta_5 V_t + \varepsilon_{i,t} \tag{12}$$

where $r_{i,t}$ is the raw return of stock *i* at time *t* and α is the regression intercept. $\sigma_{\varepsilon,i,t-1}$ is the idiosyncratic volatility of stock *i* at time *t*-1, $MV_{i,t}$ the market value and $BTMV_{i,t}$ the market value and book-to-market-ratio for stock *i* at time *t*. M_t and V_t are the dummy variables for the market state and volatility shock respectively. Finally, $\varepsilon_{i,t}$ is the regression error term.

Traditional financial theory such as the CAPM expects a linear relation between a security's sensitivity to the market risk and the expected return. However, as idiosyncratic volatility is not expected to be priced, a return profile such as the security market line is not established for idiosyncratic volatility. To investigate the possibility of a different return profile for idiosyncratic

volatility than a linear relationship we also run (12) with logarithmic values of past idiosyncratic volatility ($\ln(\sigma_{\varepsilon,i,t-1})$) and squared values of the idiosyncratic volatility ($\sigma_{\varepsilon,i,t-1}$^2). The choice to square the values rather raising the values to any other power is arbitrary. The aim of these alternative regression specifications is not to find the exact relation, if there is one, but rather to give guidance to which return profile is most probable as theory does not predict a specific one as is the case for the market risk. However, a linear relation between idiosyncratic risk and expected return ought to be theoretically reasonable as CAPM predict linearity between market risk and expected return.

To determine which of the three models is most appropriate we use Akaike's Information Criterion (AIC). AIC is a rank based test to see which of a number of competing models is relatively most appropriate. When economic theory does not imply that a certain model should be correct, the AIC can be used to compare models (Brooks 2008, p.58). Although theory implicitly suggests that the relation between (idiosyncratic) risk and expected return should be linear the AIC can provide further guidance to the choice of regression specification. The AIC is calculated as follows:

$$AIC = log\frac{1}{N}\sum_{i=1}^{N} e_i^2 + \frac{2K}{N} \tag{13}$$

where N is the number of observations, e_i^2 is the regression error term from (12) and K is the number of restrictions in (12). The model with the lowest AIC is generally to prefer if the difference between the AIC-values is big (Ibid., p.58).

As with the time series regressions we run a set of residual tests for (12). We test for heteroskedacity using a manual White (1980) heteroskedacity test with the following auxiliary regression:

$$\hat{\varepsilon}_{i,t}{}^2 = \alpha + \beta_1\sigma_{\varepsilon,i,t-1}{}^2 + \beta_2 MV_{i,t}{}^2 + \beta_3 BTMV_{i,t}{}^2 + \beta_4 M_t{}^2 + \beta_5 V_t{}^2 + u_{i,t} \tag{14}$$

where $\hat{\varepsilon}_{i,t}$ is the regression residual from (12) and $u_{i,t}$ is the regression error term. The independent variables are the same as in (12). The inference of the test statistics is the same as for

(8). If the residual variance is not constant we apply White's heteroskedacity consistent variance-covariance matrix. If the model is impaired by heteroskedacity White's correction enables inference of the parameters even though the residuals are heteroskedastic (Brooks 2008, p.152).

We use the previously described Durbin Watson (1951) test to test for serial correlation.

To test for fixed effects we use the Hausman test where H_0: random effects is tested against H_1: fixed effects. The tests are conducted by running a supplementary regression with random effects. The Hausman test statistic is χ^2 distributed where H_0 is rejected if the p-value is smaller than the critical p-value.

3.4.3 Significance levels

As a general rule we follow the universally used 5 percent significance level, indicated by ** in chapter four. Complimentary to the commonly accepted significance level of 5 percent we use a less restrictive 10 percent level, indicated by * and finally a stricter level of 1 percent, indicated by ***.

4. Results and discussion

The chapter start with an overview of the data in the descriptive statistics section. Thereafter we present the results from our regressions. Discussion of the results is conducted throughout the chapter as the results are presented.

4.1 Descriptive statistics

The properties of our factor model are shown in table 2 below. From left to right there are various statistics for the market factor, the size- and book-to-market-factors and finally for the idiosyncratic volatility, $\sigma_{\varepsilon,i,t.}$.

	MKT	SMB	HML	$\sigma_{\varepsilon,i,t}$	$\sigma_{\varepsilon,i,t}$ (Annualized)
Mean	0,00%	0,03%	0,02%	2,86%	45,23%
Median	0,01%	0,01%	0,03%	2,32%	36,63%
St. dev.	1,47%	0,76%	1,14%	2,57%	40,58%
Kurtosis	4,65	10,37	53,83	1982,34	1982,34
Skewness	0,08	0,51	1,92	25,76	25,76
Min	-7,81%	-4,63%	-9,07%	0,00%	0,00%
Max	10,60%	6,46%	22,21%	249,82%	3950,05%

Table 2 - Descriptive statistics for the factor model and idiosyncratic volatility, Source: Own

The market factor, MKT, has the most resemblance to a normal distribution with a mean and median of close to zero and a slightly positive skewness. The distribution is leptokurtic, *i.*e. more peaked than a normal distribution with a kurtosis of 4,65[14]. The size- and book-to-market factors have higher means and a higher degree of (positive) skewness indicating a positive return premium for low market value- and high book-to-market stocks. SMB and HML are also more leptokurtic than the market factor. The idiosyncratic volatility, $\sigma_{\varepsilon,i,t}$ has a very high degree of kurtosis indicating that the distribution has very "fat tails" as can be seen on the range between the maximum and minimum values. Considering the extreme maximum value of the idiosyncratic volatility distribution we do not rule out that there can be errors in the data we have gathered from Datastream. More likely is that the extreme market conditions of our time period cause a number of very large outliers and therefore the distribution has a very large range and highly leptokurtic distribution. As mentioned our time period experienced two severe crises in the

[14] A standard normal distribution has a kurtosis of 3 and a skewness of 0.

beginning and end of the 2000's. Apart from the distribution of idiosyncratic risk the mean and median is somewhat in line with previous research. Ang et al. report idiosyncratic volatility estimates of between 27 and 33 percent for the three markets (Ang et al. 2009, p.4). It should be noted that their sample period ends 2003, thus not including the financially turbulent time period of the late 00's.

The future return properties of the portfolios sorted on idiosyncratic volatility is visualised in table 3 below.

	High	**Med High**	**Med**	**Med Low**	**Low**	$\mathbf{HML_t^{\sigma_{\varepsilon,i}}}$
Mean	0,45%	-0,26%	0,11%	0,15%	0,14%	0,31%
Median	-0,19%	0,43%	1,36%	0,93%	0,57%	-0,12%
St. dev.	11,54%	8,59%	6,28%	5,02%	4,62%	9,95%
Kurtosis	0,78	0,13	0,41	0,57	1,13	2,83
Skewness	0,33	-0,24	-0,48	-0,84	-0,93	0,43
Min	-27,49%	-23,75%	-18,48%	-16,16%	-13,41%	-37,24%
Max	36,77%	18,94%	16,20%	8,63%	10,80%	37,12%

Table 3 - Future return of quintile portfolios sorted on idiosyncratic volatility, Source: Own

The mean-statistics of the series does not reveal any clear pattern of higher or lower future return for high (low) idiosyncratic stocks. The mean of the HML series is close to zero but slightly positive with a value of 0,3 percent indicating a positive risk premium for idiosyncratic volatility. The standard deviation of the return series is largest for the portfolio containing high idiosyncratic volatility stocks and decreasing thereafter. The HML series is positively skewed but resembles a normal distribution with a kurtosis close to 3.

Table 4 below illustrates the level of idiosyncratic volatility of the five portfolios. The numbers are based on the average idiosyncratic volatility in each of the portfolios at each date.

	High	Med High	Med	Med Low	Low
Mean	104,96%	57,98%	43,43%	32,95%	20,69%
Median	95,85%	54,65%	41,56%	31,00%	19,54%
St. dev.	47,83%	18,86%	14,04%	10,41%	6,02%
Kurtosis	43,41	3,21	4,95	6,94	11,60
Skewness	5,31	1,36	1,59	1,88	2,51
Min	55,69%	32,51%	24,67%	19,16%	12,62%
Max	520,24%	145,90%	115,46%	90,59%	58,03%

Table 4 - Average idiosyncratic volatility of portfolios, Source: Own

In the portfolio containing the stocks with the highest idiosyncratic portfolio, High, the average idiosyncratic volatility is close to twice the size of the next portfolio, Med High. None of the portfolios have average idiosyncratic volatility distributions that resemble a normal distribution and the High and Low portfolios are most leptokurtic and skewed.

The average idiosyncratic volatility of the portfolios over our time period is visualised in figure 2. As illustrated the High portfolio experiences an extreme jump in idiosyncratic volatility in august 2001, most likely due to the dotcom crisis.

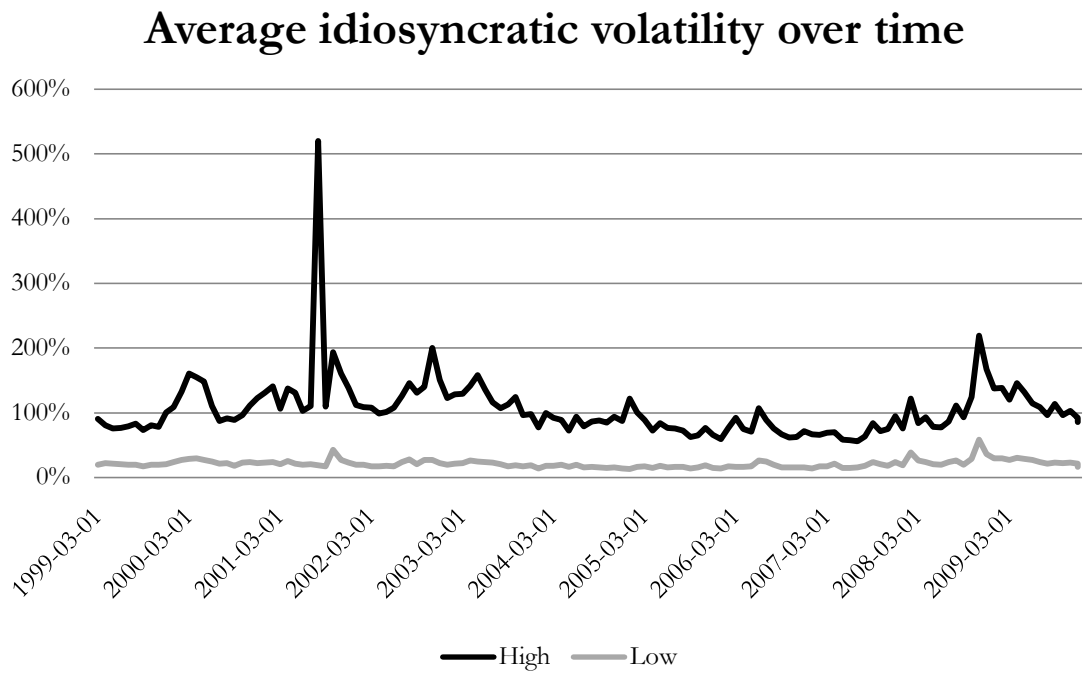


Figure 2 - Average idiosyncratic volatility over time, Source: Own

4.2 Time series regressions

To test if there is a significant positive or negative relation between idiosyncratic volatility and future equity returns we run (7) in Eviews. The results of the regression are shown in table 5 below.

Regression #	7	**R-squared**	0,032	
Sample	1999M03-2009M12	**F-statistic**	2,092	
Observations	130	**Prob. (F-statistic)**	0,128	
Method	OLS	**VIF**	1,033	
Dependent variable	$HML_t^{\sigma_{\varepsilon,i}}$	**Durbin-Watson stat**	1,751	
Ind. Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	-0,020	0,014	-1,41	0,16
MKTSTATE	0,035	0,018	1,97*	0,05*
VOLSHOCK	0,025	0,033	0,78	0,44

Table 5 - Time series portfolio based regression statistics, Source: Own

The model has many desirable characteristics as it passes the residual test needed to infer the regression parameters. The Durbin-Watson statistic of 1,751 is greater than the critical value, d_U, of 1,740 (Westerlund 2005, p.219) indicating that the model is not impaired by first order positive serial correlation. Neither do the residuals seem to be negatively auto correlated, as the DW-statistic is smaller than 4 minus d_U. We do not find evidence that the independent variables are correlated as the VIF is close to one. The output from the heteroskedacity test is shown in table 4 below.

Regression #	8	**R-squared**	0,048	
Sample	1999M03-2009M12	**F-statistic**	2,117	
Observations	130	**Prob. (F-statistic)**	0,101	
Method	OLS			
Dependent variable	Resid^2			
Ind. Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	0,009	0,003	3,00***	0,00***
MKTSTATE	-0,001	0,004	-0,34	0,74
MKTSTATE*VOLSHOCK	0,009	0,014	0,69	0,49
VOLSHOCK	0,012	0,009	1,37	0,17

Table 6 - White Heteroskedacity test for time series regression, Source: Own

As the p-value for the F-statistic is larger than our least restrictive significance level we can reject that the residuals are heteroskedastic. The RESET-test for functional form has the following test statistics.

Regression	Ramsey's RESET	**t-statistic**	1,242	
Sample	1999M03-2009M12	**F-statistic**	1,543	
Observations	130	**Prob. (F-statistic)**	0,217	
Method	OLS	**R-squared**	0,044	
Dep. Var. (Unrestricted)	$HML_t^{\sigma_{\varepsilon,i}}$			
Ind. Variable (Unrestricted)	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	-0,035	0,019	-1,88*	0,06*
MKTSTATE	0,0374	0,018	2,09**	0,04**
VOLSHOCK	0,009	0,035	0,25	0,80
FITTED^2	45,893	36,947	1,24	0,22
F-test summary:	**Sum of Sq.**	**df**	**Mean Squares**	
Test SSR	0,015	1	0,015	
Restricted SSR	1,236	127	0,010	
Unrestricted SSR	1,221	126	0,010	

Table 7 - Ramsey RESET test for time series regression, Source: Own

As the squared estimate of the HML variable is insignificant, with a p-value of 0,217, the model probably has the correct functional form.

Based on the above residual tests of (7) we believe it to be robust for inference as all the necessary assumptions behind the OLS-regression methodology are fulfilled.

As a starting point for the parameter inference, the variable of most interest is the intercept. The prediction of Markowitz's Mean-Variance criteria is an intercept of zero. However, the intercept in our model is minus two percent, indicating that a value weighted zero-investment portfolio long on stocks with high idiosyncratic volatility and short an equal amount in stocks with low idiosyncratic volatility has a monthly negative return of two percent. Hence, our results are in line with the peculiar findings by Ang et al. However, the intercept is not significant even at the least restrictive significance level with a p-value in excess of 10 percent. The p-value indicates that to a certainty of 84 percent we can accept the zero hypothesis and thus the predictions of modern portfolio theory seem to hold. Interestingly the return differential between high- and low idiosyncratic risk equities seem to be state dependent as the p-value for the market state dummy variable is significant at 10 percent significance level. Our model suggests that the variation

between the future return of the two groups of stocks is 3,5 percent if the market is in a bull state. Hence, if the market state can be characterised as a bull market our model predicts that stocks with high idiosyncratic volatility are compensated with a higher future return. This finding is counterproductive to the negative intercept. Our findings thus suggest that if the market is in a bull state, the return differential of -2 percent between the two quintiles of equities is offset by a positive risk premium of 3,5 percent averaging out the negative return of the zero-investment portfolio, HML, leading to a positive return. To conclude, if the market is in a bull state there is a positive risk premium for idiosyncratic volatility and if the market is in a bear state there is an inverse relation between idiosyncratic volatility and equity returns.

The volatility shock variable, measured by a sudden increase in market volatility, is positive at a value of 2,5 percent. However, it is highly insignificant and any inference of the parameter estimate is out of place and we rule out that shocks to market volatility explain a potential return differential between high and low idiosyncratic risk stocks.

Although we find that the market state variable is significant at a 10 percent significance level, the remaining parameters are insignificant and the model demonstrates very poor explanatory power with an R-square value of only 3 percent. Also, the p-value of the F-test, 12,8 percent, is in excess of our significance level of 10 percent indicating that there is no regression relation at all. Hence, the outcome of the regression analysis is in line with the properties of the time series as shown in section 4.1. This can seem as a nonsense finding but we regard the results to be quite the opposite as discussed below.

Our findings contradict those of both Ang et al. and Fu[15] as we do not find that stocks with high (low) idiosyncratic volatility have lower (higher) future returns. Our findings support the third possibility, that there is no return differential between the two groups of stocks. Even though our regression model intercept is negative, indicating the existence of a negative relation, the parameter is insignificant. Before we can reject the existence of an idiosyncratic volatility puzzle in these three markets and accept the predictions of modern portfolio theory, that idiosyncratic volatility is not priced, some discussion around the sources behind our findings is in place. We list some crucial concerns below.

[15] It should once again be noted that we do not apply the same methodology.

First of all, our time frame exhibit two major financial crises and is shorter than the periods studied by both Ang et al. and Fu. A longer time frame might have averaged out the effects of these two crises and would have increased the number of bear and bull markets. On the other hand, using the same time period as previous research would provide less to the research knowledge on the idiosyncratic volatility puzzle. Also, even though we find the possibility of such an explanation highly unlikely it might be that the anomaly has disappeared due to the reaction of market actors post the publication of Ang et al.'s 2006 article. Even though market anomalies can diminish or disappear over time (Schwert 2003, pp.943-944) we do not believe this to be the case for the idiosyncratic volatility puzzle. Since the previous findings are dispersed and point in two different directions along with our third result, market actors have probably not taken advantage of a potential mispricing of idiosyncratic risk as the implications are uncertain. Another factor that could have been of interest to investigate is the use of different formation periods for the idiosyncratic risk and future return calculation. The results might have been different if e.g. a longer or shorter time frame would have been used to calculate the idiosyncratic volatility of each stock. We find such a pursuit of results questionable and the "one-month past idiosyncratic volatility - one-month future return"-methodology to be sufficient as this is the principal method used by Ang et al. Since different formation and holding periods should not inflict on the results (Ang et al. 2006, pp.292-293) we find our estimation and holding period to be sufficient. Another difference between our methodology and the research conducted by Ang et al. and Brookman et al. is that we do not conduct country specific investigations of the idiosyncratic volatility puzzle. Even though Ang et al. (2009) use both a country specific model and a "world" model to calculate idiosyncratic volatility they demonstrate the results on a country specific basis. Our sample is not sub divided according to each stock exchange and this might be a reason for the discrepancy between previous findings and ours.

Even though our findings suggest a positive relation between idiosyncratic volatility in bull markets and a negative relation in bear markets the absence of significance in our model imply that investors are not compensated for idiosyncratic volatility exposure. Thus, we reject the information cost hypothesis proposed by Merton as a cause for investors to be compensated for firm specific risk. We also oppose the previous findings by Ang et al. that there is a negative risk premium associated with idiosyncratic volatility in Germany, France and the Netherlands. Rather, our findings suggest that idiosyncratic risk is not priced; hence, investors are not compensated for

exposure to idiosyncratic volatility. Consequently, our findings instead support the Mean-Variance criteria based on a Fama and French factor model.

4.3 Panel data regressions

As an alternative approach to test whether past idiosyncratic volatility has predictive power for future returns we use our panel data set. Since we have tested the model with three different specifications of the idiosyncratic volatility variable, a first step is to decide the most likely model, and thus the idiosyncratic risk-return profile. The AIC-values of the three models are: linear model: -0,9697, ln-model: -0,9694 and the squared model: -0,9692. Even though the difference is very small and does not provide so much of guidance, the linear model has the lowest AIC and should therefore be chosen. As the linear model also is theoretically most feasible we find it reasonable to proceed the regression analysis with this model as opposed to the ln and squared model. The statistics from (12) are shown in table 8 below while the supplementary models are available in appendix 2.

Regression #	12	**Method**	Panel OLS	
Sample	1999M04-2009M12	**R-squared**	0,049	
Periods	130	**F-statistic**	516,744	
Cross-sections	389	**Prob. (F-statistic)**	0,000***	
Observations	50486	**Durbin-Watson stat**	2,052	
Dependent variable	$r_{i,t}$	**AIC**	-0,9697	
Ind. Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	-0,013	0,001	-8,62***	0,00***
$\sigma_{\varepsilon,i,t-1}$	0,125	0,026	4,80***	0,00***
MV	5,35E-08	4,70E-08	1,13	0,26
BTMV	-0,002	0,001	-3,53***	0,00***
MKTSTATE	0,042	0,001	30,18***	0,00***
VOLSHOCK	-0,076	0,002	-33,42***	0,00***

Table 8 - Initial panel regression, Source: Own

As a fixed effects model is appropriate for our data we test for fixed effects in the cross section with a Hausman test. The χ^2 test statistics from the test are shown in table 9 below together with the auxiliary random effects regression.

Regression	Hausman test	**Cross section effects**	Random	
Sample	1999M04-2009M12	**Chi-Sq. Statistic**	56,121	
Periods	130	**Prob. Chi-Sq.**	0,000***	
Cross-sections	389	**R-squared Unweighted**	0,049	
Method	Panel EGLS	**R-squared Weighted**	0,049	
Observations	50486	**Durbin-Watson Unweighted**	2,051	
Dependent variable	$r_{i,t}$	**Durbin-Watson Weighted**	2,051	
Ind. Variable	**Coefficient**	**Std, Error**	**t-Statistic**	**Prob.**
INTERCEPT	-0,013	0,002	-8,62***	0,00***
$\sigma_{\varepsilon,i,t-1}$	0,125	0,026	4,79***	0,00***
MV	5,35E-08	4,71E-08	1,14	0,26
BTMV	-0,001	0,001	-3,52***	0,00***
MKTSTATE	0,0423	0,001	30,16***	0,00***
VOLSHOCK	-0,076	0,002	-33,40***	0,00***
Effects specification	**S.D.**	**Rho**		
Cross-section random	0,000	0,000		
Idiosyncratic random	0,149	1,000		

Table 9 - Hausman test for fixed effects, Source: Own

We reject the zero hypothesis, that a random effects specification is more suitable, as the p-value of the χ^2 test statistic is virtually zero. As the fixed effects model seem appropriate we run (12) with fixed effects in the cross section. The regression statistics are shown in table 10 below:

Regression	12	**Dependent variable**	$r_{i,t}$	
Sample	1999M04-2009M12	**Cross section effects**	Fixed	
Periods	130	**F-statistic**	7,374	
Cross-sections	389	**Prob. F-statistic**	0,000***	
Method	Panel OLS	**R-squared**	0,055	
Observations	50486	**Durbin-Watson**	2,060	
Ind. Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	-0,017	0,002	-10,24***	0,00***
$\sigma_{\varepsilon,i,t-1}$	0,114	0,028	4,03***	0,00***
MV	8,88E-07	1,27E-07	6,99**	0,00***
BTMV	-0,002	0,001	-2,71***	0,007***
MKTSTATE	0,042	0,001	30,19***	0,00***
VOLSHOCK	-0,076	0,002	-33,49***	0,00***

Table 10 - Panel regression with fixed effects, Source: Own

The Durbin Watson statistic of 2,06 is in excess of the critical upper value 1,74 (Westerlund 2005, p.219), indicating that first order positive auto correlation is unlikely. Neither is first order negative serial correlation likely as the DW statistic is smaller than 4-1,74.

To determine the properties of the residual variance we run a manual White heteroskedacity test according to (13). The test reveals if the squared regressors affect the residual variance. The test statistics are shown in table 11 below.

Regression #	13			
Sample	1999M04-2010M01	**Method**	Panel OLS	
Periods	130	**R-squared**	0,000	
Cross-sections	389	**F-statistic**	0,597	
Total observations	50486	**Prob. (F-statistic)**	0,702	
Dependent variable	Residual^2	**Durbin-Watson stat**	2,022	
Ind. Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	0,020	0,008	2,63***	0,009***
$\sigma_{\varepsilon,i,t-1}$^2	0,144	0,147	0,98	0,32
MV^2	-1,70E-12	3,30E-12	-0,52	0,61
BTMV^2	8,71E-05	7,55E-05	1,15	0,25
MKTSTATE^2	0,004	0,009	0,44	0,66
VOLSHOCK^2	-0,005	0,015	-0,35	0,73

Table 11 - White heteroskedacity test for panel fixed effects model, Source: Own

The p-value of the F-statistic is very large at a value of close to 0,6. Thus, our test indicates that the residuals are homoskedastic. However, the test is not completely reliable as it only includes the squared regressors[16] and by examining the residual plot from the regression, depicted in appendix 3, we rather find the residual variance to be heteroskedastic. To be able to conduct inference of the parameter estimates we apply White's heteroskedacity consistent variance-covariance matrix in the cross-section. The regression statistics of (12) adjusted for heteroskedacity with fixed effects is illustrated in table 12.

[16] It is not possible to run White's test with both the regressors and squared regressors or cross terms.

Regression	12	**Dependent variable**	$r_{i,t}$	
Sample	1999M04-2010M01	**Cross section effects**	Fixed	
Periods	130	**F-statistic**	7,374	
Cross-sections	389	**Prob. F-statistic**	0,000***	
Method	Panel OLS (White)	**R-squared**	0,055	
Observations	50486	**Durbin-Watson**	2,060	
Ind. Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	-0,017	0,008	-2,18**	0,03**
$\sigma_{\varepsilon,i,t-1}$	0,114	0,157	0,73	0,47
MV	8,88E-07	3,38E-07	2,63***	0,009***
BTMV	-0,002	0,002	-0,67	0,501
MKTSTATE	0,042	0,009	4,52***	0,00***
VOLSHOCK	-0,076	0,016	-4,87***	0,00***

Table 12 - Panel regression with fixed effects, White heteroskedacity consistent

Contradictive to the (insignificant) finding from the time series regressions the parameter estimate relating to the past idiosyncratic volatility is positive indicating that there is a positive risk premium for idiosyncratic volatility. Our model suggests that if the daily idiosyncratic volatility of a stock rises by 1 percent the expected return ought to rise by 0,11 percent. However, the parameter estimate is not close to significant with a p-value of 0,47. Therefore, our model rather suggests that idiosyncratic volatility is not priced at all. The market value variable is highly significant and passes the *** significance level. However, we did not expect the parameter to be positive. While classic asset pricing theory does not expect the size of a company's market value to have predictive power for stock market returns, empirical tests and models such as the Fama and French three-factor model suggest that small capitalization stocks earn higher returns on average than large capitalization stocks. Hence, the strong significance and the reverse sign of the parameter is an unexpected finding from the model. The book-to-market equity parameter is negative, also an unexpected result but it is not significant. Both the market state variable and the volatility shock variable have expected signs and they are both significant. The significance and sign of the market state variable can seem trivial as one would expect that the average return of individual securities are higher if the market is in a bull state. The negative parameter estimate for the volatility shock variable is not expected by traditional financial theories but it supports the asymmetric volatility finding. Our model suggest that the stocks in our sample on average experience a negative monthly return effect of 7 percent due to a sudden rise in market volatility.

Our panel model show some interesting results such as the unexpected reverse size effect but overall it has very weak explanatory power with an R-square value of only 5,5 percent. However, our aim is not to find a new model for explaining the cross section of equity returns but to investigate the idiosyncratic volatility puzzle. Thus, the low R-squared is not unexpected. What is more interesting though is the absence of results that support either a positive or a negative risk premium for idiosyncratic volatility as our results are insignificant. The time series- and panel data tests thus point in the same direction if we reject the opposite premium achieved through the two methods.

5. Conclusions

The final chapter provides a review and brief discussion of the results. Some concluding remarks are presented and we provide suggestions for future research.

The aim of our thesis has been to further investigate the idiosyncratic volatility puzzle. Our results reject the existence of neither a positive nor a negative risk premium for idiosyncratic volatility exposure. For our time series portfolio based regressions it seems that the market state has explanatory power for the difference in future returns between high- and low idiosyncratic volatility stocks. Our model suggests that the premium is positive if the market is in a bull state and negative during bear states. However, the insignificance of the entire model and its poor explanatory power makes this result questionable. This promotes the predictions of modern portfolio theory, idiosyncratic risk is not priced.

We have also investigated the idiosyncratic volatility puzzle using a panel data methodology. Our results from the panel regression support the findings of the time series regression. Although the effect of idiosyncratic volatility on future returns is reversed in the two regression models, they both lack significance and therefore support the Mean-Variance approach.

Even though we do not find support for an idiosyncratic volatility puzzle in the three markets we investigate our thesis has some other interesting findings. Our panel model suggests that the size-effect is inverted in the three markets, indicating that larger capitalization stocks on average earn higher returns than small capitalization stocks. A potential explanation can be that smaller stocks have suffered harder from the two crises in our time period. The results also support that the effects of market volatility on equity returns is negative and therefore asymmetric. If the market volatility experiences a sudden sharp increase, equity returns are on average negative. However, we do not find proof that market volatility shocks can explain a difference in returns between stocks with high and low idiosyncratic volatility.

Altogether our thesis rejects the existence of an idiosyncratic volatility puzzle in the three markets. Asymmetric volatility in the sense of volatility shocks cannot explain difference in return between stocks with high and low idiosyncratic volatility. However, our model provides some support for a negative premium in bear markets and a positive premium in bull markets. These

findings, and primarily the absence of an idiosyncratic volatility puzzle, contribute to the knowledge in the subject and stand contradictive to previous research. As we apply a similar methodology compared to previous works, we conclude that more research on the "idiosyncratic volatility – return"-relation is needed. We leave to future research the question whether the model specification is essential for the results. Since we cannot find a statistically significant relation based on our pooled sample from the three markets, in opposite to the country specific investigations of Ang et al. and Fu, we believe that further investigations of this finding is needed. Ignoring the insignificance of our model, the risk premium for idiosyncratic volatility seems to differ across bear and bull markets. Thus, a more thorough analysis of the importance of the market state is needed to assess whether it can explain, or give any guidance, to the properties of the "idiosyncratic volatility – return"-relation. To conclude, the "be or not to be" of the idiosyncratic volatility puzzle is still to be determined and poses an interesting field of research for academics and practitioners in the field of financial economics.

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Databases

Thomson Datastream Advance, available through Lund University Finance Society

Elin@Lund, database for scientific articles

Appendix 1

AEX

3W Power Holdings
Aalberts Inds.
Accell Group
Accsys Technologies(Ams)
Aegon
Afc Ajax
Ageas (Ex-Fortis)
Ahold Kon.
Air France-Klm
Akzo Nobel
Alanheri
Amg Advd.Metallurgical Group
Amsterdam Commodities
Amt Holding
And Intl.Publishers
Antonov (Ams)
Arcadis
Arcelormittal
Arseus (D)
Asm International
Asml Holding
Atrium European (Ams) Rlst.
Ballast Nedam
Bam Groep Kon.
Batenburg Beheer
Be Semiconductor
Beter Bed Holding
Binckbank
Boskalis Westminster
Brill (Kon.)
Brunel Intl.
Corio
Crown Van Gelder
Crucell
Cryo Save Group
Csm Certs.
Ctac Nm
Delta Lloyd Group
Docdata
Dockwise
Dpa Group
Draka Holdings
Dsm Koninklijke
Eurocommercial
Exact Holding
Fornix Biosciences
Fugro
Galapagos
Gamma Holding
Grontmij
Groothandelsgeb.
Hal Trust
Heijmans
Heineken
Hes - Beheer
Hitt Nm
Holland Colours
Homburg Invest 'A' (Ams) Subd. Vtg.
Hydratec Industries
Ict Automatisering
Imtech
Ing Groep
Innoconcepts Nm
Kardan N V
Kas Bank
Kendrion
Kpn Kon
Lbi International
Logica (Ams)
Macintosh Retail
Mdxhealth
Mediq
Nedap
Nedsense Enterprises
Neways Elec.Intl.
Nieuwe Steen Inv.
Nutreco
Octoplus
Oranjewoud 'A'
Ordina
Pharming Group
Philips Eltn.Koninklijke
Phoenix Group Holdings Dead - 17/11/10
Porceleyne Fles
Prologis Euro Prop
Punch Graphix
Qurius
Randstad Holding
Reed Elsevier (Ams)
Roodmicrotec
Roto Smeets
Royal Dutch Shell A
Sbm Offshore
Simac Techniek
Sligro Food Group
Sns Reaal
Sopheon Nm (Ams)
Spyker Cars
Stern Groep
Telegraaf Media Groep
Ten Cate
Tie Holding
Tkh Group
Tnt
Tom Tom
Unibail-Rodamco
Unilever Certs.
Unit 4
Usg People
Van Lanschot
Vastned Offices Indl.
Vastned Retail
Vivenda Media Groep
Vopak
Wavin
Wereldhave
Wessanen Kon.Certs.
Wolters Kluwer
Yatra

CAC

Abc Arbitrage
Acanthe Dvppt.
Accor
Acteos
Actia Group
Adlpartner
Adp
Adt Siic
Advini
Aedian
Affine (Ex Immobail)
Affiparis
Afone

Air France-Klm
Air Liquide
Akka Technologies
Alcatel-Lucent
Alpha Mos
Alstom
Altamir Amboise
Alten
Altran Tech.
Anf
Anovo
April Group
Aprr
Arcelormittal
Archos
Areva Ci
Argan
Arkema
Artprice.Com
Assystem
Ast Groupe
Atari
Atos Origin
Aubay
Audika
Aufeminin.Com
Augros Cp
Aurea
Aures Technologies
Ausy
Avanquest Software
Avenir Finance
Avenir Telecom
Axa
Bac Majestic
Bains Mer Monaco
Barbara Bui Up
Bastide(Confort Med.)
Bci Navigation
Belvedere Opa
Beneteau
Bernard Loiseau
Bic
Big Ben Interactive
Bioalliance Pharma
Biomerieux
Bnp Paribas
Boiron
Bonduelle
Bongrain
Bourbon
Bourse Direct
Boursorama (Ex Fimatex)
Bouygues
Bull Regpt
Bureau Veritas
Business Et Decision
Cafom
Cameleon Software
Canal +
Cap Gemini
Capelli
Carrefour
Casino Guichard-P
Cast
Catering Intl.Svs.
Cegedim
Cegereal
Cegid Group
Cesar
Cfao
Chargeurs
Christian Dior
Cibox Interactive
Cie.Gl.De Gphyq.-Vert.
Ciments Francais
Clayeux
Club Mediterranee
Cnp Assurances
Cnut.Istls.De_La_Mdtn.
Cofidur
Cofigeo Cie.Finc.Geo
Coheris Atix
Compagnie Des Alpes
Cottin Freres
Courtois
Credit Agricole
Cs Comm.Systems
Cyberdeck Susp - 30/09/10
Cybergun
Cybernetix
Dalet
Dane-Elec Memory
Danone
Dassault Systemes
Delachaux
Delta Plus Group
Derichebourg
Devoteam
Dexia
Digigram Susp - 01/10/10
Dms
Dreamnex
Dynaction
Eads (Par)
Ebizcuss.Com
Eca
Edf
Edf Energies Nouv.
Egide
Eiffage
Electricite Madagascar
Encres Dubuit
Entrepose Contracting
Eramet
Esi Group
Esr
Essilor Intl.
Esso
Etam Developement
Euler Hermes
Eurazeo
Euro Disney Sca
Euro Ressources
Eurofins Scientific
Euromedis Groupe
Europacorp Promesses
Eurosic
Eutelsat Communications
Faiveley Transport
Faurecia
Fimalac

Fleury Michon
Fonciere Des Regions
Fonciere Paris France
France Telecom
Gameloft
Gascogne
Gdf Suez
Gea
Geci International
Gecina
Gemalto
Generix
Ipsen
Ipsos
It Link
Itesoft
Its Group
Jcdecaux
Kaufman Et Broad
Keyrus
Kindy
Klepierre
L'Oreal
La Perla World
Lacie
Lacroix
Lafarge
Lafuma
Lagardere Groupe
Latecoere
Laurent Perrier
Ldc
Ldlc.Com
Le Belier
Le Noble Age
Le Tanneur Et Cie
Lebon
Lectra
Legrand
Lesnxconstructeurs
Lexibook
Linedata Services
Lisi
Locindus
Lvl Medical Groupe
Lvmh
M6-Metropole Tv
Maison France Confort
Manitou
Marocaine(Cie.)
Maurel Et Prom
Mecelec
Medasys
Media 6
Meetic
Memscap Regpt
Mercialys
Mersen (Ex Lcl)
Metabolic Explorer
Metrologic Group
Michelin
Micropole
Millimages
Modelabs Group
Montupet
Mr Bricolage
Natixis
Naturex
Neopost
Netgem
Neurones
Nexans
Nexity
Nextradiotv
Nicox
Norbert Dentressangle
Nrj Group
Oeneo
Ofi Private Equity Cap.
Ol Groupe
Orapi
Orchestra-Kazibao Regrt
Orpea
Osiatis
Outremer Telecom
Overlap Groupe
Oxymetal
Pagesjaunes
Paref
Parrot
Parsys
Passat
Pcas
Pernod-Ricard
Peugeot
Pharmagest Interactive
Pierre & Vacances
Piscines Desjoyaux
Plastic Omnium
Plstq.Du Val De Loire
Poncin Yachts
Ppr
Prismaflex International
Prologue
Psb Industries
Public Systeme Hopscotch
Publicis Groupe
Quantel
Radiall
Rallye
Recylex
Remy Cointreau
Renault
Rexel
Rhodia
Riber
Risc Group
Rodriguez Group
Rougier
Rubis
Rue Du Commerce
Safran
Saft
Saint Gobain
Sam
Sanofi-Aventis
Sartorius Stedim Biotech
Sc.Fonfnc.Et De Parts.
Schaeffer
Schneider Electric
Scor Se
Seb

Seche Environnement
Sechilienne
Securidev
Seloger.Com
Sequana
Ses Fdr (Par)
Sii
Silic
Siparex
Siraga
Smtpc
Societe Finc.De Comm.Et Du Mltm.
Societe Generale
Sodexo
Soditech Ingenierie
Soft Computing
Sogeclair
Soitec
Solucom
Solving Efeso Intl.
Sopra Group
Spir Comm.
Sqli
St Dupont
Stallergenes
Stef-Tfe
Stmicroelectronics (Par)
Store Electronics
Suez Environnement
Sword Group
Systar Up
Systran
Team Partner Susp - 22/09/10
Technicolor
Technip
Telecom Reseaux Svs.
Teleperformance
Terreis
Tessi
Tf1 (Tv.Fse.1)
Thales
Theolia
Thermador Gpe.
Thermocompact
Tonna Electq.
Tonnellerie Fnoi.Freres
Total
Touax
Toupargel Groupe
Tour Eiffel
Transgene
Trigano
U10
Ubisoft Entm.
Umanis
Unibail-Rodamco
Union Tchg.Inf.
Universal Multimedia
Valeo
Vallourec
Valtech
Veolia Environnement
Vet Affaires
Vetoquinol
Vicat
Vilmorin & Cie
Vinci (Ex Sge)
Virbac
Visiodent
Vivalis
Vivendi
Vm Materiaux
Vranken-Pommery Monopole
Wendel
Xilam Animation
Zodiac Aerospace
Zublin Immobiliere

Xetra

118000 (Xet)
3U Holding (Xet)
4 Sc (Xet)
A S Creation (Xet)
Aap Implantate (Xet)
Aareal Bank (Xet)
Ad Pepper Media (Xet) Intl.
Adidas (Xet)
Adv.Vision Tech. (Xet)
Adva Optical Netwg.(Xet)
Agennix (Xet)
Ahlers (Xet)
Ahlers Pref (Xet)
Air Berlin (Xet)
Aire (Xet)
Aixtron (Xet)
Aleo Solar (Xet)
All For One (Xet) Midmarket
Allianz (Xet)
Alphaform (Xet)
Alstria Office Reit(Xet)
Amadeus Fire (Xet)
Analytik Jena (Xet)
Arques Industries (Xet)
Artnet (Xet)
Asian Bamboo (Xet)
Atoss Software (Xet)
Augusta Tchg. (Xet)
Aurubis (Xet)
Axel Springer (Xet)
Balda (Xet)
Basf (Xet)
Basler (Xet)
Bauer (Xet)
Bayer (Xet)
Baywa (Xet)
Baywa Regd. (Xet)
Bb Biotech (Xet)
Bdi-Bioenergy Intl.(Xet)
Beate Uhse (Xet)
Bechtle (Xet)
Beiersdorf (Xet)
Bertrandt (Xet)
Beta Sys.Sftw. (Xet)
Bilfinger Berger (Xet)
Biolitec (Xet)
Biotest (Xet)
Biotest Pref. (Xet)
Bmp (Xet)
Bmw (Xet)
Bmw Pref. (Xet)
Boss (Hugo) (Xet)
Boss (Hugo) Pref. (Xet)

Bruder Mannesmann (Xet)
C A *t* Oil (Xet)
C-Quadrat Inv. (Xet)
Cancom It Systeme (Xet)
Carl Zeiss Meditec (Xet)
Celesio (Xet)
Cenit (Xet)
Centrosolar Group (Xet)
Centrotec Sust. (Xet)
Centrotherm Phto. (Xet)
Ceotronics (Xet)
Cewe Color Holding (Xet)
Colexon Energy (Xet)
Colonia Real Estate(Xet)
Comarch Sftw.& (Xet) Beratung
Comdirect Bank (Xet)
Commerzbank (Xet)
Compugroup Medical (Xet)
Conergy (Xet)
Constantin Medien (Xet)
Continental (Xet)
Cor&Fja (Xet)
Corporate Eq.Ptns. (Xet)
Cropenergies (Xet)
Cts Eventim (Xet)
Curanum (Xet)
D Logistics (Xet)
Dab Bank (Xet)
Daimler (Xet)
Data Modul (Xet)
Deag Deutsche Entm.(Xet)
Delticom (Xet)
Demag Cranes (Xet)
Deutsche Bank (Xet)
Deutsche Bet. (Xet)
Deutsche Boerse (Xet)
Deutsche Euroshop (Xet)
Deutsche Lufthansa (Xet)
Deutsche Post (Xet)
Deutsche Postbank (Xet)
Deutsche Telekom (Xet)
Deutsche Wohnen (Xet)
Deutsche Wohnen (Xet) Br.Shs.
Deutz (Xet)
Df Deutsche Forfait(Xet)
Dialog Semicon. (Xet)
Dic Asset (Xet)
Douglas Holding (Xet)
Dr Hoenle (Xet)
Draegerwerk Pref. (Xet)
Drillisch (Xet)
Duerr (Xet)
Dyckerhoff (Xet)
Dyckerhoff Pref. (Xet)
E On (Xet)
Eads (Xet)
Eckert & Ziegler (Xet)
Ecotel Comm. (Xet)
Einhell Germany (Xet)
Elexis (Xet)
Elmos Semicon. (Xet)
Elringklinger (Xet)
Envitec Biogas (Xet)
Epigenomics (Xet)
Ermn.Comm.& Cntl. (Xet) Tech.
Essanelle Hair Gp. (Xet)
Estavis (Xet)
Evotec (Xet)
Fabasoft (Xet)
Fair Value Reit (Xet)
Fielmann (Xet)
Fortec Electronik (Xet)
Francotyp-Postalia (Xet) Hldg.
Fraport (Xet)
Freenet (Xet)
Fresenius (Xet)
Fresenius Med.Care (Xet)
Fresenius Med.Care (Xet) Pref.
Fresenius Pref. (Xet)
Fuchs Petrolub (Xet)
Fuchs Petrolub Pf. (Xet)
Funkwerk (Xet)
Gagfah (Xet)
Gea Group (Xet)
Generali Dtl.Hldg. (Xet)
Geratherm Medical (Xet)
Gerresheimer (Xet)
Gerry Weber Intl. (Xet)
Gesco (Xet)
Gfk (Xet)
Gft Technologies (Xet)
Gildemeister (Xet)
Gk Software (Xet)
Grammer (Xet)
Graphit Kropfmuhl (Xet)
Grenkeleasing (Xet)
Gwb Immobilien (Xet)
H & R Wasag (Xet)
Hamborner Reit (Xet)
Hamburger Hafen Und(Xet) Logistik
Hannover Ruck. (Xet)
Hawesko Hldg. (Xet)
Hci Capital (Xet)
Heidelbergcement (Xet)
Heidelberger (Xet) Druckmaschinen
Heiler Software (Xet)
Heliad Eq.Partners (Xet)
Henkel (Xet)
Henkel Pref (Xet)
Highlight Comms. (Xet)
Hochtief (Xet)
Hoeft & Wessel (Xet)
Homag Group (Xet)
Hornbach Hdg.Pref. (Xet)
Hornbach-Baumarkt (Xet)
Hypoport Finance (Xet)
Ibs (Xet)
Identive Group (Xet)
Ifco Systems (Xet)
Ifm Immobilien (Xet)
Indus Holding (Xet)
Infineon Techs. (Xet)
Init (Xet)
Integralis (Xet)
Interhyp (Xet)
Intershop Comms. (Xet)
Intica Systems (Xet)
Invision Software (Xet)
Isra Vision (Xet)
Itelligence (Xet)
Ivg Immobilien (Xet)
Ivu Traffic Techs. (Xet)

Jaxx (Xet)
Jenoptik (Xet)
Jetter (Xet)
Jungheinrich (Xet)
K + S (Xet)
Kloeckner & Co (Xet)
Kloeckner-Werke (Xet)
Koenig &Bauer (Xet)
Kontron (Xet)
Kromi Logistik (Xet)
Krones (Xet)
Kuka (Xet)
Kws Saat (Xet)
Lanxess (Xet)
Leifheit (Xet)
Leoni (Xet)
Linde (Xet)
Lloyd Fonds (Xet)
Loewe (Xet)
Logwin (Xet)
Lpkf Laser & Eltn. (Xet)
Ludwig Beck (Xet)
Magix (Xet)
Man (Xet)
Man Pref (Xet)
Manz Automation (Xet)
Marseille Kliniken (Xet)
Masterflex (Xet)
Mbb Industries (Xet)
Mediclin (Xet)
Medigene (Xet)
Medion (Xet)
Merck Kgaa (Xet)
Metro (Xet)
Metro Pref. (Xet)
Mevis Medical Sltn.(Xet)
Mlp (Xet)
Mobotix (Xet)
Mologen (Xet)
Morphosys (Xet)
Mpc Muenchmeyer Cap(Xet)
Mtu Aero Engines (Xet) Hldg.
Muehlbauer Holding (Xet)
Muenchener Ruck. (Xet)
Mvv Energie (Xet)
Nemetschek (Xet)
Nexus (Xet)
Nordex (Xet)
Novavisions (Xet)
November (Xet)
Ohb Technology (Xet)
Orad Hi-Tech Sys. (Xet)
Orco Germany (Xet)
Ovb Holding (Xet)
P & *i* Psnl.& (Xet) Informatik
Paion (Xet)
Paragon (Xet)
Patrizia Immobilien(Xet)
Petrotec (Xet)
Pfeiffer Vacuum (Xet) Tech.
Pfleiderer (Xet)
Phoenix Solar (Xet)
Pne Wind (Xet)
Polis Immobilien (Xet)
Prak.Bauheim.Hldg. (Xet)
Princess Priv.Eq. (Xet) Hldg.
Procon Multimedia (Xet)
Progress-Werk (Xet) Oberkirch
Prosieben Sat 1 Pf.(Xet)
Psi (Xet)
Pulsion Med Sys. (Xet)
Puma Rudolf Dassler(Xet) Sot.
Pva Tepla (Xet)
Q-Cells (Xet)
Qiagen (Xet)
Qsc (Xet)
Quanmax (Xet)
R Stahl (Xet)
Rational (Xet)
Realtech (Xet)
Repower Systems (Xet)
Rheinmetall (Xet)
Rhoen-Klinikum (Xet)
Rofin-Sinar Techs. (Xet)
Roth & Rau (Xet)
Ruecker (Xet)
Rwe (Xet)
Rwe Pref. (Xet)
Saf Simul.Analysis (Xet) & Frcas.
Saf-Holland (Xet)
Salzgitter (Xet)
Sap (Xet)
Sartorius (Xet)
Sartorius Pref. (Xet)
Schaltbau Holding (Xet)
Schlott Gruppe (Xet)
Secunet Scty.Net. (Xet)
Sedo Holding (Xet)
Sfc Energy (Xet)
Sgl Carbon (Xet)
Siemens (Xet)
Silicon Sensor (Xet) Intl.
Singulus Techs. (Xet)
Sinnerschrader (Xet)
Sixt (Xet)
Sixt Pref. (Xet)
Skw Stahl-Metgie. (Xet) Hldg.
Sky Deutschland (Xet)
Sma Solar Tech. (Xet)
Smartrac (Xet)
Smt Scharf (Xet)
Softing (Xet)
Software (Xet)
Solar Fabrik (Xet)
Solarworld (Xet)
Solon (Xet)
Stada Arzneimittel (Xet)
Stratec Biomedical (Xet) Sys.
Suedzucker (Xet)
Suess Microtec (Xet)
Sunways (Xet)
Surteco (Xet)
Sygnis Pharma (Xet)
Symrise (Xet)
Synaxon (Xet)
Syskoplan (Xet)
Systaic (Xet)
Syzygy (Xet)
Tag Immobilien (Xet)
Takkt (Xet)
Technotrans (Xet)
Telegate (Xet)

Teleplan Intl. (Xet)
Teles (Xet)
Thyssenkrupp (Xet)
Tipp24 (Xet)
Tognum (Xet)
Tomorrow Focus (Xet)
Travel24.Com (Xet)
Tria It-Solutions (Xet)
Tui (Xet)
Ums Utd.Med.Sys. (Xet) Intl.
United Internet (Xet)
United Labels (Xet)
Usu Software (Xet)
Vbh Holding (Xet)
Verbio Ver. (Xet) Bioenergie
Versatel (Xet)
Villeroy & Boch (Xet)
Vita 34 Intl. (Xet)
Volkswagen (Xet)
Volkswagen Pref. (Xet)
Vossloh (Xet)
Vtg (Xet)
Vtion Wireless (Xet) Tech.
Wacker Chemie (Xet)
Wacker Neuson (Xet)
Washtec (Xet)
Westag & Getalit (Xet)
Westag&Getalit Pf. (Xet)
Wilex (Xet)
Wincor Nixdorf (Xet)
Wirecard (Xet)
Wizcom Techs. (Xet)
Xing (Xet)
Yoc (Xet)
Zapf Creation (Xet)
Zhongde Waste Tech.(Xet)
Zooplus (Xet)

Appendix 2

Regression #	12 (ln)	**Method**	Panel OLS	
Sample	1999M04-2009M12	**R-squared**	0,048	
Periods	130	**F-statistic**	513,843	
Cross-sections	389	**Prob. (F-statistic)**	0,000	
Observations	50486	**Durbin-Watson stat**	2,037	
Dependent variable	$r_{i,t}$	**AIC**	-0,9694	
Ind. Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	-0,001	0,003	-0,30	0,76
LN($\sigma_{\varepsilon,i,t-1}$)	0,002	0,001	3,03***	0,00***
MV	4,44E-08	4,70E-08	0,94	0,34
BTMV	-0,002	0,001	-3,72***	0,00***
MKTSTATE	0,042	0,001	29,94***	0,00***
VOLSHOCK	-0,076	0,002	-33,55***	0,00***

Table 13 - Panel regression with ln($\sigma_{\varepsilon,i,t-1}$), Source: Own

Regression #	12 (squared)	**Method**	Panel OLS	
Sample	1999M04-2009M12	**R-squared**	0,048	
Periods	130	**F-statistic**	512,043	
Cross-sections	389	**Prob. (F-statistic)**	0,000***	
Observations	50486	**Durbin-Watson stat**	2,032	
Dependent variable	$r_{i,t}$	**AIC**	-0,9692	
Ind. Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
INTERCEPT	-0,009	0,001	-7,14***	0,00***
$(\sigma_{\varepsilon,i,t-1})$^2	-0,017	0,022	-0,79	0,43
MV	4,17E-08	4,70E-08	0,89	0,37
BTMV	-0,002	0,001	-3,62***	0,00***
MKTSTATE	0,041	0,001	29,80***	0,00***
VOLSHOCK	-0,076	0,002	-33,69***	0,00***

Table 14 - Panel regression with $\sigma_{\varepsilon,i,t-1}$^2, Source: Own

Appendix 3

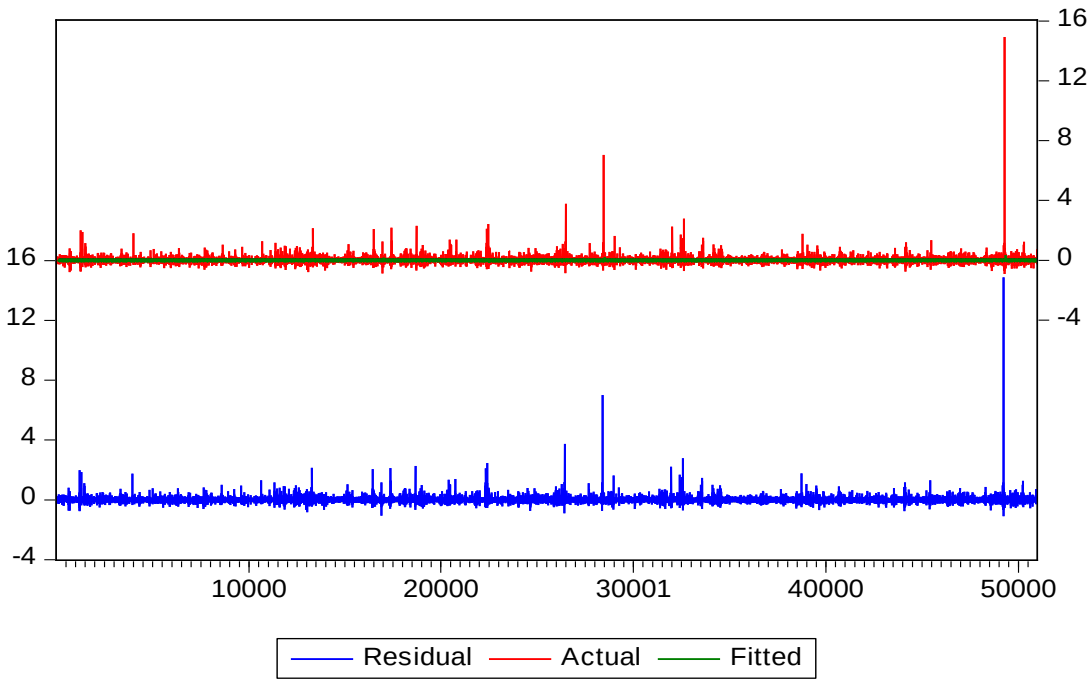

Figure 3 - Residual plot for panel regression with fixed effects, Source: Own