Lund University
School of Economics and Management

Master Thesis (1 year)

15 ECTS Credits

Volatility Patterns and Idiosyncratic Risk on the Swedish Stock Market

Kristoffer Blomqvist

Supervisors: Hossein Asgharian and Lu Liu

Department of Economics, Lund University, Sweden

Abstract

Using the methodology introduced by Campbell et al. (2001), we decompose and evaluate the historical volatility patterns of the Swedish stock market in the time period 1985 - 2012. The volatility at all component levels, including idiosyncratic risk, appear to be fairly stable throughout the sample, with the exception of temporary dramatic increases during periods of economic distress. As opposed to Campbell et al. (2001), we do not find an upward trend in idiosyncratic volatility in the full sample period. Increased competition or an increased number of listed firms does not appear to cause an increase in idiosyncratic risk in Sweden. A similar approach is used to study the volatility of individual industries. The results are mixed. Six out of 19 industries exhibit a significant trend in the full sample period, of which four have negative trend coefficients.

Keywords: Idiosyncratic volatility, volatility decomposition, stock market volatility, predictive power, industry volatility

---

I would like to thank Hossein Asgharian and Lu Liu for excellent supervision and helpful comments, as well as Fredrik NG Andersson for useful advices regarding trend tests.

Table of Contents

1. Introduction

At present date, many countries, institutions, banks and other companies are still struggling in the aftermath of the subprime crisis that emerged in the autumn of 2008. The general notion seems to proclaim that the riskiness and volatility of the stock market is as high as ever, and some research points out that, in particular, the idiosyncratic volatility follows a positive linear trend (e.g. Campbell et al. (2001)). This would have significant consequences for investors and the market as a whole. However, the overall results from research made on the matter are ambiguous. Nevertheless, with the recent and historically severe crisis fresh in mind, along with its long-term consequences, the subject of stock market volatility and the mechanisms behind the fluctuations remains highly topical.

In fact, the volatility of equity markets is one of the most fundamental and important elements of financial economics. Ever since Markowitz' Modern Portfolio Theory (1952) and the development of CAPM by Sharpe (1964) and Lintner (1965), numerous studies have been made on the subject of aggregated volatility, mainly on the U.S. stock market. However, during the last decade we have seen a rather dramatic increase in the literature covering the *idiosyncratic volatility*. One of the first papers that focused on a decomposed volatility approach, written by Campbell, Lettau, Malkiel and Xu (2001)[1], found evidence for an upward trend in the firm-specific (or idiosyncratic-) volatility on the American stock market in the time period between 1962 and 1997. Authors of follow-up papers and other related literature have made various attempts to explain the phenomena, its causes and consequences in greater detail, which indeed has increased the interest for idiosyncratic risk[2]. Some of the conclusions and ideas from previous authors will be presented and discussed below.

The purpose of this thesis is to evaluate the historical movement of the average volatility of the stocks traded on the Swedish market using the same approach and decomposition method as Campbell et al. (2001). Thus, we are paying extra attention to the measure of idiosyncratic risk. We decompose the total stock market volatility into a market-specific (MKT), industry-specific

[1] Henceforth Campbell et al. (2001)

[2] In this text, volatility refers to the standard deviation (or variance) of the return. This is directly connected with the concept of financial risk. Thus, volatility and risk will be used interchangeably.

(IND) and firm-specific (FIRM) component, where FIRM represents the average idiosyncratic volatility. Observations are obtained on quarterly basis using monthly gross stock returns. Moreover, the three measures are averages over industries, which enables us to disregard estimations of firm-, and industry-specific beta values. This is one of the most appealing benefits with the method, since a proper estimation of time varying betas is a difficult task, and may end up in results that are hard to interpret.

Since we follow the empirical methodology applied by Campbell et al. (2001), our main focus is to evaluate the volatility patterns of the three measures over time, again, with particular interest in the FIRM component. In short, we will test whether the FIRM component, as well as the other volatility measures, follows a linear trend throughout the sample by performing a simple trend test. Moreover, we will investigate the lead relationship between the measures, as well as forecasting power on GDP growth and stock market returns using regression analysis in order to see if the components can help us predict general economic and financial movements. In a similar but not as detailed manner, we will present an overview of the volatility of individual industries in an effort to better understand the volatility behaviour.

Our contribution to the economic literature mainly constitutes of the fact that the thesis provides an updated and robust statistical description and evaluation of the volatility patterns of the Swedish stock market. The sample covers three time periods of economic distress (i.e. the banking crisis in the 1990's, the dotcom bubble in the early 2000's and the more recent subprime crisis in 2008/2009), making the study current and up to date, providing further evidence of the behaviour of stock market volatility in times of economic and financial crises. The same holds for our study of individual industries, which also, in practise, may have a great value to investors that are particularly interested in-, or restricted to, the Swedish market. This has, as far as we know, not been done with Swedish data before.

The paper is organised as follows: in *Section 2*, we briefly present a theoretical background for the study and provide a summary of the most important research on the topic. *Section 3* describes the data. In *Section 4*, we explain the empirical method. The results are presented in *Section 5*. *Section 6* provides an analysis and discussion about the results, and in *Section 7* we come with conclusions and suggestions for future research.

2. Theoretical Framework

In this section, we will briefly introduce the theoretical fundaments upon which we base our analysis, discussions and conclusions. We will also discuss the importance and relevance of idiosyncratic volatility.

2.1 Portfolio Theory and CAPM

The very foundation of modern portfolio theory can to a very high extent be attributable to Harry M. Markowitzs' work in the 1950's, when he introduced the concept of mean-variance efficient portfolios. That is, portfolios that cannot achieve any lower risk through diversification without also lowering the expected return (alternatively, portfolios that cannot gain any expected return without an increased risk). Markowitz also introduced the Efficient Frontier, which is a set of assets that, combined, has the highest possible expected return for a given level of risk. William Sharpe (1964) and John Lintner (1965) soon developed the work of Markowitz into the famous Capital Asset Pricing Model (CAPM), which still is widely used to price individual assets and portfolios.

The model is built upon assumptions about the market and the investors. For instance, the model assumes that investors have homogenous expectations, hold mean-variance efficient portfolios and that transaction costs are absent. Moreover, according to this theory, idiosyncratic risk is easily eliminated through diversification. Therefore, the exposure of non-diversifiable (systematic) risk is the only measure of risk that is included in the CAPM. The original CAPM equation is (Campbell, Lo and MacKinlay (1997, Chapter 5, p. 182)):

$$E[R_i] = R_f + \beta_{im}(E[R_m] - R_f) \tag{1}$$

Where $E[R_i]$ is the expected return of asset *i*, R_f is the risk-free rate, β_{im} is the beta value of asset *i* with respect to the market and $E[R_m]$ is the expected market return. Although the basic CAPM model has been subject to some criticism during the years (see for instance Roll (1977)), and numerous variations of the model have been applied to different fields of financial economics, the model is still one of the great fundaments of the financial science.

2.2 Idiosyncratic Volatility

Unlike systematic volatility, idiosyncratic (also: firm-specific-, or unsystematic-) volatility is the part of the total volatility of a stock or asset that depends exclusively on the asset itself. That is, in theory, it has little or no correlation with the volatility of the market as a whole. To illustrate, we can rewrite and rearrange the CAPM equation (equation (1)) and include a residual term (Bali et al. (2005)):

(2) $$Z_i = \beta_{im} Z_m + \varepsilon_i$$

Here, Z_i is the excess return of asset *i*, Z_m is the excess return of the market and ε_i is the return that is specific to asset *i*, i.e. the idiosyncratic return of asset *i*. Taking the volatilities, we have:

(3) $$\sigma_{Zi}^2 = \beta_{im}^2 \sigma_{Zm}^2 + \sigma_{\varepsilon i}^2$$

Where σ_{Zi}^2 is the total volatility of asset *i*, $\beta_{im}^2 \sigma_{Zm}^2$ is asset *i*'s systematic risk component and $\sigma_{\varepsilon i}^2$ is the assets idiosyncratic, or asset-specific, volatility. Rearranging again, we see that one can express the idiosyncratic volatility as the total volatility of an asset minus its systematic volatility:

(4) $$\sigma_{\varepsilon i}^2 = \sigma_{Zi}^2 - \beta_{im}^2 \sigma_{Zm}^2$$

However, according to the CAPM, the idiosyncratic risk can be diversified away and that Z_m is common for all assets, β_{im} is the only asset-specific factor included in the model for determining the expected return of asset *i*. Hence, the model disregards the idiosyncratic volatility, $\sigma_{\varepsilon i}^2$.

Nevertheless, even though CAPM does not take idiosyncratic risk into account, the assumptions behind the model are rarely realistic. Thus, there are several reasons why knowledge of the behaviour and properties of idiosyncratic risk is both important and valuable. To begin with, many investors are restricted in one way or another with respect to investment possibilities, or may, by some other reason, be incapable to hold a well-diversified portfolio in accordance with financial theory. This lack of optimisation makes investors vulnerable to changes in volatility on both industry- and firm level (Campbell et al. (2001)). Furthermore, the number of stocks needed to achieve a well-diversified portfolio highly depends on the level of idiosyncratic volatility. A common rule-of-thumb suggests that a portfolio of approximately 20 to 30 stocks should be enough to eliminate almost all of the idiosyncratic fluctuations. However, the rule may be invalid in the presence of high levels of idiosyncratic volatility. That is, an investor may in reality need twice the number of assets to eliminate the idiosyncratic risk (Campbell et al. (2001)).

Another important aspect to take into consideration is the possibility of large pricing errors of individual stocks. High levels of idiosyncratic volatility increases the risk faced by arbitrageurs who try to exploit mispricing of a particular stock, which could make them less inclined to take market action. On a large scale, such a scenario may lower the overall efficiency of the market.

Moreover, idiosyncratic volatility plays a great role in event studies. This is because the statistical significance of the abnormal returns of interest (at least considering studies of individual stocks) is determined by the volatility of individual assets in relation to the market. Also, the level of idiosyncratic volatility affects option pricing, since the price of an option written on a stock is determined by the total return volatility of the stock. This, in turn, implies that volatility on firm-, industry-, and market level are all a part of the pricing mechanism (Campbell et al. (2001)).

2.3. Literature Review

During the last decade, much attention has been brought to the subject of idiosyncratic volatility, its consequences and causes. Below follows a summary of some of the most important literature to date.

Xu and Malkiel (2001) use two approaches for constructing idiosyncratic volatility; the indirect approach proposed by Campbell et al. (2001), as well as an alternative, direct approach, applying the Fama-French three-factor methodology. Their paper confirms the previous findings of Campbell et al. (2001) that the volatility of individual stocks has increased over time (albeit the volatility of the total market has been stable). Furthermore, they find that movements of the NASDAQ exchange seem to contribute to the increase of the idiosyncratic volatility, although it only accounts for a fraction of the explanation for the upward trend in idiosyncratic volatility. Similarly, Goyal and Santa-Clara (2003) find an upward linear trend in idiosyncratic volatility, which correspond to previous studies, as well as a positive relationship between average stock variance and market returns. They argue that the trade-off between risk and return in the stock market should include not only systematic risk, but idiosyncratic risk as well. Moreover, Goyal and Santa-Clara (2003), find that idiosyncratic volatility represents a large portion of the total stock risk. Finally, they propose an explanation of their findings based on prospect theory.

Goyal and Santa-Clara are, however, criticized by Wei and Zhang (2005) and Bali, Cakici, Yan and Zhang (2005). Wei and Zhang suggest that the forecasting power found by Goyal and Santa-Clara (2003) is mainly driven by data in the 1990's. Bali et al. (2005) argues that most of the results in Goyal and Santa-Clara (2003) are not robust across different stock portfolios or for different sample periods. Furthermore, Bali et al. (2005) finds no forecasting power of the stock market returns. They argue that the results from Goyal and Santa-Clara are partly driven by a liquidity premium.

A more general study is made by Guo and Savickas (2008), who use monthly stock return data from the G7 countries to show that idiosyncratic volatility to some extent can predict aggregate stock market returns over time, and that idiosyncratic volatility explains the cross-section of stock returns just as well as the book-to-market factor. They also show that, because of high correlation, idiosyncratic volatility from the U.S. forecasts stock market returns in the other G7 countries, and vice versa. Finally, Guo and Savickas suggest that average idiosyncratic volatility might be a proxy for systematic risk, as well as for risk factors omitted from the CAPM.

Wei and Zhang (2006) make an attempt to answer the following questions: 1.) To which extent can the upward trend in the average return volatility be attributed to the changes in the fundamentals of firms? 2.) How is the increased average return volatility divided between existing firms and newly listed firms? Using quarterly accounting data at the firm level, the authors find two variables that are useful for explaining the upward trend of the average stock volatility, namely: 1.) Average return-on-equity, and 2.) average sample variance of the return-on-equity in the past three years. They confirm the previous findings that average stock volatility has increased on the U.S. market. They also find that the age and size of firms can explain much of the cross-sectional differences in return variances, but are not responsible for the upward trend over time. Since newly listed stocks tend to be smaller, with lower- and more volatile earnings than older stocks, Wei and Zhang (2006) conclude that the main reason for the increase in the average return volatility is because of the characteristics exhibited by newly listed stocks. Similar findings are made by Angelidis and Tessaromatis (2008) who suggest that the average idiosyncratic volatility of small stocks is the main driving factor that can help predict stock returns. They argue further that it is the idiosyncratic volatility of small stocks (as opposed to large stocks) that matter for asset pricing.

Gaspar and Massa (2006) chose to investigate the relationship between idiosyncratic volatility and market competition. Their results show that firms with a high degree of market power exhibit lower idiosyncratic volatility. The reasons for this seems to be that market power works as a hedging instrument since it smoothes out the idiosyncratic volatility (i.e. decreases cash flow fluctuations), and that information for firms with large market power is more certain than for small firms, which decreases return volatility. Gaspar and Massa (2006) finally conclude that the increase in idiosyncratic volatility is due to increased market competition (which is an effect of deregulation and globalization). Similar findings are made by Irwine and Pontiff (2009), who find that the increase in idiosyncratic volatility is attributable to an increase in economy-wide competition. Moreover, they argue that the increased idiosyncratic risk is driven mainly by individual firm's earnings, cash flows and sales.

Putting less emphasis on fundamentals, Chua, Goh and Zhang (2006) examine the relation between idiosyncratic volatility and the cross-section of stock returns on the U.S. market. They use a method with which they decompose the idiosyncratic volatility into two parts; expected- and unexpected idiosyncratic volatility. Their main finding is that expected volatility seems to be positively related to expected returns.

In contrast to most of the previous authors, Brandt, Brav, Graham and Kumar (2009) argue that the upward tendency in idiosyncratic volatility is nothing but an episodic phenomenon, and thus not a linear trend. In fact, they show that idiosyncratic volatility has decreased during the last few years of the sample. Furthermore, they find that low-priced stocks are more volatile than high-priced stocks, which they suggest is because low-price stocks are not widely held by large institutions (as opposed to high-priced stocks). Moreover, they argue that an increase in retail trading (which dominates the trading with low-priced stocks) can explain the decrease in idiosyncratic volatility post 1990's. Similar results are found by Bekaert, Hodrick and Zhang (2009), who present several various methods to examine the aggregate idiosyncratic volatility of 23 developed equity markets (including Sweden). According to their results, there are no signs of an upward linear trend for any country in the sample, which runs from 1980 to 2008.

Instead, the authors find that high levels of idiosyncratic volatility are temporary. Bekaert et al. (2009) conclude that growth opportunities, total market volatility and variance premium explains most of the variation in idiosyncratic volatility. The findings are in line with Zhang (2010), who argue that the level of idiosyncratic volatility in the U.S. has declined during the last decade. To further explain why the stock return volatility varies over different periods, Zhang use various methods to compare two main strands of theories: fundamentals-based theories and trading volume-based theories. Zhang (2010) conclude, in line with the findings of many other authors, that fundamentals-based theories better explain the volatility patterns.

3. Data

We use monthly observations of stock returns from all stocks traded on the Swedish stock market that are available in Thompson DataStream between January 1985 and December 2012. The corresponding market capitalization for each stock and month is also found in DataStream, as well as data over OMXS returns and GDP growth. Campbell et al. (2001) use excess returns, but for simplicity and convenience, we choose to compute the volatility measures using gross stock returns (see for example Campbell, Lo and MacKinlay (1997, Chapter 7, p. 268)). This should not have any significant effect on the results.

Some of the firms in the sample issue several kinds of stocks (e.g. A-, B-, and C-shares) with different voting power or other special properties. We keep only one of these stocks for each firm. We prefer B-shares when available since they tend to be most liquid. Furthermore, a handful of extreme outliers are removed, together with stocks that we strongly suspect suffer from inaccurate data. The final sample consists of 1 079 stocks, in total 101 279 observations. We use the industry classification ICBSSN available in DataStream. Firms that do not have an industry classification are removed from the sample. Furthermore, the industries *Media*, *Oil & Gas*, *Telecommunications* and *Utilities* do not have data reaching as far back as 1985, but each industry is included as soon as sufficient data is available.

3.1. Choice of Weighing Scheme

Some authors, for instance Goyal and Santa-Clara (2003), Guo and Savickas (2008), perform similar studies like this one, but experiment with equal-weighted indices in excess of value-weighted ones. One reason for using equal-weighted series may be the pure convenience of putting all weights equal. However, we chose to work exclusively with value-weighted returns for reasons stated below.

To begin with, we can look at the return correlation between a value-weighted index and the OMXS, and compare this to the correlation between the same index with equal weights and the OMXS. The correlations are presented in *Table 1*.

Table 1 – Return Correlations

Return Correlations	
VW, OMXS	EW, OMXS
0.9875	0.8164

The left column shows the return correlation between a value-weighted index (denoted VW) constructed by all stock in our sample and the OMXS index. The right column displays the return correlation between an equal-weighted index (denoted EW) consisting of all stocks in our sample and the OMXS index.

As shown, the value weighted index (VW) has a significantly higher (and almost perfect) correlation with the actual returns on the Swedish stock market, than the equal weighted index (EW). To make a further illustration of the differences between value- and equal-weighted series, we can study *Figure 1*, where the two MKT components are graphically compared.

Figure 1 – Comparison of MKT Components

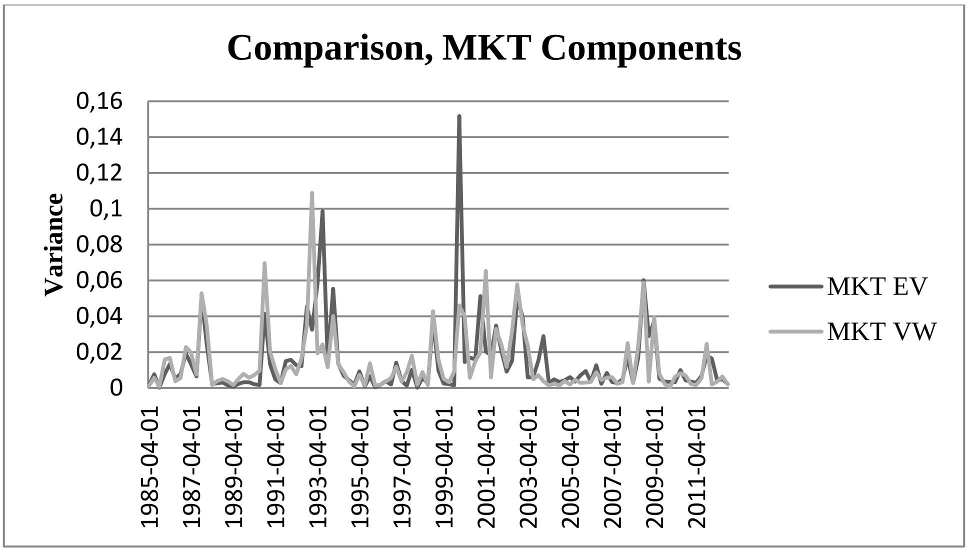


Figure 1 shows a graphical comparison between our value-weighted MKT component which we use in our study (here denoted MKT VW) and an equal-weighted version of the MKT component (denoted MKT EW).

Phenomenon like the spike in early 2000 in the equal weighted series could lead to misinterpretation and a blunted analysis. We conclude that using value weighted series is superior for achieving adequate results.

4. Empirical Method

We use the decomposition method proposed by Campbell et al. (2001) to examine the volatility on the Swedish stock market between 1985 and 2012 at the market-, industry- and firm-level. For a more detailed derivation on how the measures are constructed, see *Appendix I*. One of the main goals with this "market-adjusted-return-model" approach is to eliminate the necessity of estimating industry- and firm-specific betas, since the estimation is difficult and the results may be unstable over time.

Campbell et al. (2001) construct the volatility measures using daily observations. However, robustness tests show that the results do not differ when weekly and monthly frequencies are applied. We chose to compute the volatility measures with monthly data.

The three volatility measures are computed as follows: Here, *t* denotes quarters and *s* denotes months. Market-level volatility is denoted MKT, and is defined as:

(5) $$MKT_t = \hat{\sigma}_{mt}^2 = \sum_{s\in t}(R_{ms} - \mu_m)^2$$

Where μ_m is the mean of the total market return over the full sample period. As in Campbell et al. (2001), the market returns are computed using all firms available in each period, and the stock returns are based on each stock's market capitalization.

To compute the industry-specific volatility, we first need to sum the squares of the industry-specific residual in $R_{it} = R_{mt} + \epsilon_{it}$ (see equation (18) in *Appendix I*):

(6) $$\hat{\sigma}_{\epsilon it}^2 = \sum_{s\in t} \epsilon_{is}^2$$

Since we do not want to estimate any covariances or betas, we have to average over industries (see *Appendix 1*). Thus, the average industry-level volatility is:

(7) $$IND_t = \sum_i w_{it}\, \hat{\sigma}_{\epsilon it}^2$$

The procedure is very similar when we compute the volatility at firm-level. Just as in the industry-level case, we sum the firm-specific residual in $R_{ijt} = R_{mt} + \epsilon_{it} + \eta_{ijt}$ (see equation (22) in *Appendix I*):

(8) $$\hat{\sigma}^2_{\eta ijt} = \sum_{s \in t} \eta^2_{ijs}$$

We then compute the weighted average of the firm-specific volatilities within an industry:

(9) $$\hat{\sigma}^2_{\eta it} = \sum_{j \in i} w_{ijt} \, \hat{\sigma}^2_{\eta ijt}$$

To complete the computation of average firm-level volatility, we again average over industries to ensure that all firm-specific covariances cancel out:

(10) $$FIRM_t = \sum_i w_{it} \, \hat{\sigma}^2_{\eta it}$$

Once we have obtained the volatility components MKT, IND and FIRM, we continue to follow the empirical methodology of Campbell et al. (2001). First, we present descriptive statistics and perform a graphical analysis of the components to see how the volatility patterns behave over time. This is the most basic analysis, but it provides an easily accessible overview of the results. Furthermore, we will look at the correlation structure as well as the autocorrelation structure, and test if the MKT, IND and FIRM series contain unit roots. This is important if we want to feel confident about the validity and reliability of our results. If the series contain unit roots, they exhibit infinite variance and the interpretation of the volatility measures, particularly from regression analyzes (e.g. spurious regressions), may thus be invalid.

Moreover, since the most influential finding of Campbell et al. (2001) is the seemingly upward sloping linear trend of the idiosyncratic volatility on the U.S stock market, we will test if the volatility components (in particular FIRM) exhibit the same pattern on the Swedish market. Some of the consequences in the case of such findings are discussed in *Section 2.2*. We will also test the lead relationship between the three components to see if each respective measure has any explanatory power on the others. Lastly, again in line with Campbell et al. (2001), we will examine the cyclical behavior and explanatory power of the components on GDP growth and stock market returns to see if they can help predict the general economic movements.

5. Results

In this main section, we present the results from the computations of our volatility components and the volatility of individual industries. Descriptive statistics are found in *Section 5.1.1.*, *Section 5.1.2.* provides a graphical analysis of the series and *Section 5.1.3.* presents the correlation-, and autocorrelation structure of our measures. In *Section 5.1.4.*, we look at the results from a trend test, *Section 5.1.5* provides the results from a Granger-causality test and in *Section 5.1.6.* we evaluate the predictive power of our volatility components on GDP growth and stock market returns. *Section 5.2.1.* presents the descriptive statistics for individual industries, in *Section 5.2.2.* we perform a graphical analysis of the volatility of individual industries, and lastly, in *Section 5.2.3.*, we test for unit roots and trends for individual industries.

5.1. Volatility Components

This subsection provides the results from computations and tests of our volatility components.

5.1.1 Descriptive Statistics

Table 2 presents the descriptive statistics for the three volatility components MKT, IND and FIRM. Bold numbers indicate the highest value, while numbers in italics indicate the lowest. As we can see, FIRM's values are the highest in every measure, and we conclude that out of the three components, FIRM is the most volatile one.

Table 2 – Descriptive Statistics: Volatility Components

Descriptive Statistics			
	MKT	IND	FIRM
Mean	0.0138	*0.0107*	**0.0276**
Median	*0.0069*	0.0074	**0.0188**
Max	0.1088	*0.0719*	**0.1585**
Min	*0.0002*	0.0020	**0.0064**
Std. Dev.	0.0175	*0.0100*	**0.0258**
Obs.	111	111	111

Table 2 displays the descriptive statistics of the three volatility components MKT, IND and FIRM. Numbers in italics indicate the lowest value, while bold numbers indicate the highest.

5.1.2. Graphical Analysis

A graphic overview of our volatility components (MKT, IND and FIRM) is given in *Figure 2*. The measures are calculated according to the formulas in *Section 4.* (equations (5) to (10)) and is plotted against time. A quick look at the figure suggests that all three measures of volatility have been fairly stable throughout the sample. A few peaks emerge during the period, but the values seem to always return to their long-term mean. This is at odds with the findings of e.g. Campbell et al. (2001), Xu and Malkiel (2001) and Wei and Zhang (2006) among others.

Figure 2 – Plotted MKT, IND and FIRM Component

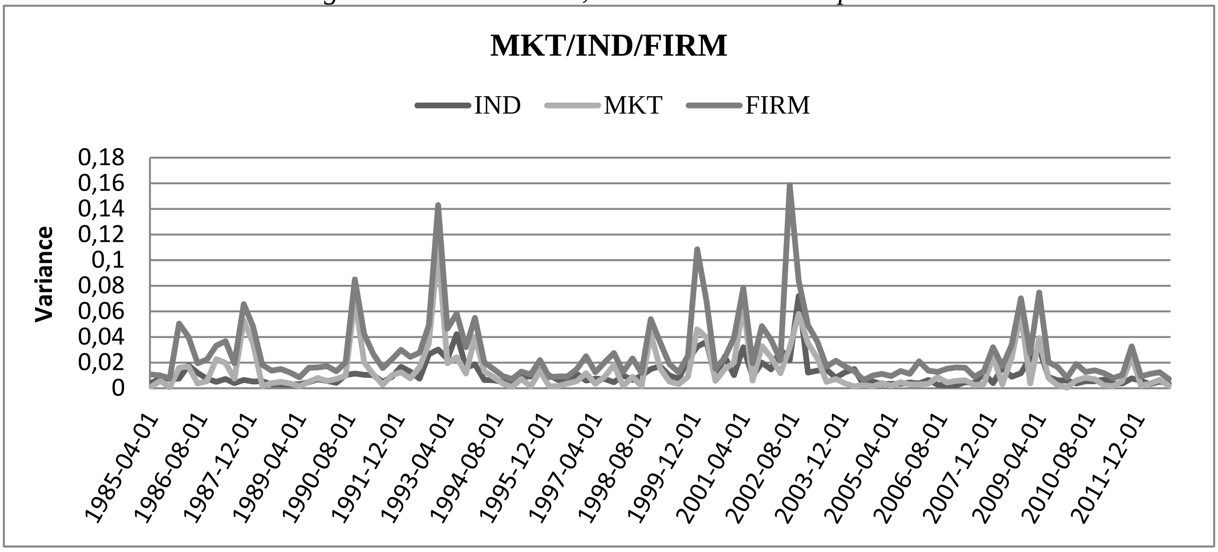


Figure 2 shows a plot of our three volatility measures MKT, IND and FIRM against time.

A more convenient overview of the components' share of the total volatility is given in *Figure 3*. FIRM's average share is 54%, while the average for MKT and IND is 22% and 24% respectively. The proportion of the components with respect to the total volatility is fairly stable in the full sample.

Figure 3 – Volatility Components' Share of Total Volatility

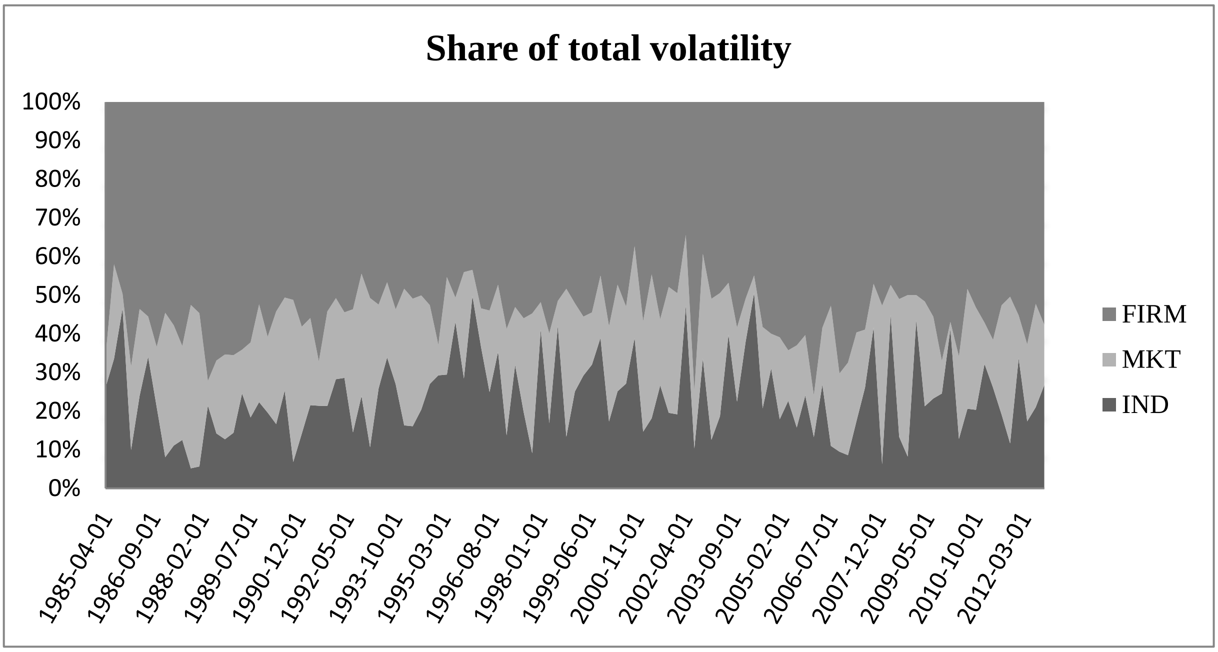


Figure 3 displays the proportions of MKT, IND and FIRM in relation to the total volatility.

Similar to the U.S., we have seen an increase of listed firms in Sweden during the past 30 years. For our sample, the number ranges from 135 in 1985 to 461 in the end of 2012. It is interesting to note that the graph in *Figure 4* displays visible bumps in connection to the three main economic crises that we mentioned in the introduction. The number of firms tends to decrease; alternatively stagnate, when economic distress occurs.

Figure 4 – Number of Firms In Sample

Figure 4 is a plot of the total number of firms that are included in our sample at each point in time.

5.1.3. Correlation and Autocorrelation Structure

We begin this subsection by looking at the correlation structure of the three volatility series.

Table 3 – Correlations Between Volatility Measures

Correlations			
	MKT	IND	FIRM
MKT	1.0000		
IND	0.5763	1.0000	
FIRM	0.8744	0.6321	1.0000

Table 3 shows the correlations between our three volatility measures MKT, IND and FIRM

In *Table 3*, we see that MKT and FIRM are highly correlated. MKT and IND exhibit approximately the same level of correlation as IND and FIRM. Moreover, in *Table 4*, we note that the series are autocorrelated, and that the autocorrelations are rather persistent. Thus, we need to test the presence of unit roots to be confident about the reliability of our results. We perform Augmented Dickey-Fuller tests on all three series, where the lag length is determined with Akaike Information Criterion (AIC). The tests are performed both with intercept, as well as with intercept and trend. The results are shown in *Table 5*.

Table 4 – Autocorrelations and Partial Autocorrelations

Autocorrelations						
	MKT		IND		FIRM	
Lag	AC	PAC	AC	PAC	AC	PAC
1	0.251***	0.251***	0.415***	0.415***	0.364***	0.364***
2	0.136***	0.077***	0.444***	0.329***	0.190***	0.066***
3	0.047**	-0.004**	0.228***	-0.043***	0.109***	0.023***
4	0.122**	0.109**	0.255***	0.073***	0.108***	0.060***
5	0.076**	0.023**	0.128***	-0.029***	0.165***	0.116***
6	-0.029*	-0.080*	0.230***	0.137***	-0.027***	-0.157***
12	0.022	0.062	-0.059***	-0.201***	-0.057***	-0.032***

Table 4 presents the autocorrelation (AC), and partial autocorrelation (PAC) structure of our three volatility measures. The left column shows the number of lags. The numbers in the other columns represent the value of the coefficients. Significance level is denoted with one, two or three asterisks, representing significance at the 10%, 5% and 1% level, respectively.

Table 5 – Unit Root Test, Augmented Dickey-Fuller

Unit Root Test - Augmented Dickey-Fuller			
	MKT	IND	FIRM
Specification	t-stat		
Intercept	-8.0332***	-3.9144***	-7.0704***
Intercept and Trend	-8.0800***	-3.8945**	-7.1105***

Table 5 shows the results from Augmented Dickey-Fuller tests performed on each volatility measure. The numbers represent the t-value obtained from the regressions. Significance level is denoted with one, two or three asterisks, representing significance at the 10%, 5% and 1% level, respectively.

Clearly, we reject the null hypothesis of a unit root for all series at the 1% level, with exception for IND where both an intercept and a trend coefficient is included, where we reject the null at the 5% level. Thus, we can feel confident that the series are stationary and the analysis of the volatility measures continues in levels.

5.1.4. Trends

Campbell et al. (2001) detect an increasing trend in their sample for the FIRM component (while MKT and IND remained stable). Since the linear increase in firm-level (idiosyncratic) volatility is one of their main and most important findings, we want to see if our sample exhibits the same pattern. We perform a simple trend test with the following specification:

(11) $$Y_t = \alpha_0 + \beta_1 t + \beta_2 Y_{t-1} + \varepsilon_t$$

Where Y_t is the dependent variable, α_0 is a constant, t is the trend and Y_{t-1} is the lagged dependent variable. The results from the test are presented in *Table 6*.

Table 6 – Trend Tests

Trend test			
Variable	MKT	IND	FIRM
	Coefficient		
α_0	0.0132***	0.0066***	0.0213***
t	-0,484[1]	-0,0545[1]	-0,633[1]
Y_{t-1}	0.2445**	0.4172***	0.3595***

Table 6 presents the outcomes of the trend tests performed on each volatility measure. Numbers represent the value of the regressors' coefficients. Significance level is denoted with one, two or three asterisks, representing significance at the 10%, 5% and 1% level, respectively.

[1] *The numeric values of the trend coefficients are multiplied by 10^4.*

As we can see, the trend coefficient is statistically insignificant for all series, indicating no presence of a linear trend. This confirms the initial graphic analysis from *Figure 2*.

To see if there are periods in our sample in which a statistically significant trend can be found, we perform the same trend tests for different time periods. The periods are: 1985:1-1992:4, 1993:1-2002:4 and 2003:1-2012:4. We find a significant positive trend for MKT and FIRM at the 5% level, as well as for IND at the 10% level in the period between 1993:1 and 2002:4. All trend coefficients in the other periods are insignificant. In line with Wei and Zhang (2005), we suggest that the trend in volatility during this particular period is almost entirely driven by the bull market in the 1990's and the dotcom bubble in the early 2000's.

5.1.5. Lead Relationship

In this section, we study the lead relationship between MKT, IND and FIRM by performing a Granger causality test. Again, the lag length is based upon the Akaike Information Criterion. From a VAR analysis, the AIC suggests that the optimal lag length is 2. The results from the Granger causality tests are presented in *Table 7*.

Table 7 – Granger Causality

Granger causality			
	MKT	IND	FIRM
MKT_{t-2}	-	0.4884	0.2949
IND_{t-2}	0.0198**	-	0.0041***
$FIRM_{t-2}$	0.0186**	0.0000***	-

Table 7 displays the results from our Granger Causality tests on our MKT, IND and FIRM component. The left column shows each variable at time t-2, while the upper row presents each variable at time t. The numbers represent p-values, and significance level is denoted with one, two or three asterisks, representing significance at the 10%, 5% and 1% level, respectively.

As shown, MKT does not tend Granger-cause any of the other volatility measures, while IND tends to Granger-cause both MKT and FIRM at the 5% and 1% level, respectively. We also note that FIRM tends to Granger-cause MKT and IND at the 5% and 1% level, respectively. We conclude that both FIRM and IND help predict the variation in the other measures, while MKT does not. This result is not entirely in line with Campbell et al. (2001), whose findings state that MKT and FIRM have a lead relation with the other measures, while IND does not.

5.1.6. Predictive Power

We continue to follow Campbell et al. (2001) by investigating the predictive power of the three volatility measures on GDP growth. We perform OLS regressions with eight different specifications, where GDP growth is regressed on lagged GDP growth, lagged OMXS returns and combinations of lagged volatility measures. The results from the regressions can be viewed in *Table 8.*

Table 8 – Cyclical Properties: GDP Growth

Dependent Variable: Quarterly GDP Growth								
Variable	Coefficient							
Constant	0.0081 (0.0049)	0.0087* (0.0050)	0.0099** (0.0045)	0.0085* (0.0049)	0.0094** (0.0045)	0.0069 (0.0052)	0.0108** (0.0043)	0.0049 (0.0049)
GDP_{t-1}	0.7949*** (0.0969)	0.7878*** (0.0980)	0.7822*** (0.0937)	0.7946*** (0.0965)	0.7832*** (0.0951)	0.7850*** (0.1012)	0.7801*** (0.0920)	0.7929*** (0.1054)
$OMXS_{t-1}$	0.0004 (0.0283)	0.0215 (0.0365)	0.0066 (0.0301)	0.0007 (0.0295)	0.0225 (0.0379)	0.0328 (0.0394)	0.0079 (0.0330)	0.0353 (0.0380)
MKT_{t-1}	-0.7201*** (0.1939)	-	-0.5881*** (0.1992)	-0.6414*** (0.1685)	-	-	-0.4272*** (0.1397)	-
IND_{t-1}	0.3902** (0.1892)	0.1418 (0.2164)	-	0.4170** (0.2007)	-	-0.1583 (0.1536)	-	-
$FIRM_{t-1}$	0.0645 (0.0514)	-0.1987* (0.1174)	0.1122 (0.0821)	-	-0.1593* (0.0837)	-	-	-
Adj. R^2	0.6721	0.6339	0.6652	0.6757	0.6398	0.6233	0.6665	0.6248

Table 8 shows the results from the regressions with GDP growth as dependent variable. The left column presents the regressors, of which all is lagged by one time period except for the constant. The numbers represent the value of the coefficients in each regression, and the significance level is denoted with one, two or three asterisks, representing significance at the 10%, 5% and 1% level, respectively. (-) indicate that the variable is omitted from the model. The bottom row displays the adjusted R^2 value. All regressions are performed using Newey-West robust standard errors.

We see that MKT, when included, is highly statistically significant with a negative coefficient in all regressions. This suggests that the market-specific volatility is countercyclical in relation to GDP growth, which is in line with the findings of Campbell et al. (2001). It is interesting to note that FIRM is insignificant or just weakly significant in all regressions, despite its close correlation with MKT (see *Table 3*). Furthermore, FIRM is only weakly significant when MKT is omitted from the regression. The R^2 values are much higher than those obtained by Campbell et al. (2001), whose regressions result in a maximum R^2-value of 0.222.

Performing the same regressions but with OMXS returns as dependent variable (see *Table 10* in *Appendix II*), we do not find much interesting results. No volatility measures are statistically significant, except for lagged IND when MKT and FIRM are omitted from the model. This particular specification also achieves the highest adjusted R^2 value (0.1470). However, in general, the adjusted R^2 values are low, and the models seem to be ill fitted. In short, our volatility measures do not explain much of the variation of the OMXS returns.

5.2. Individual Industries

In this subsection, we will take a closer look at the different industries. The intention is to perform a similar (but simplified) analysis as for MKT, IND and FIRM. Our main focus is to see how the volatility pattern of individual industries behaves during- and in-between economic crises.

To compute a measure of volatility for individual industries, we perform the same calculations as for the MKT measure, but here we consider the specific industry being the entire market Thus, we start by isolating industry *i*, and compute:.

(12) $$IND_t^i = \hat{\sigma}_{it}^2 = \sum_{s \in t}(R_{is} - \mu_i)^2$$

Where the subscript *i* denotes the specific industry, *t* denotes quarter and *s* denotes month just as in previous cases. IND_t^i can be interpreted as the average industry-specific volatility of a specific industry. Here, we average over stocks instead of industries, so that the sum of the weighted stock betas with respect to its industry equals unity. Again, the measure is based on each stock’s market capitalization, but in this case, with respect to the industry instead of the total market.

5.2.1. Descriptive Statistics

In *Table 9,* we present the descriptive statistics for our IND_t^i measures. *Media, Oil & Gas, Telecommunications* and *Utilities* do not have data available as early as 1985, which explains the number of observations. As we can see in the table, *Banks* exhibit a very high maximum value (1.4449), which occurred during the banking crisis in the early 1990’s. The volatility of *Banks* also has the highest standard deviation (0.1420) of all industry-specific measures in the sample. *Technology* has the highest mean (0.0540), as well as the highest beta value (1.50). This is not surprising, since the industry historically is characterized of many small firms with volatile returns. On the flipside, despite the low number of firms, *Utilities* is one of the most stable industries, with the lowest mean (0.0136), median (0.0070), maximum (0.0903) and beta value (0.32). It is also one of the industries with the lowest standard deviation (0.0185). *Industrial Goods & Services* is by far the largest industry, in total 285 firms, which likely explains the low standard deviation (0.0164).

Table 9 – Descriptive Statistics: Individual Industries

Industry	Mean	Median	Min	Max	Std. Dev.	Beta	Obs.	Firms
Automobiles & Parts	0.0267	0.0126	0.0010	0.1928	0.0345	0.94	111	12
Banks	0.0406	0.0117	0.0002	**1.4449**	**0.1420**	1.05	111	20
Basic Resources	0.0248	0.0113	0.0002	0.3082	0.0407	0.93	111	50
Chemicals	0.0265	0.0144	0.0006	0.1816	0.0345	0.61	111	14
Construction & Materials	0.0193	0.0096	0.0003	0.1984	0.0274	0.92	111	40
Financial Services	0.0154	0.0078	0.0001	0.1300	0.0188	0.98	111	74
Food & Beverage	0.0230	0.0080	*0.0000*	0.3130	0.0465	0.42	111	19
Health Care	0.0164	0.0086	0.0001	0.1340	0.0221	0.73	111	99
Industrial Goods & Services	*0.0136*	0.0079	0.0001	0.0953	*0.0164*	0.87	111	**285**
Insurance	0.0503	**0.0253**	0.0020	0.5949	0.0830	1.27	111	*11*
Media	0.0342	0.0148	*0.0000*	0.4824	0.0619	0.93	110	28
Oil & Gas	0.0446	0.0248	**0.0030**	0.2970	0.0509	0.66	94	25
Personal & Household Goods	0.0150	0.0088	0.0001	0.1914	0.0222	0.78	111	77
Real Estate	0.0226	0.0093	0.0001	0.3313	0.0468	0.83	111	71
Retail	0.0176	0.0106	0.0010	0.1482	0.0201	0.70	111	48
Technology	**0.0540**	0.0223	0.0006	1.1375	0.1160	**1.50**	111	137
Telecommunications	0.0248	0.0132	0.0004	0.1726	0.0306	0.73	74	15
Travel & Leisure	0.0271	0.0128	0.0006	0.5928	0.0593	0.81	111	41
Utilities	*0.0136*	*0.0070*	0.0001	*0.0903*	0.0185	*0.32*	97	13

Table 9 presents the descriptive statistics for all industries. Bold numbers indicate the highest value, while number in italics represent the lowest. The standard deviation regards the variation of the volatility measure, in a sense, the standard deviation of the variance. Beta values are calculated using the following regression: $R_{is} = \beta_i R_{ms}$, where R_{is} is the industry return, R_{ms} is the market return and β_i is the industry beta. Here, s denotes month just as in previous cases. Data for Media, Oil & Gas, Telecommunications and Utilities are available from 1985:2, 1989:1, 1994:1 and 1988:2, respectively.

5.2.2. Graphical Analysis

In this subsection, we plot some of the most interesting time series of our industry measure. We begin with *Media*.

Figure 5 – Volatility Plot: Media

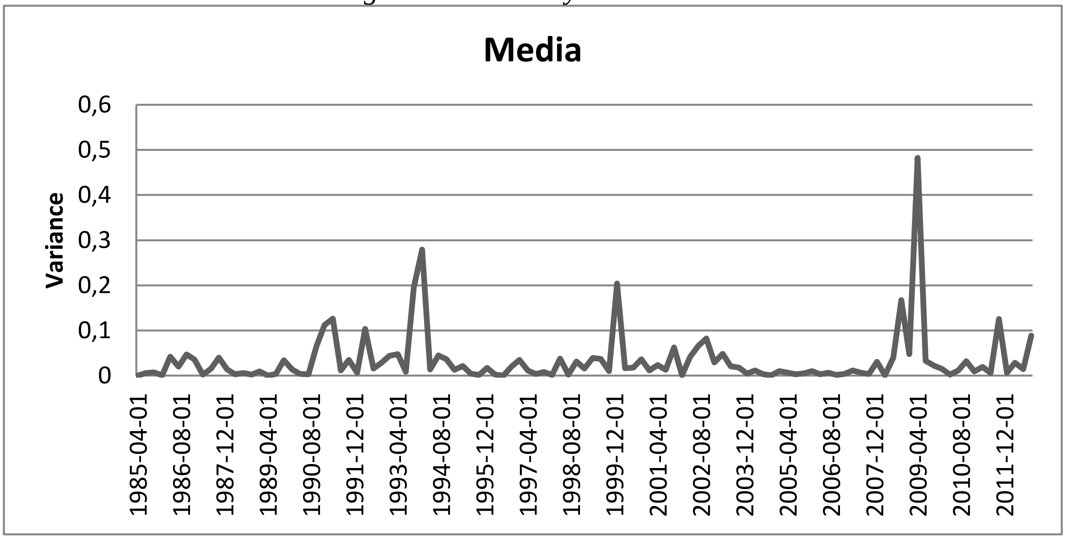


Figure 5 displays a plot of the volatility for media against time.

What is rather surprising with this graph is that *Media* actually has the highest volatility peak of all industries during the 2008/2009 subprime crisis. One could possibly expect a more volatile industry, or an industry in direct connection with the financial markets to react more violently to the events in the late 2008. Other than that, we see the expected spikes in the early 1990's and early 2000's. Finally, there are no signs of a visible trend in the series.

Figure 6 – Volatility Plot: Industrial Goods & Services

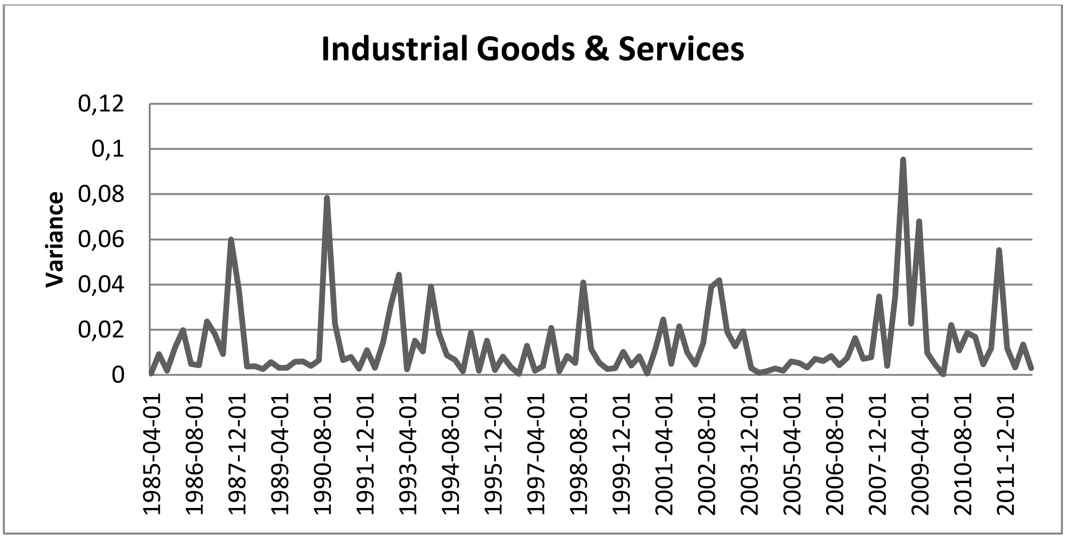


Figure 6 presents a plot of the volatility for industrial goods & services against time.

Industrial Goods & Services may, due to its large market cap, serve as a benchmark industry in this context. Looking at the graph, we can see spikes in the early 1990's as well as during the subprime crisis. However, the industry seems just marginally affected by the dotcom bubble in the early 2000's. We cannot distinguish any visible signs of a trend in the series.

Figure 7 – Volatility Plot: Banks

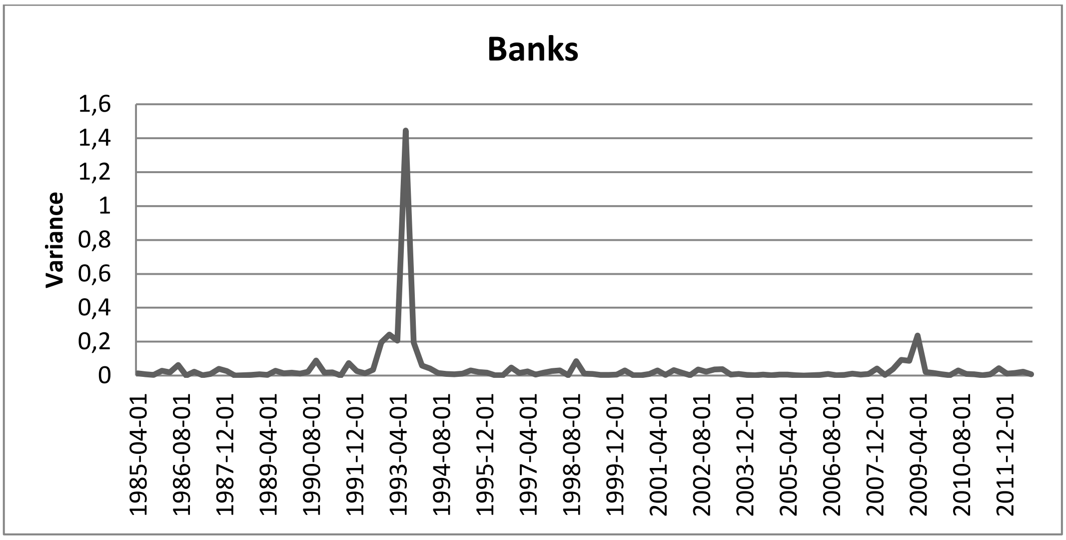


Figure 7 shows a plot of the volatility for banks against time.

For *Banks*, we immediately note an extreme spike in the early 1990's as a consequence of the Swedish banking crisis. The increased volatility during the subprime crisis is very modest in comparison. Nor here, the graph suggests the presence of a linear trend.

Figure 8 – Volatility Plot: Utilities

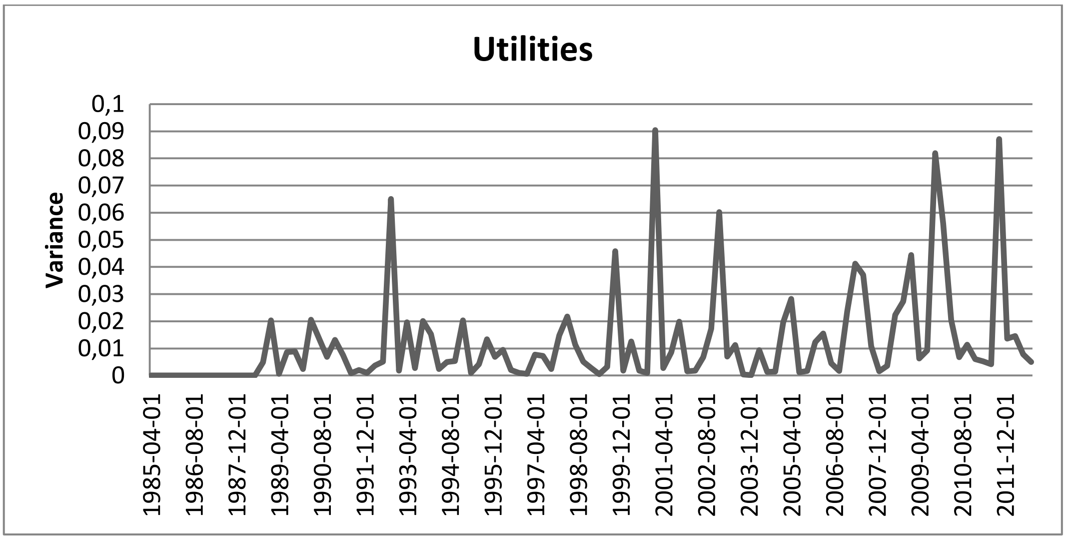


Figure 8 displays a plot of the volatility for utilities against time.

The pattern for *Utilities* show increased volatility during the three crises. However, overall, the volatility is low (note the scaling on the y-axis) and fairly even over time. The graph may suggest a weak upward trend, but not very obvious.

Figure 9 – Volatility Plot: Chemicals

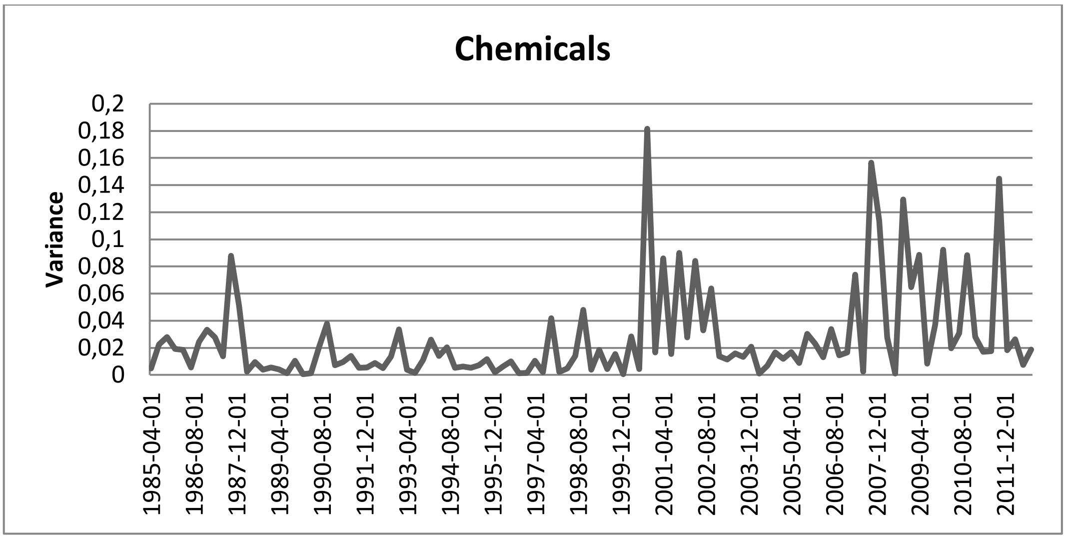


Figure 9 presents a plot of the volatility for chemicals against time.

Chemicals do not seem to have responded to the banking crisis in the early 1990's, but we see increased volatility during the dotcom bubble. Also, we note that the volatility seems to have reached higher levels just before the subprime crisis, and that the (relatively) high levels of volatility have persisted ever since.

Figure 10 – Volatility Plot: Technology

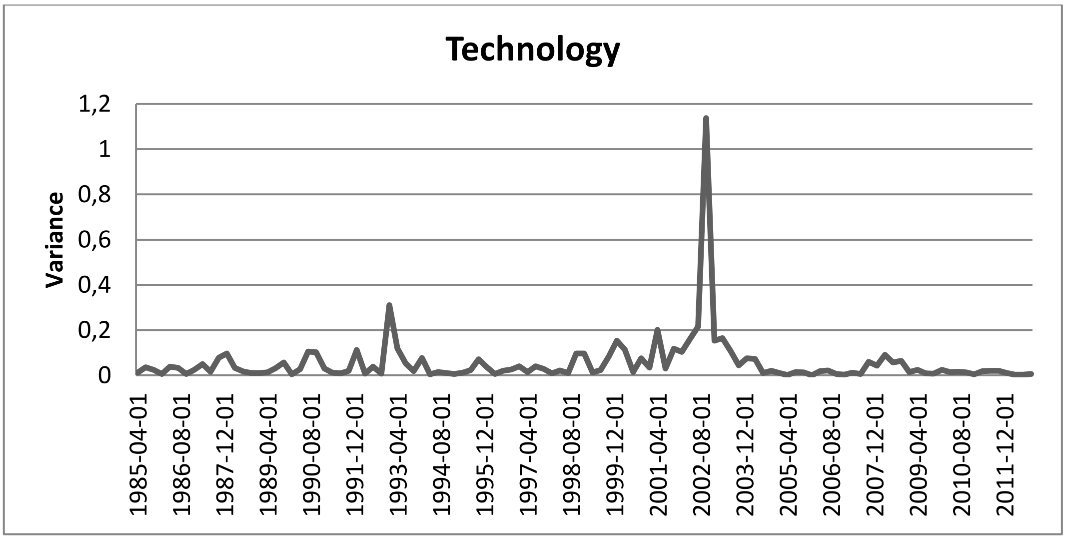


Figure 10 shows a plot of the volatility for technology against time.

Finally, we look at the graph for *Technology*. Not surprisingly, a distinct spike appears during the dotcom bubble. We see small bumps during the other two main crises as well, but they appear almost insignificant in comparison. Once again, the graph does not suggest the presence of a trend in the time series. Plots over all industry-specific time series are presented in *Appendix III*.

5.2.3. Tests for Unit Roots and Trends

Just as in the case with MKT, IND and FIRM, we are interested to see if the IND_t^i series contain unit roots and trends. The trend tests can be seen as a control for our main results in *Section 5*. If we find general trends in the volatility of individual industries that point in a certain direction, we may have to re-evaluate our previous findings. Also, in order to perform the trend tests (using regression analysis), we have to be confident that the variables are stationary. We run Augmented Dickey-Fuller tests, including a constant and a trend, on all series. Again, the lag length is set by AIC.

The results show us that we accept the null hypothesis of a unit root for *Automobiles & Parts*. Testing again in first difference, we reject the null at the 1% level, and conclude that the variable is *I(1)*. For *Food & Beverage* and *Chemicals* we reject the null at the 10% level and for *Real Estate* we reject the null at the 5% level. For all other industries we reject the null at the 1% level. As for the presence of trends in our series, we perform the same trend test as before (see equation (11) in *Section 5.2.*), but with each industry as dependent (and lagged dependent) variable. *Automobiles & Parts* are regressed in first difference since we cannot confidently reject that the series contains a unit root. The tests are performed over the full sample period, and the results are presented in *Table 11* (see *Appendix IV*).

Looking at the table, we note that only the trend coefficients for a handful industries (that is: *Chemicals, Food & Beverage, Health Care, Personal & Household Goods, Telecommunications* and *Utilities*) are statistically significant. The industries in which we find a trend exhibit very different characteristics, but a common factor in our sample is the relatively low beta value with regard to the entire market, where all betas for the industries with significant coefficients are 0.78 or below. We can also point out that of the significant coefficients; four out of six are negative, which may imply that those industries have become *less* volatile over time.

6. Analysis and Discussion

In this section, we will discuss some of our results and possible explanations further.

We find that our MKT, IND and FIRM measures are autocorrelated, but reject the hypothesis that they contain unit roots. Furthermore, we find a fairly high correlation between MKT and FIRM, and that FIRM tends to Granger-cause MKT (as well as IND). We also note that FIRM constitutes the largest part of the total market volatility.

We find no signs or evidence suggesting that our FIRM component follows an increasing linear trend. The same holds for MKT and IND. The trend coefficients are consistently non-significant, except for the time period between 1993:1 and 2002:4, in which we believe that the bull market in the 1990's and the dotcom bubble explains most of the upward volatility trend. This result diverges somewhat from the findings of Campbell et al. (2001), Xu and Malkiel (2001), Goyal and Santa-Clara (2003) and Wei and Zhang (2006) among others. Wei and Zhang (2006) argue that an increase in the amount of newly listed stocks can, since they tend to be more volatile than stocks issued by older companies with larger market capitalization, increase the average idiosyncratic volatility on the market. We have not performed any tests on this issue, but one can interpret this in two ways; long-term and short-term increases in volatility due to increasing numbers of newly listed stocks. The long-term perspective clearly does not hold for the Swedish market. We see the number of firms increase from 135 in 1985 to 461 in 2012 (341%), but no upward trend in idiosyncratic volatility. However, we note that the number of firms in the sample seems to increase just before a crisis emerges, which may suggest that the rate of new listings may have predictive power on economic distress (and thus also increases in idiosyncratic risk because of the observed co-movement with total market volatility).

A possible explanation for our results may be the same as Brandt et al. (2009) suggests, namely that the upward (or downward) tendencies in volatility levels that some authors find (mostly for data previous to year 2000), is just an episodic phenomenon and a part of the cyclical behaviour of the economy. We clearly see periods in our sample where the volatility level of all measures increases, but they soon revert back to their long-term mean.

Guo and Savickas (2008), conclude that the average idiosyncratic volatility is highly correlated across the G7 countries, and that the volatility of the U.S. market tends to Granger-cause the volatility in the other G7 countries (and vice versa). The high correlation of idiosyncratic volatility across countries is also found by Bekaert et al. (2009). Because of the relatively developed character of the Swedish stock market, we have reasonably good reasons to believe that the correlation holds for Sweden as well. Some more recent articles (see for instance Brandt et al. (2009) and Zhang (2010)) on the subject conclude that the upward trend in idiosyncratic volatility on the U.S. market has diminished or stagnated during the last decade, and if the correlation holds, we should find similar patterns in Sweden. This would support our findings.

When it comes to individual industries, we see that only a handful of our IND_t^i measures exhibit a statistically significant trend over the full sample period. In fact, four out of six significant trend coefficients are negative, which may imply that those industries have become less volatile over time. We also note that the industries with a significant trend have very low beta values, which in general is characteristic for relatively stable industries. Furthermore, we see that *Media* has the highest volatility peak of all industries during the subprime crisis in the late 2008/early 2009. This is a fairly surprising result, since one might expect a more volatile industry, alternatively, an industry that is directly connected to the financial markets, to be affected more than *Media* during a financial crisis of the magnitude as the one we just experienced. Lastly, we note out that the volatility of 13 out of 19 industries does not follow a linear trend, which is in line with the main results from the analysis of the MKT, IND and FIRM component.

We conclude that the level of idiosyncratic volatility has been stable over the sample. That is, on average, the problems briefly introduced in *Section 2.2.* regarding high and increasing levels of idiosyncratic volatility, should in general not apply to the Swedish market. The exception, of course, is during times of economic distress when the idiosyncratic volatility temporarily increases considerably. During these periods, mispricing of stocks and options, as well as under-diversification, may lead to unintended and unwanted levels of risk exposure. Also, the number of stocks needed in a portfolio in order to diversify away the increased idiosyncratic (unsystematic) risk during these periods may be significantly higher than the usual rule-of-thumb of 20 to 30 stocks. This implies that in very volatile periods, not only the systematic risk increases, but it is also more difficult to eliminate the idiosyncratic risk from one's portfolio.

7. Conclusion and Suggestions for Further Research

We reach the conclusion, after performing a study in the same manner as Campbell et al. (2001), that the average idiosyncratic volatility of the Swedish stock market between 1985 and 2012 does not follow a long-term linear (upward) trend. Nor does the average volatility at market-, or industry level. We have found evidence suggesting that there are periods in which the levels of volatility drastically increases for all measures, but this appears to be only a temporary effect, mostly caused by general economic distress and/or economic "bubbles"/extreme bull markets such as the dotcom bubble in the early 2000's. Moreover, we find that average firm-level volatility constitutes the largest part of the total volatility on the Swedish stock market, which is entirely in line with the findings of Campbell et al. (2001). Our results also suggest that average market-level volatility is significantly and negatively related to GDP growth.

As for our measure of volatility for individual industries, we conclude that some industries have had extreme volatility peaks in different periods depending on the characteristics of each industry (for instance *Banks* during the banking crisis in the early 1990's), and, rather surprisingly, that *Media* had the highest volatility level of all industries during the subprime crisis. Furthermore, we find that six industries exhibit a linear trend in the full sample period, out of which four are negative (suggesting a decrease in volatility, as opposed to an increase). We also note that every industry with a significant trend coefficient has a low beta value with respect to the total market.

However, since the scope (or purpose) of this thesis does not allow for testing the actual cause for volatility fluctuations (or lack of fluctuations), we cannot draw any in-depth conclusions regarding explanations for the observed patterns. A few possible explanations have been touched upon, but we leave this for future research on the Swedish market. Additionally, although we have provided evidence and a statistical overview of the volatility patterns for individual industries, a more rigorous study on the topic would be of great interest for investors that, for some reason, may be restricted to the Swedish market. For instance, our study raises questions about the trending industries. Are the trends persistent? Are the low beta values just a coincidence?

References

Angelidis, T. and Tessaromatis, N., 2008, “Idiosyncratic Volatility and Equity Returns: UK Evidence”, International Review of Financial Analysis, Vol. 17, Issue 3, p. 539-556.

Bali, T. G., Cakici, N., Yan, X. and Zhang, Z., 2005, “Does Idiosyncratic Risk Really Matter?”, The Journal of Finance, 60, p. 905–929.

Bekaert, G., Hodrick, R. J. and Zhang, X., 2009, ”Is There a Trend in Idiosyncratic Volatility?”, working paper, Columbia University.

Brandt, M. W., Brav, A. P., Graham, J. R. and Kumar, A., 2009, “The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Episodes?”, The Review of Financial Studies, Vol. 23, Issue 2, p. 863-899.

Campbell, J., Lettau, M., Malkiel, B. G. and Xu, Y., 2001, “Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk”, Journal of Finance, 56, 1-43.

Campbell, J., Lo, A. and MacKinlay, A. C., 1997, “The Econometrics of Financial Markets”, Princeton University Press, Princeton, NJ.

Chua, C. T., Goh, J. and Zhang, Z., 2006, “Idiosyncratic Volatility Matters for the Cross-Section of Returns - in More Ways Than One!”, *2006 China International Conference in Finance, Xian, China.*

Gaspar, J-M. and Massimo, Massa., 2006, “Idiosyncratic Volatility and Product Market Competition”, The Journal of Business , Vol. 79, No. 6, p. 3125-3152.

Goyal, A. and Santa-Clara, P., 2003, “Idiosyncratic Risk Matters!”, The Journal of Finance, 58, p. 975–1008.

Guo, H. and Savickas, R., 2008, “Average Idiosyncratic Volatility in G7 Countries”, 2008, Review of Financial Studies, Vol. 21, Issue 3, p. 1259-1296.

Irwine, P. J. and Pontiff, J., 2009, “Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition”, Review of Financial Studies, Vol. 22, Issue 3, p. 1149-1177.

Lintner, J., 1965, “The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets”, *The Review of Economics and Statistics,* Vol. 47, No. 1, p. 13-37.

Markowitz, H. M., 1952, “Portfolio Selection”, The Journal of Finance, 7, p. 77–91.

Roll, R., 1977, “A Critique of the Asset Pricing Theory's Tests Part I: On Past and Potential Testability of the Theory”, Journal of Financial Economics, Vol. 2, Issue 2, p. 129-176.

Sharpe, W. F., 1964, “Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk”, The Journal of Finance, 19, p. 425–442.

Wei, S. X. and Zhang, C., 2005, “Idiosyncratic Volatility Does Not Matter: A Re-examination of the Relationship Between Average Returns and Average Volatilities”, Journal of Banking and Finance, Vol. 29, Issue 3, p. 603-621.

Wei, S. X. and Zhang, C., 2006, “Why Did Individual Stocks Become More Volatile?”, The Journal of Business, Vol. 79, No. 1, p. 259-292.

Zhang, C., 2010, A Reexamination of the Causes of Time-Varying Stock Return Volatilities”, Journal of Financial and Quantitative Analysis”, Vol. 45, Issue 3, p. 663-684.

Appendix

Appendix I

Below follows a detailed derivation of the volatility decomposition as proposed by Campbell et al. (2001):

Industries are denoted with the subscript *j*, and individual firms with the subscript *i*. As opposed to Campbell et al. (2001), we chose to use simple returns instead of excess returns. The return of firm *j* in industry *i* in period *t* is denoted R_{ijt}, and the weight of firm *j* in industry *i* in period *t* is denoted w_{ijt}.

The return of industry *i* in period *t* is defined as $R_{it} = \sum_{j \in i} w_{ijt} R_{ijt}$. Moreover, the weight of industry *i* in the total market is denoted by $w_{it} = \sum_{j \in i} w_{ijt}$, and the return of the total market is denoted as $R_{mt} = \sum_i w_{it} R_{it}$.

We start by writing down a decomposition based on the CAPM with zero-intercept. For industry returns, we have:

(13) $$R_{it} = \beta_{mi} R_{mt} + \tilde{\epsilon}_{it}$$

and for individual firms:

(14) $$R_{ijt} = \beta_{mj} R_{mt} + \beta_{ij} \tilde{\epsilon}_{it} + \tilde{\eta}_{ijt}$$

In (13), β_{mi} is the beta for industry *i* with respect to the market return, and $\tilde{\epsilon}_{it}$ is an industry-specific residual. In (14), β_{mj} is the beta of firm *j* with respect to the market, β_{ij} is the beta of firm *j* in industry *i* with respect to the industry fluctuations and $\tilde{\eta}_{ijt}$ is a firm-specific residual. If we take the weighted sums of the different beta-values, we have:

(15) $$\sum_i w_{it} \beta_{mi} = 1 \qquad \sum_{j \in i} w_{ijt} \beta_{mj} = 1 \qquad \sum_{j \in i} w_{ijt} \beta_{ji} = 1$$

Using (13) and (14), we can assure ourselves that the different components of firm returns are orthogonal, which allows for a decomposition in which all covariance terms are equal to zero:

(16) $$Var(R_{it}) = \beta_{mi}^2 Var(R_{mt}) + Var(\tilde{\epsilon}_{it})$$

(17) $$Var\left(R_{ijt}\right) = \beta_{mj}^2 Var(R_{mt}) + \beta_{ij}^2 Var(\tilde{\epsilon}_{it}) + Var(\tilde{\eta}_{ijt})$$

In order to decompose the different volatility measures without estimating betas, we use a simplified industry return decomposition in which we omit the industry beta-coefficient:

(18) $$R_{it} = R_{mt} + \epsilon_{it}$$

Here, ϵ_{it} is simply the difference between the industry return (R_{it}) and the market return (R_{mt}). This is referred to as a "market-adjusted-return-model". If we compare (13) and (18), we have:

(19) $$\epsilon_{it} = \tilde{\epsilon}_{it} + (\beta_{mi} - 1)R_{mt}$$

Here, R_{mt} and ϵ_{it} are not orthogonal, implying that covariances cannot be ignored. The variance of the industry return is:

(20) $$\begin{aligned} Var(R_{it}) &= Var(R_{mt}) + Var(\epsilon_{it}) + 2Cov(R_{mt}, \epsilon_{it}) \\ &= Var(R_{mt}) + Var(\epsilon_{it}) + 2(\beta_{mi} - 1)Var(R_{mt}) \end{aligned}$$

However, since the *weighted average of variances across industries* is free of individual covariances, we have:

(21) $$\textstyle\sum_i w_{it}\, Var(R_{it}) = Var(R_{mt}) + \sum_i w_{it}\, Var(\epsilon_{it}) = \sigma_{mt}^2 + \sigma_{\epsilon t}^2$$

Where $\sigma_{mt}^2 \equiv Var(R_{mt})$ and $\sigma_{\epsilon t}^2 \equiv \sum_i w_{it}\, Var(\epsilon_{it})$. Since $\sum_i w_{it}\, \beta_{mi} = 1$ we can use the residual from (14), ϵ_{it}, to measure the average industry-level volatility without estimating any betas. $\sum_i w_{it}\, Var(R_{it})$ can be interpreted as the expected volatility of a randomly drawn industry.

The procedure is similar for individual firms. We omit the beta from (14):

(22) $$R_{ijt} = R_{mt} + \epsilon_{it} + \eta_{ijt}$$

Where ϵ_{it} is the same as in (19) and η_{ijt} is the difference between the firm return and the sum of the market- and industry return:

(23) $$\eta_{ijt} = \tilde{\eta}_{ijt} + \left(\beta_{mj} - 1\right)R_{mt} + (\beta_{ij} - 1)\tilde{\epsilon}_{it}$$

Similar to the industry case, the variance of the firm return is:

(24) $$\begin{aligned} Var\left(R_{ijt}\right) &= Var(R_{mt}) + Var(\epsilon_{it}) + Var\left(\eta_{ijt}\right) \\ &+2Cov(R_{mt}, \epsilon_{it}) + 2Cov\left(\epsilon_{it}, \eta_{ijt}\right) + 2Cov(R_{mt}, \eta_{ijt}) \end{aligned}$$

The covariances can be expressed in terms of betas and variances:

(25) $$\begin{aligned} Cov\left(\epsilon_{it}, \eta_{ijt}\right) &= Cov(\tilde{\epsilon}_{it} + (\beta_{mi} - 1)R_{mt}, \tilde{\eta}_{ijt} + \left(\beta_{mj} - 1\right)R_{mt} + \left(\beta_{ij} - 1\right)\tilde{\epsilon}_{it}) \\ &= \left(\beta_{ij} - 1\right)Var(\tilde{\epsilon}_{it}) + (\beta_{mi} - 1)\left(\beta_{mj} - 1\right)Var(R_{mt}) \end{aligned}$$

(26) $$Cov(R_{mt}, \eta_{ijt}) = \left(\beta_{mj} - 1\right)Var(R_{mt})$$

Hence, we have that the weighted average of firm variances in industry *i* is:

(27) $$\sum_{j\in i} w_{ijt} Var(R_{ijt}) = Var(R_{mt}) + Var(\epsilon_{it}) + \sigma_{\eta it}^2 + 2(\beta_{mi} - 1)Var(R_{mt})$$

Where $\sigma_{\eta it}^2 \equiv \sum_{j\in i} w_{ijt} Var\,(\eta_{ijt})$ is the weighted average of firm-level volatility in industry *i*.

If we now compute the weighted average across industries, we obtain a variance decomposition that does not require any estimation of betas (since the industry betas sum to one):

(28) $$\begin{aligned} \sum_i w_{it} \sum_{j\in i} w_{ijt}\, Var\left(R_{ijt}\right) &= Var(R_{mt}) + \sum_i w_{it}\, Var(\epsilon_{it}) + \sum_i w_{it}\, \sigma_{\eta it}^2 \\ &= \sigma_{mt}^2 + \sigma_{\epsilon t}^2 + \sigma_{\eta t}^2 \end{aligned}$$

Where $\sigma_{\eta t}^2 \equiv \sum_i w_{it}\, \sigma_{\eta it}^2 = \sum_i w_{it} \sum_{j\in i} w_{ijt}\, Var\left(\eta_{ijt}\right)$ is the weighted average of firm-level volatility across all firms.

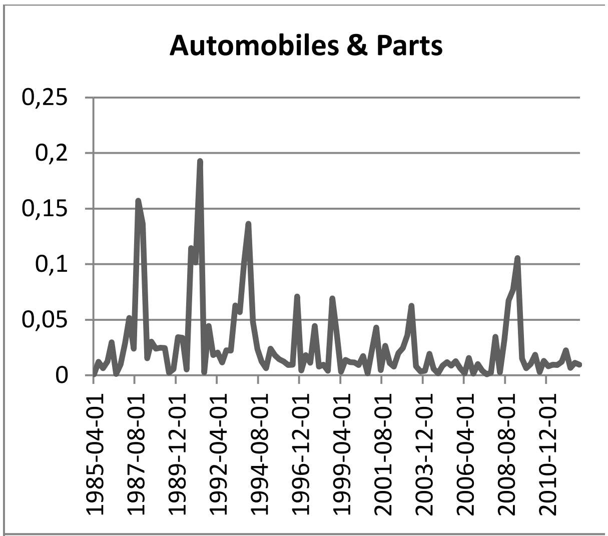
Appendix II

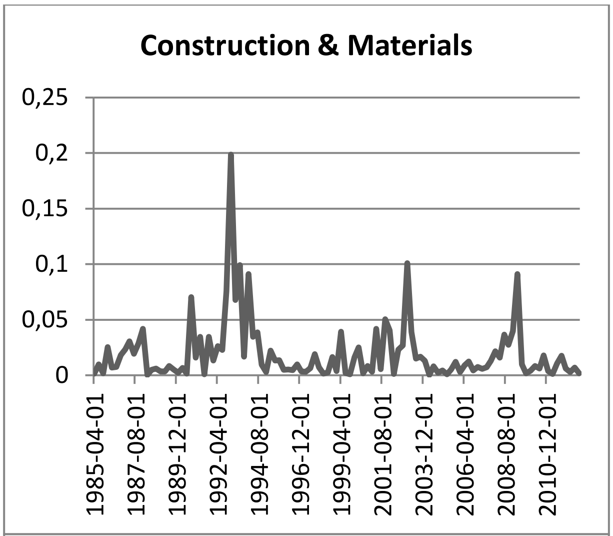
Table 10 – Cyclical Properties: Stock Market Returns

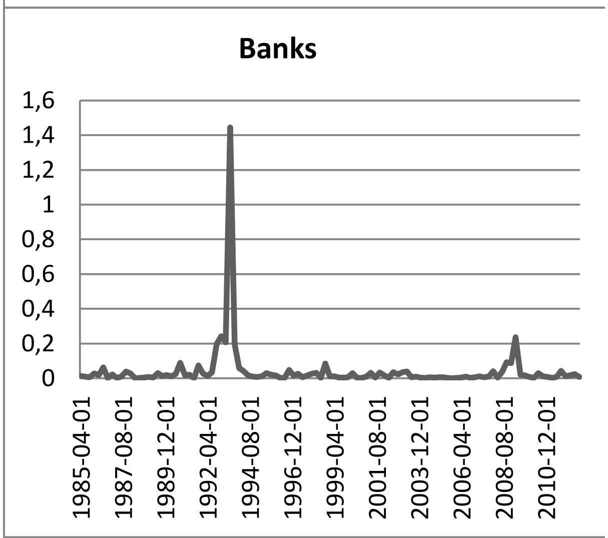
Cyclical Properties: Stock Market Returns ***Dependent Variable: Quarterly OMXS Returns***								
Variable	Coefficient							
Constant	0.0429*** (0.0141)	0.0430*** (0.0143)	0.0334* (0.0171)	0.0442*** (0.0141)	0.0327* (0.0176)	0.0445*** (0.0137)	0.0329* (0.0170)	0.0201 (0.0138)
$OMXS_{t-1}$	0.3060*** (0.1133)	0.3092*** (0.1079)	0.2727*** (0.0999)	0.3068*** (0.1129)	0.2949*** (0.0995)	0.3002*** (0.1004)	0.2721*** (0.1003)	0.3299*** (0.0950)
GDP_{t-1}	-0.4467 (0.2821)	-0.4477 (0.2862)	-0.3751 (0.2910)	-0.4478 (0.2848)	-0.3730 (0.2922)	-0.4460 (0.2905)	-0.3739 (0.2914)	-0.3420 (0.2712)
MKT_{t-1}	-0.1084 (0.8999)	-	-0.8189 (0.6767)	0.1321 (0.9633)	-	-	-0.9023 (0.4661)	-
IND_{t-1}	-2.1062 (1.4155)	-2.1436 (1.1831)	-	-2.0246 (1.3885)	-	-1.9065*** (0.6769)	-	-
$FIRM_{t-1}$	0.1973 (0.2655)	0.1577 (0.4359)	-0.0583 (0.2786)	-	-0.4356* (0.2374)	-	-	-
Adj. R^2	0.1234	0.1360	0.0963	0.1349	0.1024	0.1470	0.1091	0.0976

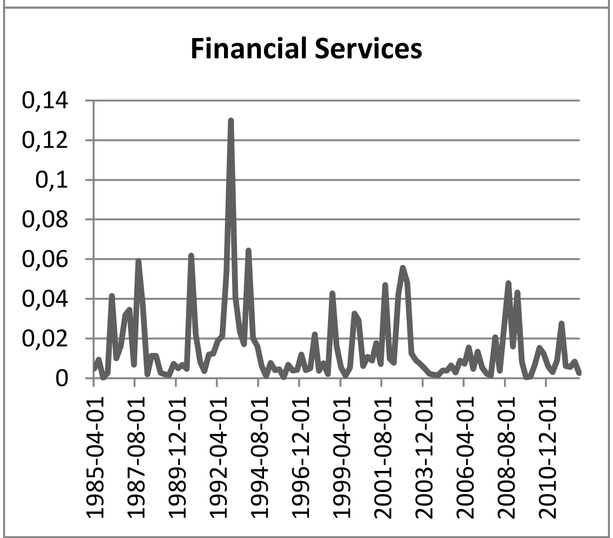
Table 10 presents the results from the regressions with quarterly OMXS returns as dependent variable. The left column presents the regressors, of which all is lagged by one time period except for the constant. The numbers represent the value of the coefficients in each regression, and the significance level is denoted with one, two or three asterisks, representing significance at the 10%, 5% and 1% level, respectively. (-) indicate that the variable is omitted from the model. The bottom row displays the adjusted R^2 value. All regressions are performed using Newey-West robust standard errors.

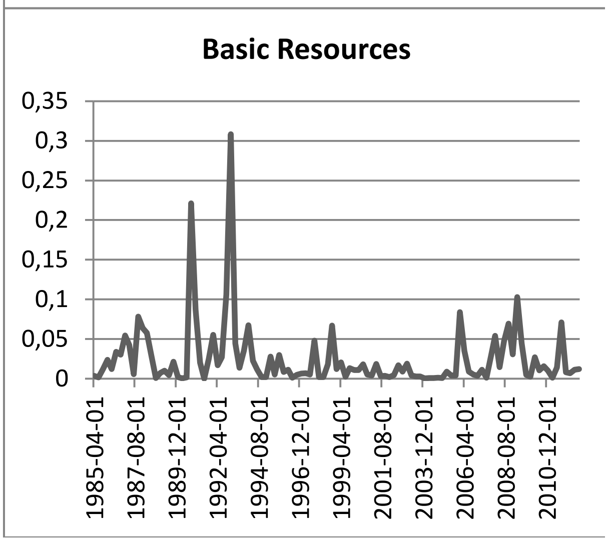
Appendix III

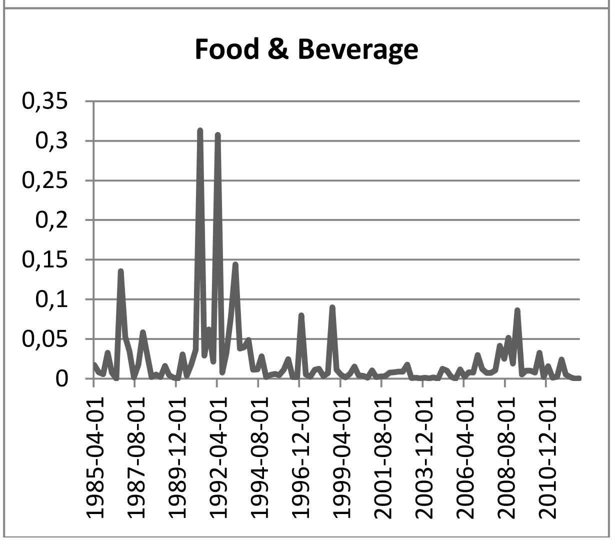


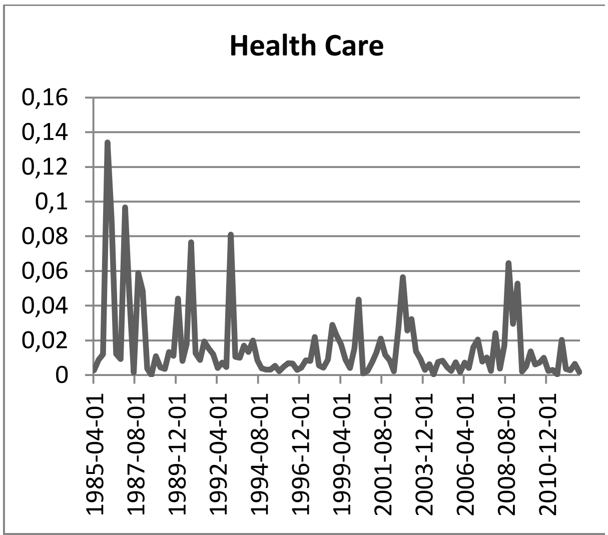


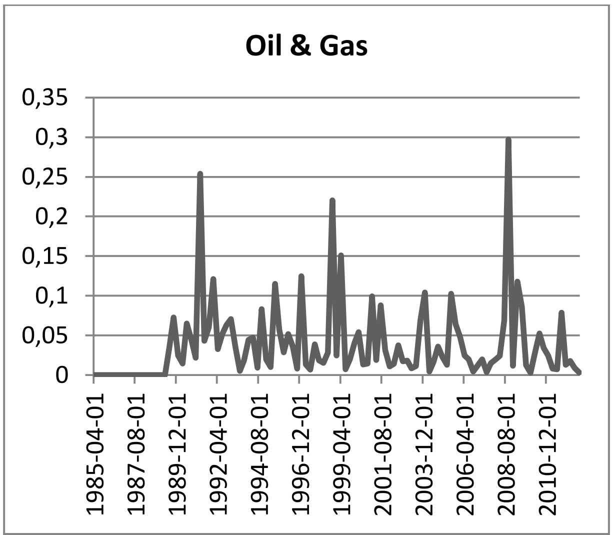


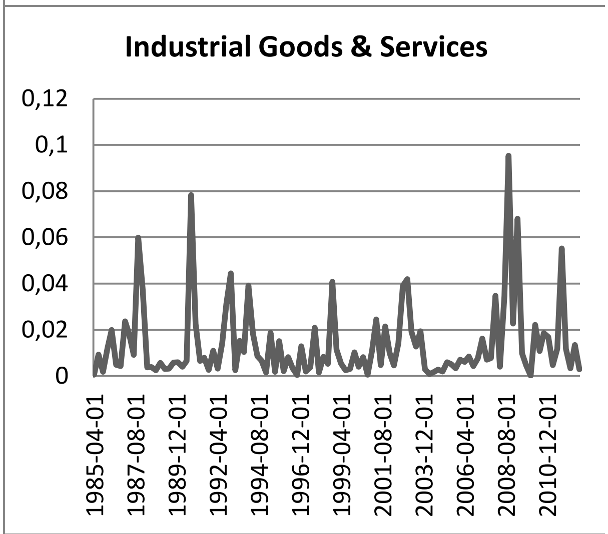


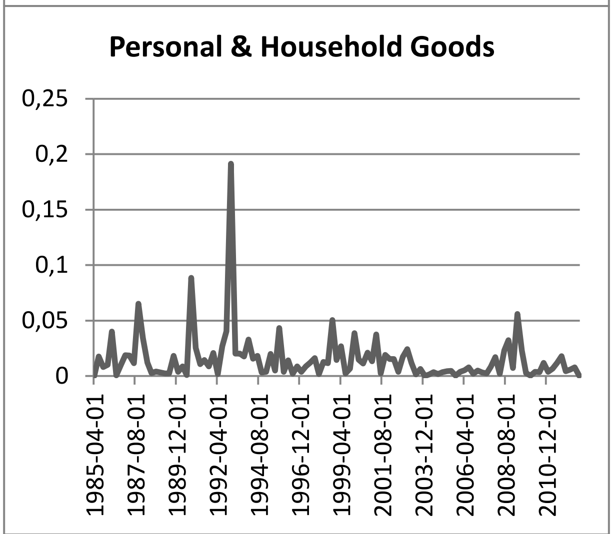


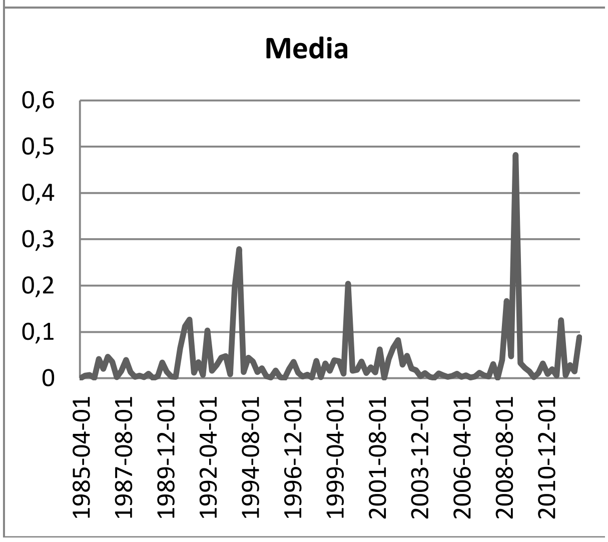


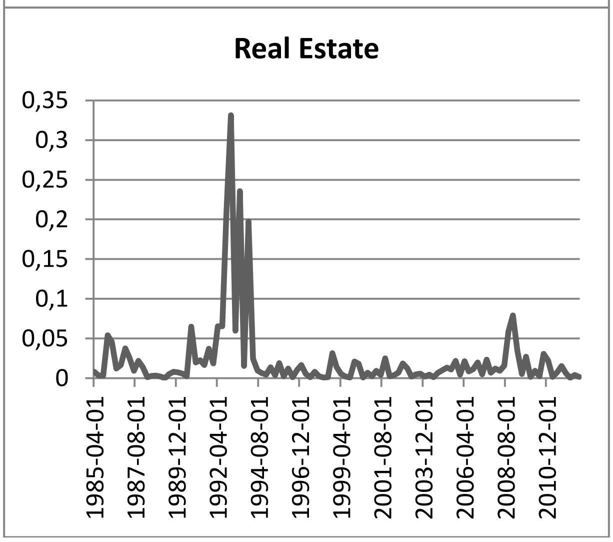

Health Care
0,16
0,14
0,12
0,1
0,08
0,06
0,04
0,02
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01

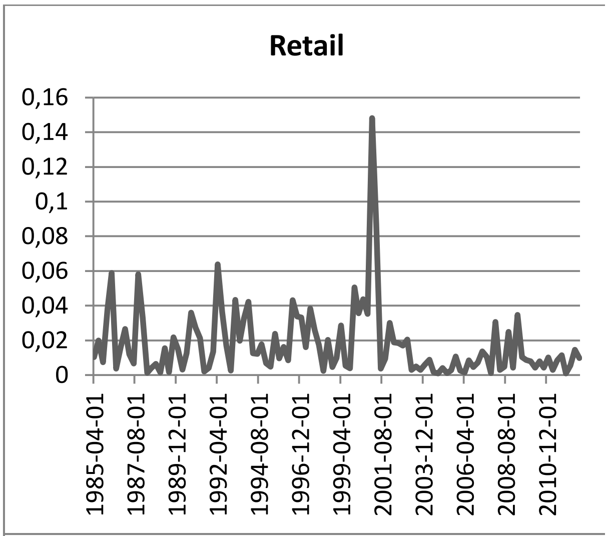

Oil & Gas
0,35
0,3
0,25
0,2
0,15
0,1
0,05
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01

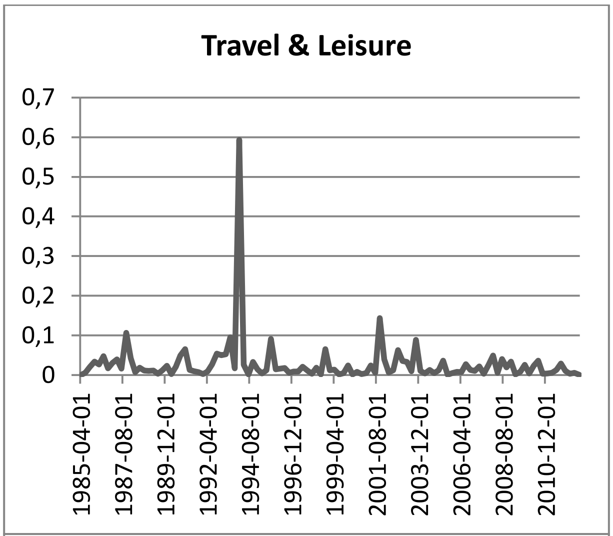

Industrial Goods & Services
0,12
0,1
0,08
0,06
0,04
0,02
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01

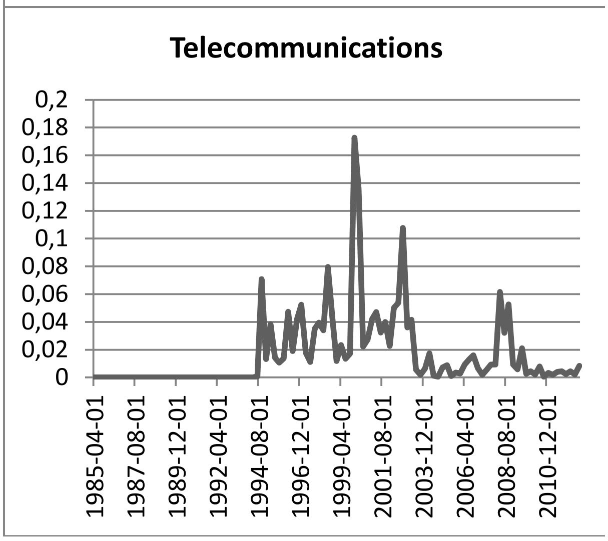

Personal & Household Goods
0,25
0,2
0,15
0,1
0,05
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01

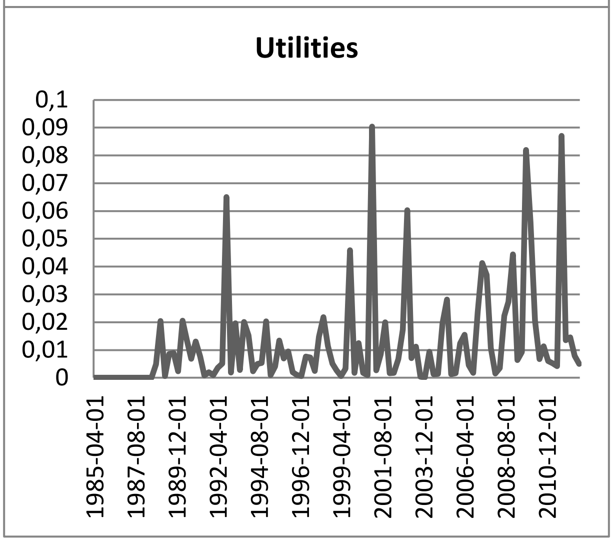

Media
0,6
0,5
0,4
0,3
0,2
0,1
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01


Real Estate
0,35
0,3
0,25
0,2
0,15
0,1
0,05
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01


Retail
0,16
0,14
0,12
0,1
0,08
0,06
0,04
0,02
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01


Travel & Leisure
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01


Telecommunications
0,2
0,18
0,16
0,14
0,12
0,1
0,08
0,06
0,04
0,02
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01


Utilities
0,1
0,09
0,08
0,07
0,06
0,05
0,04
0,03
0,02
0,01
0
1985-04-01
1987-08-01
1989-12-01
1992-04-01
1994-08-01
1996-12-01
1999-04-01
2001-08-01
2003-12-01
2006-04-01
2008-08-01
2010-12-01

Appendix IV

Table 11 – Trend Tests: Individual Industries

Trend Test - Individual Industries	
Industry	Trend coefficient*10^4
Automobiles & Parts[1]	-0.236
Banks	-3.17
Basic Resources	-1.49
Chemicals	3.39***
Construction & Materials	-0.754
Financial Services	-0.651
Food & Beverage	-3.2**
Health Care	-1.56**
Industrial Goods & Services	0.253
Insurance	0.226
Media	1.09
Oil & Gas	-2.88
Personal & Household Goods	-1.27*
Real Estate	-1.61
Retail	-0.846
Technology	0.142
Telecommunications	-3.96**
Travel & Leisure	-2.33
Utilities	1.44**

Table 11 presents the results from the trend tests performed on the volatility measure for each individual industry. Numbers represent the value of the trend coefficient multiplied by 10^4.

The regression is specified as $IND_t^i = \alpha_0 + \beta_1 t + \beta_t IND_{t-1}^i + \varepsilon_t$, where IND_t^i is the industry-specific volatility measure at time t, α_0 is a constant, t is the trend and IND_{t-1}^i is the industry-specific volatility measure, lagged by one time period.

[1] Automobiles & parts is tested in first differences, since we cannot reject the presence of a unit root.