Volatility Decomposition

Empirical Patterns of the Idiosyncratic Risk on the

Swedish Stock Market

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Abstract

We decompose total stock market volatility into market-, industry- and firm-specific components to empirically explore if and how the level of idiosyncratic volatility has changed over time. The econometric methods of Campbell, Lettau, Malkiel and Xu (2001) are applied to the Swedish stock market 1985 to 2004. We find evidence for an upward trend and show that there is a significant increase in idiosyncratic volatility over time. Industry-specific volatility shows a weaker upward trend and market-specific volatility remains flat. The firm-specific volatility tends to lead the other series and market-specific volatility tends to lead industry-specific volatility. None of the volatility series have the power to forecast GDP growth or market returns. We suggest that a higher degree of competition on the market and an increase of newly listed firms during the bull-market of the late 1990s contribute to the upward trend in idiosyncratic volatility.

Keywords: Idiosyncratic Volatility, Stock Market Volatility, Unit Root, Trend Testing, Granger-causality, Predictive Power.

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1. Introduction

The research on idiosyncratic volatility and the causes behind its patterns have increased remarkably during the last years. First Campbell, Lettau, Malkiel and Xu (2001) show that US aggregate idiosyncratic volatility has a significant upward trend from 1962 to 1997. They compute monthly average stock return volatility as the cross-sectional value-weighted average of the variances of all traded stocks during that particular month. Their findings challenge the hypothesis that unconditional volatility is constant over time and that conditional volatility of future returns depends on shocks in the present volatility, see Wei and Zhang (2003). Several follow-up papers have emerged in the field that argues for different reasons and causes behind the increase. It is even suggested that the increase stems from episodic turbulence and is not a trend. Wei and Zhang (2003), Guo and Savickas (2005), among others, argue that the upward volatility trend is a result of increased institutional ownership, a higher degree of competition and increased volatility of cash flows for listed firms. Malkiel and Xu (2002) argue that increased trading by financial institutions partly cause the upward trend. Campbell et al. (2001) mention several possible reasons such as that companies are more specialized in single industries, earlier stock issues in the lifecycle of companies, leverage, technological progress and other reasons that will be further discussed in Section 2.

The fact that research has paid much attention to increased idiosyncratic volatility during the last years can be looked at from several perspectives. From the view of a fundamentalist, the current stock price is the present value of all discounted future cash flows. According to this statement, increased idiosyncratic volatility originates from a higher variance in cash flows or discount rates. From the view of individual and institutional investors it affects the possibilities of hedging and construction of portfolios due to their desire for diversification. A higher degree of idiosyncratic volatility requires more stocks to make a portfolio fully diversified and makes the holding of single stocks more risky. From the view of traders, analysts and researchers, higher firm-level volatility might cause large pricing errors and make event studies insignificant, see Campbell et al. (2001).

An increase in the idiosyncratic volatility affects all types of investors and is of interest for all actors on the financial markets. The risk associated with future outcomes is in focus in an environment where individuals and institutions store future consumption in financial instruments over the period before it is consumed. In financial theory investors are faced with the relation between risk and expected return. Higher risk means higher uncertainty about future consumption possibilities and is undesired among risk-averse investors. According to the detected increase of idiosyncratic risk, investors are faced with a higher risk given the same level of expected return. Therefore investors have to accept the higher risk level or decrease their expectations for future returns when individual stocks become more volatile. This brings more pressure on the success of portfolio managers and opens up a market for instruments with guaranteed levels of return, which is associated with increased costs. When a portfolio manager use derivatives to hedge a portfolio, a part of the return is eaten up of increased management fees. In the end effect, risk-averse investors loose on possible return and have to pay the higher costs that are passed over from the managers to the investors.

The main purpose of this paper is to replicate the analysis of Campbell, Lettau, Malkiel and Xu (2001) on Swedish stock market data and compare the results to their findings. We focus on the idiosyncratic risk on the Swedish stock market during the last twenty years from 1985 to 2004. Further we study if there are any trends in volatility, if the volatility measures can help to forecast each other, help to forecast GDP[1] growth and market return. Finally we discuss reasons that might explain the empirical patterns of idiosyncratic volatility on the Swedish stock market[2].

We decompose aggregate stock market volatility into three components; market-specific, industry-specific and firm-specific volatility.[3] Using equal-weighted monthly return index data for constructing volatility series with quarterly intervals, we find strong evidence for that idiosyncratic volatility exhibits an upward trend. The industry-specific

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[1] General Domestic Production.
[2] In this paper we define "volatility" as variance or standard deviation which refers to risk.
[3] Firm-level (idiosyncratic) volatility is also called idiosyncratic risk, non-systematic risk or diversifiable risk.

volatility shows an upward trend too, but at a lower significance level than the idiosyncratic. For market-specific volatility we fail to reject the null hypothesis of a stochastic trend. Firm-specific volatility tends to lead the other two volatility measures and market-specific volatility tends to lead industry-specific volatility. The volatility measures do neither help to forecast GDP growth nor market returns. Our finding of a significant upward trend in firm-specific volatility is in line with the results in Campbell et al. (2001).

The paper is organized as follows. In Section 2 we discuss the literature and selected research papers of interest. In Section 3 we discuss the processing of the data material and how we use it to create indexes. In Section 4 we discuss the central theory behind the decomposition and show how we calculate the volatility measures. Section 5 presents evidence for increased idiosyncratic volatility. We perform a statistical and graphical analysis, identify possible trends and study the predictive power of the volatility measures. In Section 6 we discuss possible causes behind the results. Section 7 is a short conclusion. Section 8 contains the references.

2. Previous research

In this section we make a review of selected papers in the field. The purpose is to present a view of the current work in the field and its bandwidth.

2.1 Campbell, Lettau, Malkiel, and Xu (2001)

John Y. Campbell, Martin Lettau, Burton G. Malkiel and Yexiao Xu wrote a paper titled "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk" that was published in The Journal of Finance February 2001 edition. They decompose total stock market volatility into market-, industry-, and firm-specific volatilities without having to estimate covariances or betas. The time series of realized volatility are used to investigate trends, correlations across individual stocks, explanatory power of the market model for individual stocks, the number of stocks needed to achieve a given level of diversification, lead-lag relations and predictability of GDP growth.

For estimation the CRSP[4] data set is used. This include the stocks traded on NYSE, AMEX and NASDAQ with a sample width from 2,047 firms in 1962 to 8,927 firms in 1997, aggregated in 49 industries. The estimation frequency is the daily excess returns used to construct volatility estimates of monthly intervals.

Their main results are that idiosyncratic volatility shows a stable increase over the time period, while industry volatility remains almost flat and market volatility shows no systematic trend behavior. Correlations among individual stock returns have diminished and the number of stocks necessary to obtain a required level of diversification in a portfolio has increased because of the rise in idiosyncratic volatility. The market model's explanatory power has decreased for an average stock. All volatility measures are countercyclical where market volatility tends to lead the other volatility measures and they all help to forecast GDP growth. The authors argue that there are several reasons behind the upward trend, without identifying any in particular. Among the ones previously mentioned are increased leverage, improved information technology, financial innovations, an increase of institutional ownership, changes in corporate governance, and

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[4] Center for Research in Security Prices, Graduate School of Business at University of Chicago

earlier stock issues in the life cycle of companies as well as day trading. In Section 5 p. 29 these themes will be further discussed.

2.2 Other papers of interest

Before Campbell et al. (2001) published their paper there was little empirical research on the volatility at the firm or industry level. But after their contribution to the field, several papers have followed with different approaches to answer the questions that their precursors left behind. We select and submit some of them here.

Wei and Zhang (2003) explore why individual stocks have become more volatile. They examine the causes empirically and try to analyze if the upward trend in the average return volatility can be traced back to changes in fundamentals, and if there is a divergence between existing stocks and newly listed stocks. Two variables are found that explain the increased volatility using accounting data from 1976 to 2000. The first one is average return-on-equity, which is earnings divided by the book-value of equity. The second one is average sample variance of past return-on-equity. The results show that equally weighted return-on-equity declined while the sample variance of return-on-equity rose. This explains most of the upward trend in equally-weighted return variances, and the entire upward trend in value-weighted return variances. The authors argue that this makes economic sense because stock prices are the discounted value of future profits and return volatility is the reflection for its uncertainty. They also argue that return volatility of newly listed stocks is the main reason for the increasing average return volatility for all firms. Variables such as firm size, firm age, leverage and book-to-market equity ratio do not help to explain the upward trend in return volatility.

Gaspar and Massa (2004) explore the relation between a firm's competitive surrounding and the idiosyncratic volatility of its stock returns. They use stock return data from 1962 to 2001 and find that the competitive positioning of firms may influence the impact of firm specific shocks. They argue that market power works as a hedging instrument which smoothes idiosyncratic fluctuations. A higher market power implies lower information

uncertainty and therefore a lower volatility of stock returns. As a consequence of deregulation and globalization the increased product market competition has probably affected the upward trend in idiosyncratic volatility. The authors show that different competitive environments may affect the value of the firm if idiosyncratic risk is priced effectively. They find that the idiosyncratic fluctuations are lower if a firm possesses a high degree of market power in relation to its competitors.

Brandt, Brav and Graham (2005) find contradictory evidence to earlier findings on an upward time trend. They argue that increased idiosyncratic volatility is an episodic phenomenon due to the similar patterns during the periods of bull markets at the end of 1920s and 1990s. Using the CRSP data set ranging from 1926 to 2004, the idiosyncratic volatility seems to revert back to normal levels after increasing during economic turmoil. "Low priced stocks, we argue, are particularly attractive to novice investors who seek gambling-like skewness. Therefore, we conjecture that high and increasing idiosyncratic volatility, driven primarily by low-priced stocks, is a phenomenon associated with speculative episodes, as opposed to being a time trend", see Brandt, Brav and Graham (2005, p. 2-3). Besides this possible explanation the authors discuss other rationales such as increased institutional ownership, increased volatility of firm fundamentals, liquidity risk and microstructure biases, without being able to manifest any significant impact from them.

Irvine and Pontiff (2005) identify two reasons that might explain the earlier documented upward trend in idiosyncratic volatility; idiosyncratic news in cash flows and/or market inefficiencies. Using the CRSP/Compustat data set ranging from 1963 to 2003, they estimate three measures to analyze cash flow volatility; earnings per share, cash flow per share and sales per share. They find evidence to conclude that increased competition has driven the upward trend in idiosyncratic volatility of stock returns. "This mosaic of evidence lends support to the notion that economy-wide competition plays a role in the recent trend toward higher levels of idiosyncratic stock return risk", according to Irvine and Pontiff (2005, p. 35). They further argue that deregulation and foreign competition

have great influence for the increase, but that the rise of entries of new firms and break up of conglomerates are incomplete explanations.

Goyal and Santa-Clara (2003) explore the predictability of stock returns using different risk measures. They use monthly data ranging from 1963 to 1999 and find a positive relationship between value-weighted average returns and lagged equally-weighted average volatility. This is a challenge to the perception that only systematic risk is relevant in determining expected returns, pointed out in a follow-up paper by Wei and Zhang (2005). In contrast, their results show that there is no relation between average return and idiosyncratic risk in an extended sample, or in sub-samples. They argue that the positive relationship found by Goyal and Santa-Clara (2003) is led by the episodic turbulence in the 1990s. Bali, Cakici, Yan and Zhang (2005) also criticize Goyal and Santa-Clara (2003) and argue that the reason for the positive relation comes from small stocks traded on the NASDAQ which express a liquidity premium. When liquidity is low the spreads are high, which has a negative impact on trading volumes.

Other papers have studied the issue with a cross-border approach. Frazzini and Marsh (2003) use US and UK stock return data and find evidence for that both countries idiosyncratic volatility is related to firm's business risk. They identify a positive relation between future stock returns and idiosyncratic volatility. Guo and Savickas (2005) compare the empirical development of idiosyncratic volatility in the G7 countries (Canada, France, Germany, Italy, Japan, UK and US). They find an upward trend in US and Canada, but not in the other countries. Further they provide evidence for a high positive correlation of idiosyncratic volatility across these countries.

Note that the different results shown in these papers might partially be explained by different quantitative approaches, such as using monthly or quarterly intervals and value-weighted or equal-weighted series. It may also depend on the different time periods that are used. We will return to some of these issues in the discussion in Section 7, p 30.

## 3. Data on individual stocks and index construction

The data material is collected from the Thomson DataStream data set, and includes all stocks traded on the Swedish stock exchange from 1985 to 2004. Stocks listed on the A, Attract 40, O, OTC and NGM-list (former SBI-list) are included. The A-list is the list with the highest turnover frequency and contains the largest Swedish listed firms. The other lists contain generally smaller firms, which can be transferred to the A-list after fulfilling determined requirements. We do not include stocks from the smallest lists such as Nya marknaden or Göteborgslistan due to a lack of proper data. All data is presented in return index form (RI), which is the price index with compound dividends corrected for splits and emissions. The time series are based on monthly returns with the last observation for every month from Jan. 1985 to Dec. 2004. Campbell et al. (2001) use daily, monthly and yearly frequencies to test sensitivities. The results do not diverge and therefore we conclude that monthly data is appropriate for the research at hand.

3.1 Processing

The first step to process the data material is to construct a cross sectional matrix of all firms listed in the time period covered. To construct the matrix we use the work of Sven-Ivan Sundqvist[5] to define listing years for every individual stock. In this matrix, 758 rows and 20 columns, we also have to consider mergers, acquisitions, name changes, bankruptcies, delisting and parallel listings. The total amount of listed stocks during the last 20 years is 758; see Figure 1 for a presentation of yearly listings. The number of listed stocks peaked to a maximum of 347 in 2001, which might be a consequence of the bull-market during the years before. There is data available for 621 of the listed stocks. There is no data available for the remaining 137 stocks (18%) in the data set. Among the unavailable time series we find mostly stocks with short listing periods with an average of 3.7 years. For the available time series the average listing period is 7.6 years. Among the unavailable the majority was listed during the beginning of our chosen sample period when documentation might have been insufficient.

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[5] "SIS Owners and Power in Sweden's Listed Companies", Sven-Ivan Sundqvist, vol. 1985-2004, for more information see www.aktieservice.com

Figure 1
Yearly Listings of Individual Stocks
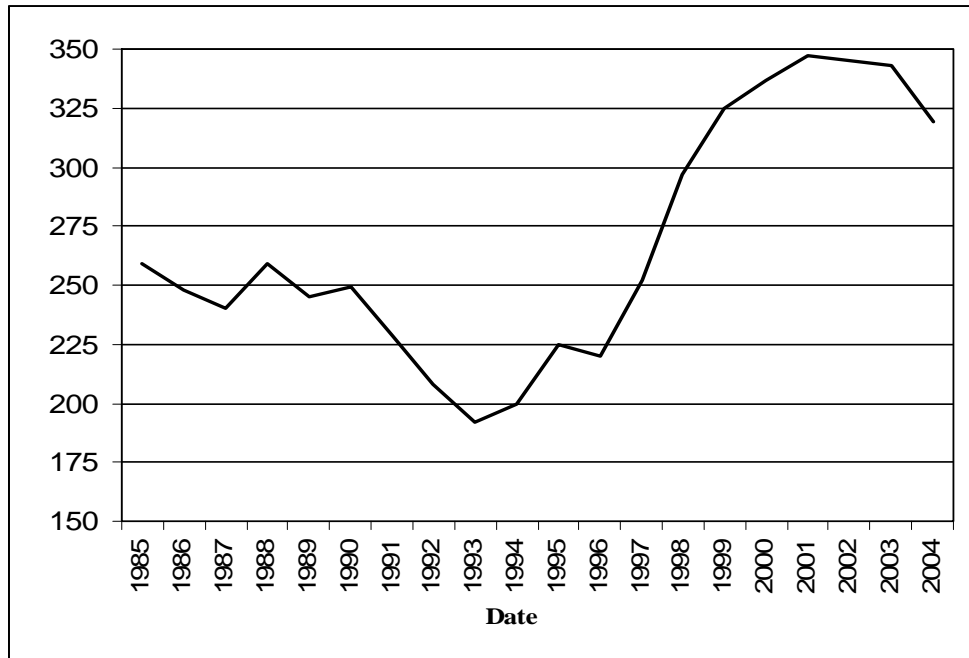
Note that the number of listed stocks tends to follow the business cycle. Although we have not made any statistical test about this fact, the number of listings seems to be particularly low during the recession in the early 1990s, and high during the boom in the early 2000s.

For many stocks in the data material there is more than one time series. This is due to the fact that in some instances Swedish stocks have different voting power. For many stocks, mostly the ones listed on the A-list there are so called A- and B-shares. The A-share has a higher voting power then the B-share, whereas the B-share is generally more liquid. Another reason for several time series per stock is the shaping of the data source. Due to this latter fact we have to construct the longest representative time series per stock by cutting together several RI series. We consistently prefer B-shares than A-shares to obtain the highest possible liquidity. Another fact that we have to consider is the occasion of missing observations and gaps in the series. We do not use linear interpolation due to the bias that it might cause. After constructing the longest possible series per stock, we calculate the percentage net returns defined as $R_t = \dfrac{P_t}{P_{t-1}} - 1$, where R is return and P is price, see for example Campbell, Lo and MacKinlay (1997 p. 9). Note that as a consequence we lose the first observation in every series. For completeness we perform

an outlier analysis to understand the reasons behind divergent observations. An investigation of a number of randomly chosen extreme observations shows that these in general seem to be caused by information shocks related to mergers, acquisitions and bankruptcies. The extreme values appear mostly in more volatile periods such as the recession in the beginning of the 1990s and the boom in the late 1990s and early 2000s. These processed return series is the starting-point when constructing volatility measures.

3.2 Index construction

Before constructing the volatility measures, we have to construct indexes both for the individual industries and for the entire market. This is a matter since the available indexes do not cover the whole time period and do not, with certainty, include dividends. Another reason is that the available indexes might not include dead stocks, which causes a survival bias when left out. It is here defined as when delisted stocks are excluded from the current indexes. For the industries we aggregate the individual stocks over the major nine peer groups from Affärsvärlden[6]. Table 1 below shows all listed stocks over the estimation period aggregated to every industry respectively.

Table 1
Selected Industries

Index	Number of stocks
Industrials	205
Financials	143
Information Technology	97
Consumer Goods	51
Health Care	51
Commodities	26
Telecommunications	26
Services	12
Media and Entertainment	10

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[6] Affärsvärlden is an approved Swedish weekly magazine covering the financial markets and providing market statistics. Their main market index AFGX is often used as a benchmark for the entire market.

The classification of stocks in individual industries has changed over the sample period. Industrials', being the dominating industry in size, has decreased from above one hundred firms 1985 to 76 in 2004. This is the historically dominating sector in Sweden. Media and Entertainment, being the smallest industry, has increased from 2 to 7 firms and is not covered for the first six months of our time period. Services' is not covered before mid 1991 due to lack of firms in this sector. These industries are first included in the calculations when they start to exist. All other industries are covered from the beginning of 1985.

Campbell et al. (2001) uses value-weighted indexes. Due to lack of data and additional reasons discussed below we instead use an equal-weighting scheme in line with Goyal and Santa-Clara (2003) and Gou and Savickas (2005). This is appropriate because our data material is characterized of few firms with a high market value in relation to the entire market, especially in the beginning of the estimation period. When using value-weighted indexes in a market with these characteristics the volatility of few individual stocks will have a high influence on the aggregated idiosyncratic volatility.

The cons are that when many small firms enter the market they increase the firm-level volatility which might give results different from when using a value-weighted scheme, see Campbell et al. (2001 p. 26). Here we have to consider the difference between our data material and the one used by Campbell et al. (2001). They start with 2,047 stocks in 1962 and end up with 8,927 in 1997 (an increase with 336%). Their indexes include at the most over 1,500 stocks. The number of stocks in our material increases from 259 in 1985 to 319 in 2004 (an increase of 23%).

Guo and Savickas (2005) find that the equal-weighted idiosyncratic volatility is much higher than its value-weighted counterpart when performing a similar study on the G7 countries. However, they find that in the markets with the smallest number of stocks the difference tends to be small. For example, in Italy, France and Germany the difference is only minor in comparison with US, UK and Canada that have a larger number of listed stocks and large differences between weighting schemes.

This evidence shows that a value-weighting scheme may be a more reliable measure when performing the study on large markets, but that the equal-weighting scheme is representative for smaller markets.

Figure 2
Index Comparison
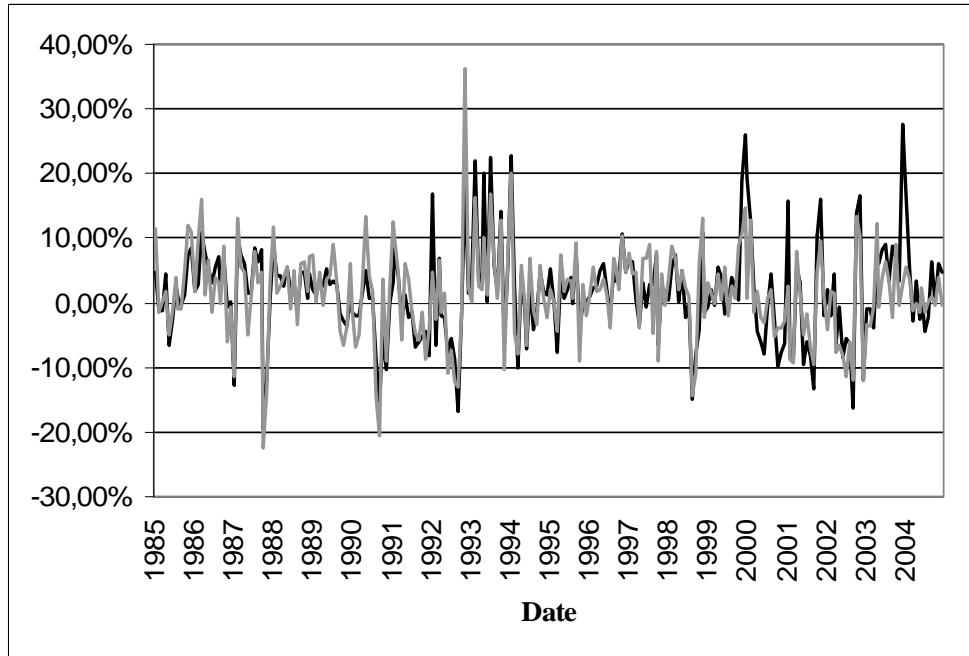
The grey line denotes AFGX, the black line denotes an equal-weighted market index. The percentage returns on the left scale are calculated with monthly RI data.

The market index is constructed by summing up all industries. There are alternative market indexes available elsewhere, but we construct an equal-weighted index to be consistent throughout the paper. To study if the calculated market index is representative we compare it to the value-weighted AFGX[7] return index, see Figure 2. The correlation is positive and high, 0.81. When AFGX differs to the equal-weighted index, especially in the more turbulent periods, a few stocks with high market value show large movements in the returns. These peaks are not captured in the equal-weighted index since all stocks have the same weight.

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[7] Affärsvärldens Generalindex, a value-weighted market index that contains all the stocks listed in Sweden. See for example www.affarsvarlden.se, Bloomberg, Reuters or Ecowin.

4. Derivation and calculation of volatility measures

4.1 Theoretical survey

This section is a reproduction of the methodological description in Campbell et al. (2001, Section 1, p. 4-9). The purpose is to produce time series of volatility measures without estimating betas or covariances for industries and firms. A selected part of the derivation is presented below. We refer to Campbell et al. (2001) for a detailed derivation and description. The starting-point is the standard CAPM with a zero intercept restriction:

$$(1) \quad R_{jit} = \beta_{ji}\beta_{im}R_{mt} + \beta_{ji}\tilde{\varepsilon}_{it} + \tilde{\eta}_{jit} \qquad \text{Campbell et al. (2001, p. 4),}$$

where R_{jit} is the return for firm j in industry i at time t and R_{mt} is the market return. β_{ji} is the beta for firm j with respect to the industry return and β_{im} the beta for industry i with respect to the market return. Due to the orthogonality condition $\beta_{jm} = \beta_{ji}\beta_{im}$. $\tilde{\varepsilon}_{it}$ is the industry-specific residual and $\tilde{\eta}_{jit}$ is the firm specific residual. The variance decomposition following from equation (1) is:

$$(2) \quad Var(R_{jit}) = \beta_{jm}^2 Var(R_{mt}) + \beta_{ji}^2 Var(\tilde{\varepsilon}_{it}) + Var(\tilde{\eta}_{jit}) \qquad \text{Campbell et al. (2001, p. 5).}$$

Using this decomposition scheme we have to estimate betas for industries and firms which might be unstable over time. Instead the "market-adjusted-return model" is used, see for example Campbell, Lo and MacKinlay (1997, Chapter 4, p. 156):

$$(3) \quad R_{it} = R_{mt} + \varepsilon_{it} \qquad \text{Campbell et al. (2001, p. 5)}$$

for industries, and

$$(4) \quad R_{jit} = R_{it} + \eta_{jit} \qquad \text{Campbell et al. (2001, p. 6)}$$

for firms. This is suitable when all firms on the market are included and beta can be assumed to one. Further the beta-free variance decomposition to the market-adjusted-return model with weighted averages across industries follows as:

$$(5) \quad \sum_i w_{it} \sum_{j \in i} w_{jit} Var(R_{jit}) = \sigma_{mt}^2 + \sigma_{\varepsilon t}^2 + \sigma_{\eta t}^2 \qquad \text{Campbell et al. (2001, p. 6)},$$

where w_{it} and w_{jit} are the industry and firm related weights respectively. The three components on the right hand side of equation (5) are the ones to be estimated in the next section and make up the volatility measures that we further examine empirically. Due to using weighted averages across industries and firms, the covariance terms cancel out, see Campbell et al. (2001, p. 6).

4.2 Estimation of volatility measures

We estimate market-, industry- and firm-level variances using the data material described in Section 3. The individual firms are aggregated into nine industries according to the classification by Affärsvärlden. We do not follow Campbell et al. (2001) in using excess returns (net returns). Instead we follow Campbell, Lo and MacKinlay (1997, Chapter 7, p. 268) in using gross stock returns.

To estimate the volatility components in equation (5), we use the "market-adjusted-return model" as starting point, see Campbell, Lo and MacKinlay (1997, Chapter 4, p. 156). First we estimate the market-specific volatility by summing up returns of interval s, to construct volatility estimates of interval t. Here s represents months and t quarters:

$$(6) \quad MKT_t = \hat{\sigma}_{mt}^2 = \sum_{s \in t} (R_{ms} - \mu_m)^2 \qquad \text{Campbell et al. (2001, p. 8)}$$

where R_{ms} is the market return at interval s and μ_m is the mean of the market return. Second, we estimate the industry-specific volatility for every industry i by first summing the squared residuals in equation (3) within interval t:

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(7) $\hat{\sigma}^2_{\varepsilon it} = \sum_{s \in t} \varepsilon^2_{is}$ 　　　Campbell et al. (2001, p. 8).

To ensure that the covariances cancel out as described in the previous section, we average over industries. This gives the industry-specific volatility:

(8) $IND_t = \sum_i w_{it} \hat{\sigma}^2_{\varepsilon it}$ 　　　Campbell et al. (2001, p. 8).

The third step is to estimate firm-specific volatilities. We begin by summing up the squares of the residuals in equation (4):

(9) $\hat{\sigma}^2_{\eta jit} = \sum_{s \in t} \eta^2_{jis}$ 　　　Campbell et al. (2001, p. 9).

Then the weighted average within every industry is calculated:

(10) $\hat{\sigma}^2_{\eta it} = \sum_{j \in i} w_{jit} \hat{\sigma}^2_{\eta jit}$ 　　　Campbell et al. (2001, p. 9).

To obtain the firm-specific volatility we finally have to take an average over all industries to make sure that the covariances cancel out:

(11) $FIRM_t = \sum_i w_{it} \hat{\sigma}^2_{\eta it}$ 　　　Campbell et al. (2001, p. 9).

Guo and Savickas (2005) simplify the procedure for equal-weighted idiosyncratic volatility (*EWIV*) by aggregating all three equations to one that is more generic:

(12) $EWIV_t = \sum_{i=1}^{N_t} \omega_{it} \left[\sum_{d=1}^{D_{it}} \eta^2_{id} + 2 \sum_{d=2}^{D_{it}} \eta_{id} \eta_{id-1} \right]$ and $\omega_{it} = \dfrac{v_{it-1}}{\sum_{j=1}^{N_t} v_{jt-1}}$,

Guo and Savickas (2005, p. 7), where N_t is the number of stocks in quarter t and D_{it} is the number of trading days for stock i in quarter t. η_{id} is the idiosyncratic shock to the excess return on stock i in day d of quarter t and $v_{it\text{-}1}$ is the market capitalization. We do not use this equation, but include it to show on the simplicity of the procedure.

This procedure yields three volatility measures which will be used to investigate the issues raised in Section 1. For data processing and storage we use Microsoft Excel and for statistical tests and regression analysis we use EViews. In the next section we proceed with a statistical survey to examine the volatility measures.

5. Statistical properties of volatility measures

In this chapter we discuss whether the volatility measures estimated in the previous section exhibit any particular trends and if they have some forecasting power for GDP growth and stock returns.

### 5.1 Descriptive statistics and graphical analysis

In this section we describe the statistical properties of the calculated volatility measures and perform a graphical analysis. Further we test for serial correlation, unit root, trend coefficients and Granger-causality. In Table 2 the descriptive statistics is tabulated. FIRM has the highest values for mean, median, maximum, minimum and standard deviation. IND is the most skewed and also has the highest kurtosis. For all series we have 80 observations, i.e. 4 quarters for 20 years.

Table 2
Descriptive statistics

	FIRM	IND	MKT
Mean	0.0698	0.0139	0.0161
Median	0.0446	0.0072	0.0073
Maximum	0.3623	0.1165	0.0881
Minimum	0.0103	0.0016	0.0002
Std. Dev.	0.0742	0.0183	0.0192
Skewness	2.4638	3.3521	1.5619
Kurtosis	9.1123	16.083	4.9309
Jarque-Bera	205.473	720.328	44.954
Probability	0.0000	0.0000	0.0000
Sum	5.5835	1.1122	1.2917
Sum Sq. Dev.	0.4353	0.0263	0.0291
Observations	80	80	80

In the graphs below we present the empirical time-series of the volatility measures. Note that all series have different scaling on the vertical axis. For MKT there are obvious peeks during the crash of 1987, first half of 1990s and the beginning of 2000s. For IND the peeks look similar as for MKT, with exception for the turmoil in 1987.

Figure 3
Market-specific volatility (MKT)
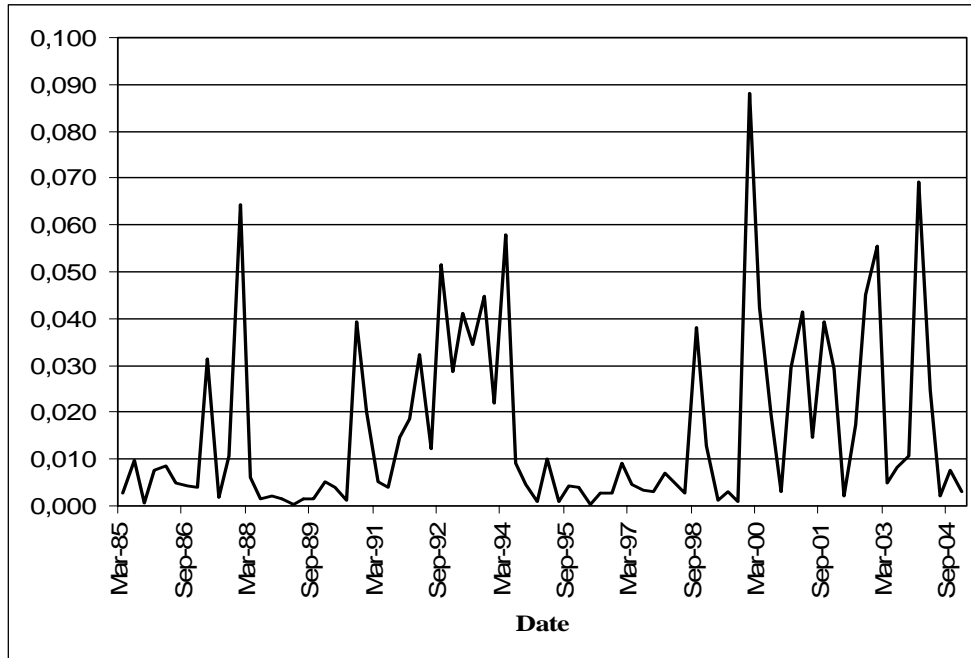
The figure shows the quarterly variance for the market-specific volatility, calculated by using equation (6).

Figure 4
Industry-specific volatility (IND)
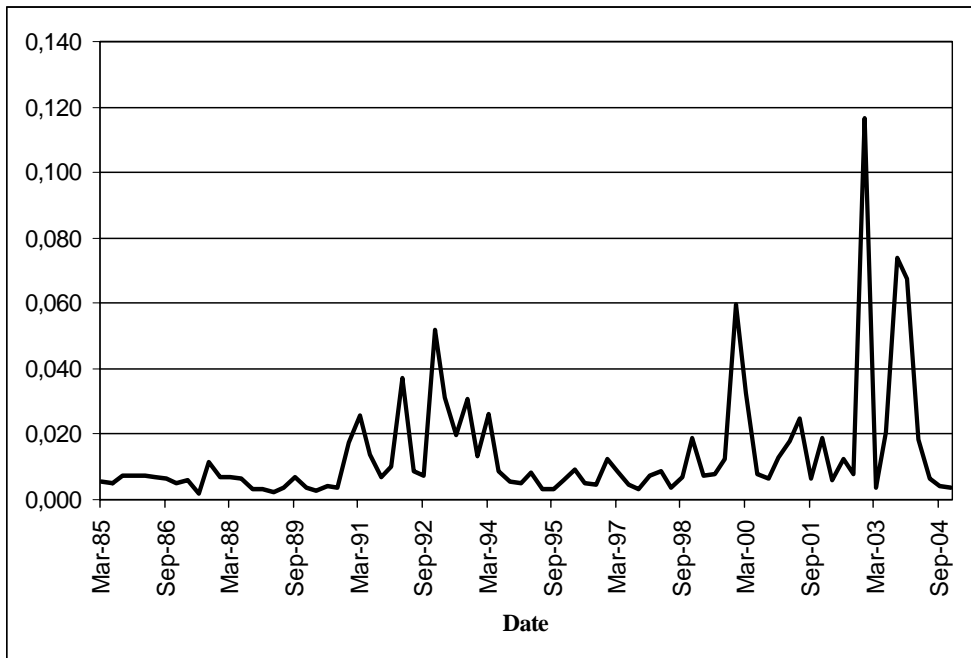
The figure shows the quarterly variance for industry-specific volatility, calculated by using equation (8).

Figure 5
Firm-specific volatility (FIRM)

The figure shows the quarterly variance for firm-specific volatility, calculated by using equation (11).

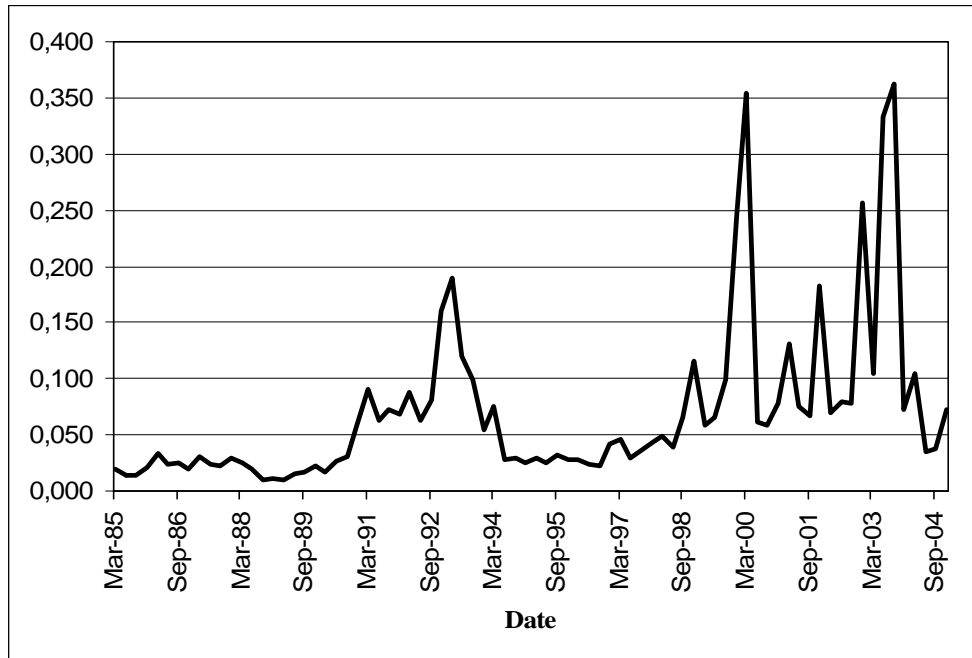As can be seen in Table 2, MKT has a slightly higher mean than IND, but IND has a higher peak in the end of 2002. FIRM (and IND) show no reaction to the 1987 turmoil, but has higher peaks and an increasing level of volatility throughout the time period, see Figure 5. During the more volatile periods in the beginning of the 1990s and 2000s FIRM has considerably higher volatility.

We observe that the last years of our sample seem to be more volatile for all volatility measures. Pastor and Veronesi (2003) argue that young firms tend to have a high idiosyncratic volatility because of a high uncertainty about their future profitability. This is of interest for our sample since many small firms became listed in the bull-market period in the end of 1990s and beginning of 2000s. A considerable proportion of these were active in the information technology industry, which is characterized of several insolvencies and above average volatility. An explanation to the fact that the volatile period lasts after the bull-market period is that many firms became listed only after the boom and that the industry grew rapidly and has maintained its size through the first half of the decade.

Figure 6
Relative shares of total volatility
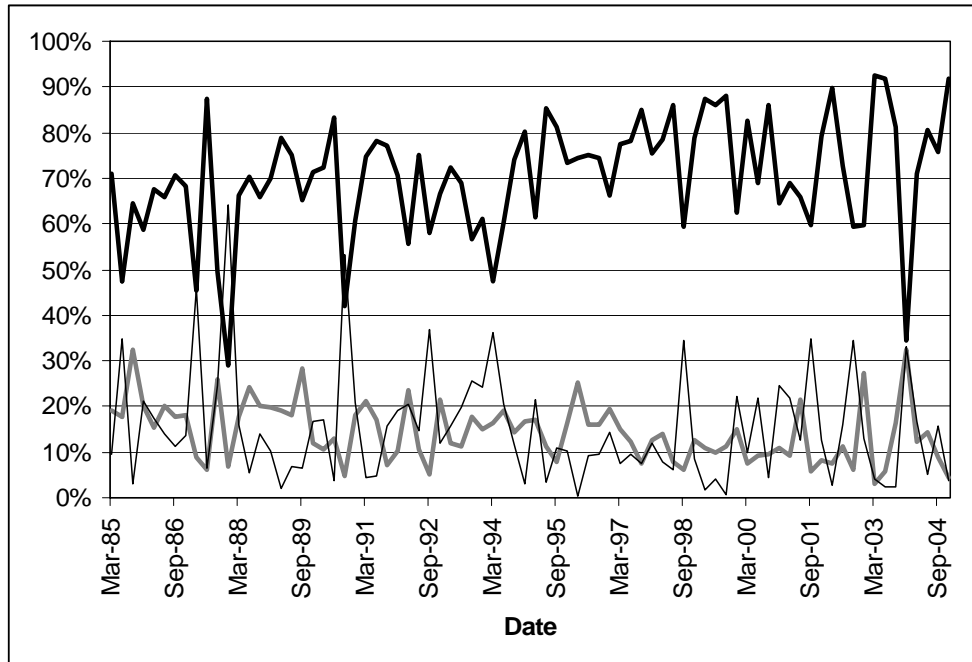
The thick black line denotes FIRM as a share of total. The thin black line denotes MKT as a share of total. The grey line denotes IND as a share of total.

The relative proportions of the three volatility measures, i.e. the share of total volatility, are depicted in Figure 6. The figure confirms the finding discussed earlier that FIRM is the dominating volatility measure. It has increased from a share of approximately 70 % in 1985 to 90 % in the beginning of 2005. During the turmoil of 1987 and the beginning of 1990s MKT had for a short period the largest share, but otherwise the shares for MKT and IND are mostly considerably smaller. The volatile periods of 1987 and the beginning of 1990s are characterized by a drop in the market as a whole, which explains the behavior of the shares during these periods. Campbell et al. (2001) and Guo and Savickas (2005) down-weight the crash in October 1987 to minimize the outlier effect. According to Hong and Stein (2003) the large fluctuations in stock prices was partly caused of microstructural distortions created of chaotic conditions on financial markets. Even though we observe a similar peak in our data we do not follow them in the down-weighting scheme, noting that our values are not that extreme.

5.2 Identification of possible trends

The figures presented above raises the question of possible trends for the volatility measures. We start by reporting a correlation matrix for the series in the Table 3.

Table 3
Correlogram

	FIRM	IND	MKT
FIRM	1	0.7025	0.4510
IND	0.7025	1	0.5729
MKT	0.4510	0.5729	1

The correlation between FIRM and IND is the highest, followed by the correlation between IND and MKT. Least correlated is FIRM and MKT. In Table 4 we report the autocorrelation structure for the volatility measures.

Table 4
Autocorrelation structure

Lag	MKT	IND	FIRM
1	**0.253**	**0.222**	**0.557**
2	0.053	0.065	**0.353**
3	0.053	**0.239**	**0.299**
4	**0.237**	**0.274**	**0.220**
5	**0.248**	0.020	**0.184**
6	**0.080**	0.028	**0.142**
12	0.055	0.144	**0.080**

Bold indicates significant autocorrelations. The
lag order is numbered to the left.

All series show high serial correlations were FIRM has the highest number of significant lags. This raises the question of whether the series contains a unit root. In Table 5 we report the Dickey-Fuller unit root test. The null hypothesis of a unit root is rejected at the 1% significance level for all volatility measures regardless of whether a deterministic trend coefficient is included in the regression, or not.

Table 5
Unit Root Test

t-values	MKT	IND	FIRM
DF	-6.915***	-7.556***	-5.533***
Trend	1.315	2.333**	2.621***

The table reports the *t*-values from the Dickey-Fuller test. *** indicates significance at the 1% level, ** at the 5% level and * at the 10% level.

The series are all trend stationary and therefore any shock to the price will only have a temporary effect. We conclude that the analysis of the volatility measures can proceed in levels rather than first differences.

For FIRM we detect a highly significant linear trend coefficient, 8.94*** (Trend • 10^4). The coefficient for IND is also significant but at a lower level and has a smaller size, 2.14** (Trend • 10^4). For MKT we are unable to identify any trend and consider it as a stochastic variable. Because all volatility measures are trend stationary the standard trend tests are not valid. Vogelsang (1998) developed a test that has good size properties, is valid in the presence of nonstationarity and robust to various forms of serial correlation. We follow Campbell et al. (2001) and Guo and Savickas (2005), among others, in performing the Vogelsang's PS test on our volatility measures. For a detailed algebraic survey, see Vogelsang (1998).

Table 6
Vogelsang's PS – statistic

t-values	MKT	IND	FIRM
PS	2.452	3.965*	5.843**

The asymptotic distributions are reported in Vogelsang's (1998) Table II, p. 135. For the 90% interval the critical value is 3.017, for 95% interval 4.537 and 99% interval 8.759.

The results from the unit root test are confirmed. The PS-statistic is significantly higher for FIRM, 11.16**, than for IND, 3.22*. For MKT we again fail to reject the null hypothesis of a stochastic trend. This implies that individual stocks have become more volatile over the past twenty years. The increase in the idiosyncratic risk is in line with Campbell et al. (2001). Guo and Savickas (2005) find trends both with a value-weighted

and equal-weighted scheme when using data ending in 1997. For data ending in 2003 they can not identify trends arguing that results are sensitive to the turmoil in the beginning of the 2000s. Because they fail to detect any trend in value-weighted idiosyncratic volatility, they also argue that this pattern is a consequence of the increasing number of publicly traded companies.

5.3 Predictive power and cyclical behavior

After having detected trends and accomplished a statistical and graphical analysis, we examine whether the volatility measures help to forecast each other. First we perform a Granger-causality test and then we run regressions to see if the volatility measures can help to forecast GDP growth and market return.

In Tables 7 and 8 we report the p-values for the estimated vector autoregressive (VAR) models. This is useful when forecasting only one variable, where past values of one series help to predict future values of other series, see Wooldridge (2002, Chapter 18, p. 625-628).

Table 7
Bivariate VAR model with 2 lags

t-1 / t	MKT	IND	FIRM
MKT	-	0.054	0.069
IND	0.210	-	0.198
FIRM	0.027	2.6E-05	-

The table reports the *p*-values from the Granger-causality bivariate VAR model. The left column is at time *t*-1 and the upper row at time *t* for every volatility measure respectively.

MKT tends to Granger-cause both IND and FIRM on the 10% significance level. IND does not Granger-cause MKT nor FIRM. But FIRM tends to Granger-cause both MKT and IND at the 5% significance level.

For completeness we repeat the same test choosing the lag length according to the Akaike Information Criterion. AIC is information criteria often reported as part of output information when performing regressions in statistical packages. A low value of AIC in regression output indicates a high fit of the model for the estimated data, for a detailed

algebraic survey see Akaike (1973). The null hypothesis is that lag 1 through q of one series does not help to predict another series a time t, see for example Guo and Savickas (2005, p. 16).

Table 8
Bivariate VAR model with optimized lag length

t-q / t	MKT	IND	FIRM
MKT	-	0.011 (5)	0.275 (5)
IND	0.306 (5)	-	0.269 (5)
FIRM	0.051 (3)	0.001 (3)	-

The table reports the *p*-values from the Granger-causality bivariate VAR model. The right column is at time *t-q*, where *q* is the optimal lag length chosen according to the Akaike information criterion, and the upper row at time *t* for every volatility measure respectively. Number of lags reported in parentheses.

MKT tends to Granger-cause IND at the 5% significance level, but not FIRM. As in the previous case, IND does not Granger-cause MKT or FIRM. FIRM tends to Granger-cause MKT at the 5% significance level (marginally insignificant) and IND at the 1% significance level. We conclude that IND does not help to predict any of the other volatility measures. MKT helps to predict IND and FIRM helps to predict both MKT and IND. These results are in line with Campbell et al. (2001). They find that both FIRM and MKT lead the other volatility measures significantly.

After concluding that the three volatility measures in some cases have a lead relation with themselves, we wish to explore if they have the power to forecast GDP growth. Table 9 presents the OLS regression of GDP growth as dependent variable and combinations of lagged volatility measures, lagged value-weighted AFGX and lagged GDP growth as independent variables. Here we use AFGX instead of the equal-weighted market index to explore the explaining power when including market values in the regressions. We do not find any noticeable difference when using the equal-weighted index instead but choose to use the value-weighted index in line with Campbell et al. (2001).

Table 9
Cyclical Properties of GDP growth

GDP_{t-1}	$AFGX_{t-1}$	MKT_{t-1}	IND_{t-1}	$FIRM_{t-1}$	R^2
0.519	**0.033**				0.437
(0.000)	(0.005)				
0.523	**0.033**	0.003	-0.034	0.009	**0.459**
(0.000)	(0.011)	(0.943)	(0.099)	(0.084)	
0.519	**0.033**	-0.003			0.437
(0.000)	(0.005)	(0.909)			
0.515	**0.035**		-0.008		0.438
(0.000)	(0.005)		(0.639)		
0.529	**0.031**			0.004	0.444
(0.000)	(0.012)			(0.397)	
0.513	**0.035**	0.004	-0.011		0.439
(0.000)	(0.008)	(0.913)	(0.671)		
0.533	**0.031**	-0.013		0.006	0.447
(0.000)	(0.014)	(0.652)		(0.256)	
0.524	**0.034**		**-0.032**	0.009	0.459
(0.000)	(0.007)		(0.036)	(0.080)	

The table reports the coefficients from OLS regressions with GDP growth at time *t* as dependent variable. *p*-values reported in parentheses. All variables are on quarterly frequency. Bold indicates significant coefficients at the 5% significance level. In the right column we report the adjusted R-square for every regression respectively. The largest adjusted R-square is marked bold. All regressions are performed with White heteroskedasticity-consistent standard errors & covariance.

When GDP growth is regressed on its own lag and lagged AFGX we observe an adjusted R-squared of 43.7%. These two variables remain significant and nearly unchanged throughout all regressions, and the measure of goodness of fit remains nearly unchanged when including combinations of the volatility measures. Next we include the volatility measures, which remain insignificant throughout the regressions (with an exception for IND_{t-1} in the last regression). This is in line with our expectations since all series are positively correlated.

We test for joint significance using the Wald-test, which is a test for multiple hypotheses. The obtained Wald statistic is asymptotically chi-square distributed, see Wooldridge (2002, Appendix E, p. 798). The coefficients are strongly jointly significant when all are included. When testing only for the volatility measures we find that they are jointly insignificant in all possible combinations, with one exception. There is no conclusive evidence for which of the volatility measures have the highest predictive power but IND_{t-1} is negative and significant in the last regression. The joint test for IND_{t-1} and $FIRM_{t-1}$ has a *p*-value of 0.074 which is significant at the 10% significance level. These results diverges somewhat form the ones in Campbell et al. (2001). They find strong joint significance among the volatility measures and individual significance when only one volatility measure is included. In line with our results, they can not point out conclusive evidence for which of the volatility measures have the highest predictive power, see Campbell et al. (2001, p. 34-35).

We also run the regressions to find out if the second up to the twelfth lag has some predictive power, without detecting any results of interest.

Further we run regressions to explore whether the lagged volatility series have the power to forecast market return. Neither for the value-weighted AFGX, for the constructed equal-weighted market index, for MSCI Sweden Value Index, nor for MSCI Sweden Growth Index is there any significant evidence[8]. We thereby conclude that the volatility series have no power to predict market return.

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[8] MSCI Sweden Value and Growth are aggregated indexes based on the stocks categorized as value and growth companies respectively. We calculate with indexes in return index form. For a detailed description and definitions, see www.msci.com

6. Discussion

We have shown that there has been a significant increase in the idiosyncratic risk on the Swedish stock market over the last 20 years. In this section we discuss possible reasons to our findings and relate to recent explanations in the literature.

From a market structure perspective the financial environment has changed considerably during this period. Information technology has made the information flows more transparent and liquid. Campbell et al. (2001) argue that this should have a decreasing effect on the idiosyncratic volatility because news arrives faster to the market. Accessibility through internet has on the other hand made it easier for private investors to be engaged in day trading. According to Frazzini and Marsh (2003) this argument combined with declining transaction costs contribute to the increase in volatility and trading volumes.

We have to consider the environment on the Swedish stock market when comparing our results to recent literature. Sweden is in an international comparison seen as a small open market with a low degree of diversification. In comparison with the main stock markets in the world, the Swedish market is characterized by a small amount of listed firms and few industries with few big actors that has a large influence. These characteristics have partly changed because of financial integration and internationalization. Due to increased harmonization, transparency and cross-border capital flows, the competition have increased remarkably over the past twenty years. Irvine and Pontiff (2005) argue that these developments in combination with deregulation have caused idiosyncratic volatility to increase. This argument is central for Sweden due to the liberalization of governmentally owned firms. Several of them have been partly or fully privatized and listed, increasing the number of listed firms but also the number of private shareholders. The government has partly played an active role to increase the number of private

shareholders due to massive lobbying and advertisement when for example the listings of AssiDomän[9] and Telia[10] took place.

Institutional ownership is argued by Frazzini and Marsh (2003), among others, to be an extensive cause for the increased idiosyncratic volatility. They argue that institutions tend to make similar investment decisions and react fast to new information that affects the market. Therefore they expect a positive relation between increased institutional ownership and the increase in idiosyncratic volatility, see Frazzini and Marsh (2003, p. 27). For Sweden we conclude that there has been an increase of institutions, for example domestic and foreign pension funds, mutual funds and other institutional investors over the past twenty years. We can however not make any statistical analysis of whether this contributes to the increase of idiosyncratic volatility or not.

The increase of newly listed stocks is according to Wei and Zhang (2003) an important reason for the upward trend in idiosyncratic volatility. They argue that a small firm that grow fast and is rather unprofitable affects the total market volatility positively. In our data material we observe an increase of newly listed firms during the bull-market at the end of 1990s. This occurs in parallel with a more volatile period on the market. We are unable to make any conclusions of whether this connection is statistically significant for Sweden, as in the previous case. Brandt, Brav and Graham (2005) argue that small low-priced stocks can co-move with different variables that reflects liquidity risk. They argue further that low-priced stocks have more volatile firm fundamentals as a reason partially explaining the upward trend. This could however show a false picture in our data material since we do not pay attention to the market value. Therefore we leave the investigation of this cause for future research in the field.

Brandt, Brav and Graham (2005) discuss the possibility of market microstructure biases contributing to increased idiosyncratic volatility. For Sweden we can however not find

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[9] AssiDomän, a governmentally owned forestry company, was partly privatized and listed in 1994, and de-listed in 2001, following a re-acquisition by the government and name change to "Sveaskog".
[10] Telia, a governmentally owned provider of telecommunication, was partly privatized and listed in 2000 following a consolidation with Finnish Sonera in 2004.

any literature that argues for an abnormal development of spreads, trading days, sales volumes and so forth. In contrast, we argue that this reason should instead have a diminishing effect on idiosyncratic volatility due to increased information transparency and standardized trading rules. Like Brandt, Brav and Graham (2005) we conclude that this rationale has little or no power in explaining the upward trend. There are several reasons suggested in the literature where authors find no evidence of significant influence. Campbell et al. (2001) discuss for example the possibility of financial innovations being a rationale. They can however not show any significant evidence to this statement.

We think that in a wealth of explanations, logic rationales for the increase of idiosyncratic risk on the Swedish stock market are increased competition and increased number of newly listed firms in high-risk industries. The arguments for increased competition are internationalization and deregulation which results in a higher number of actors on the market. For the increased number of newly listed firms in high-risk industries we refer to the boom in the information technology industry during the late 1990s and early 2000s. During this bull-market period we observe a particularly high increase of listed firm, from 19 in 1997 to 70 in 2001 (near 270%). After the boom the number of listed firms in this industry seems to revert slightly, being 59 in 2004.

This raises the question of whether the upward trend that we identify, like Brandt, Brav and Graham (2005) argues, results form episodic turbulence caused by periods of bull-market turmoil. We leave this question for future research, as well as statistically establishing significant rationales for the increase of idiosyncratic volatility.

7. Concluding Remarks

In this paper we have studied the empirical patterns of idiosyncratic risk on the Swedish stock market. We have decomposed the aggregate volatility into three components, market-specific, industry-specific and firm-specific volatility. We find evidence for a significant upward trend in firm-specific volatility and a weaker upward trend in industry-specific volatility. For market-specific volatility we can not identify any trend of significance. Firm-specific volatility tends to lead the other series and market-specific volatility tends to lead industry-specific volatility. None of the volatility series have the power to forecast GDP growth or market return. The results are in line with our precursors Campbell et al. (2001).

The suggested reasons for the upward trend are a higher degree of competition on the market and an increase of newly listed firms in industries with above average volatility. For the competition argument we refer to the globalization and internationalization of financial markets over the past two decades. Deregulation is assumed to have an important influence too. The number of newly listed firms engaged in the information technology industry boomed during the bull-market in the late 1990s and early 2000s, showing a reverting pattern in the following bear-market. Many of these firms were only listed for a short period and had the characteristics of being small and unprofitable.

A wealth of literature discusses different possible reasons for increases in idiosyncratic volatility on various stock markets around the world. We make our conclusions for possible reasons after having paid attention to the environment on the Swedish stock market. The specific characteristics for this market indicate in favor for the rationales that we identify. We do not show any statistical evidence for the causes behind the upward trend. This is leaved for future research as well as the question of whether the upward trend actually results from episodic turbulence.

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