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How wacky is the DAX? The changing structure of German stock market volatility

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Abstract

In this paper we investigate the volatility structure of the German stock market index DAX and its constituents. Using a recently developed test, we find a volatility break in 1997. Interestingly, not only is the volatility higher after 1997 but the volatility persistence also increased. That means that there is a greater likelihood of high volatility days being followed by further high volatility days. An immediate consequence is that the tails of the distribution of stock market returns become fatter or that the probability of extreme price movements becomes greater. The break in volatility is not only a phenomenon of the index itself; the returns of the underlying equities also show a volatility break. If the volatility is decomposed into market and firm-specific or idiosyncratic components, the idiosyncratic volatility is shown to have increased much more than the market volatility. This is probably connected to the declining correlations among individual stock returns and has implications for portfolio diversification.

When analysing potential reasons for the break in volatility, we find that the increase in the volatility of the German stock market cannot be attributed to international spillovers alone. Domestic factors which may help to explain the break in volatility are the growing number of institutional investors and the increase in the volatility of longer-term interest rates.

Keywords: market and idiosyncratic volatility, test on break in volatility dynamics, institutional ownership

JEL Classification: C32

Zusammenfassung

Dieses Arbeitspapier analysiert Veränderungen der Volatilität des Deutschen Aktienindex (DAX) und der in ihm enthaltenen Aktienwerte. Ein kürzlich entwickelter Test zeigt einen Bruch im Ausmaß der Schwankungen der Aktienrenditen im Jahr 1997 an. Seitdem nahm nicht nur die Volatilität der täglichen Aktienrenditen deutlich zu, sondern es stieg auch deren Persistenz an. Das heisst, auf Tage mit hohen Schwankungen folgen jetzt viel häufiger Tage mit ebenfalls hoher Volatilität. Die ebenso höhere Wahrscheinlichkeit extremer Preisschwankungen zeigt sich darin, dass die Verteilung der Aktienkurserträge deutlich mehr Masse in den Rändern aufweist. Interessanterweise lässt sich der Bruch in der Volatilität nicht nur im Index, sondern auch bei fast allen Einzelwerten etwa zum selben Zeitpunkt nachweisen. Eine Zerlegung der Volatilität in eine Marktkomponente und eine firmenspezifische oder idiosynkratische Komponente zeigt desweiteren, dass letztere viel stärker angestiegen ist als das systematische oder Marktrisiko. Im Zusammenhang damit stehen die gesunkenen Korrelationen zwischen den Einzelaktien; diese haben Auswirkungen auf die Risikodiversifikation eines Portfolios.

Als mögliche Ursachen für den Anstieg der Volatilität können nicht allein Übertragungen von Schwankungen anderer internationaler Märkte, insbesondere des amerikanischen Marktes, gelten. Heimische Faktoren, die helfen können den Bruch in der Dynamik der Schwankungen der Aktienerträge zu erklären, sind die zunehmende Rolle institutioneller Investoren am Aktienmarkt und die steigende Volatilität von Langfristzinsen.

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1 Introduction

It has now become commonplace to observe that the volatility of the stock market has increased considerably, particularly in the last few years. However, despite an ample supply of sophisticated models covering volatility phenomena, there has been no coherent analysis of structural breaks in the volatility dynamics of German asset returns and their causes.

Looking at the leading German stock index, the Deutscher Aktienindex (DAX), and its constituents from 1988 to 2002, we find a significant break in volatility. Since 1997 stock market volatility has shown a pronounced upward shift. Coinciding with the asset price boom and its following upswing, returns on individual shares and on the index have become far more erratic. In particular, there has been an increase in the volatility persistence, leading to a more pronounced clustering of extreme returns.

Furthermore, if we decompose volatility, we find that idiosyncratic risk, if measured by the idiosyncratic volatility component, has increased far more than the market component of volatility. This is probably connected to the declining correlations among individual stock returns and has implications for portfolio diversification.

We relate the increasing volatility and volatility persistence to the growing influence of institutional investors on the German market. Besides, variations in the discount factor for asset returns approximated by the volatility of interest rates would seem to play a role in explaining the volatility shift. Movements of US stock market returns, although showing marked similarities with German developments, do not completely explain the structural break in volatility.

*This paper represents the authors' personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank.

Why should we be concerned about volatility? From an orthodox economic point of view stock market volatility reflects the information processing mechanism of investors and some noise coming from liquidity traders. Higher volatility is therefore connected with a growing volume of news or a greater level of uncertainty about the future state of the economy. Inconveniences such as hedging against large and more clustered downswings have to be borne by individual investors.

However, with the growing importance of capital markets in Germany, greater attention has been paid to relations between volatile stock markets on the one side and monetary and real side macro variables on the other side. Share price volatility has an impact on output and inflation volatility and vice versa (Beltratti and Morana (2002), Schwert (1989)), can lead to ruptures in the balance sheet transmission channel of monetary policy and may hamper consumer spending via wealth effects (Mishkin (2001)). Extreme volatile blips can jeopardise the smooth functioning of financial markets if liquidity dries up or hedging becomes too costly. Consequently, the economy has become more vulnerable to risks resulting from strains on financial and, especially, stock markets in a high volatility scenario.

Although, from both the financing and the investment perspective, the German economy is less dependent on equities than many other countries, compared with stock market movements in other developed countries the increasingly high volatility of the DAX—especially in 2002—clearly indicates a need to take a closer look at stock market volatility.

The remainder of the paper is organised as follows. First, we define different concepts of volatility and explain measurement methods employed in the paper. After a brief description of the data, we test for structural changes in volatility by means of CUSUM breakpoint tests. Next, volatility is decomposed into a market and an idiosyncratic component as an initial attempt to explain the increasing volatility patterns. The role played by institutional investors, interest rates and the US stock market in explaining German stock market volatility is investigated in the subsequent section. The paper concludes by outlining the importance of our findings of increased stock market volatility and suggests future lines of research.

2 Methods

This paper focuses on the volatility structure of the German stock market. The question of how to measure volatility correctly therefore arises naturally. It is helpful to differentiate between parametric and non-parametric measures of volatility, as proposed in a recent survey by Anderson, Bollerslev, and Diebold (2002).

Among non-parametric volatility measures, rolling sample and realised volatility measures have attracted special attention. The two concepts are related but differ in the focus of the time horizon. If the price of a stock at time t is denoted as p_t, the daily log returns are:

$$r_t = \ln(p_t) - \ln(p_{t-1}).$$

Now we can calculate a backward looking rolling sample volatility estimator for each day by averaging the squared returns r_t^2 over the last n (for example, 21) days:

$$\hat{\sigma}_t^2 = \sum_{i=1}^{n} r_{t-i}^2/n. \tag{1}$$

The measure $\hat{\sigma}_t^2$ estimates the volatility for each day. By contrast, the idea behind the realised volatility is to use higher frequency data to compute lower frequency volatility estimates. In our case we use daily returns to compute volatility estimates for each month[1]:

$$\hat{\sigma}_m^2 = \sum_{i^*=1}^{n^*} r_{i^*}^2/n^*. \tag{2}$$

To analyse the relation between these two measures it is convenient to assume that the log price follows a continuous time process. An interesting example is the so-called GARCH diffusion[2]:

$$\begin{aligned} d\ln p(t) &= \sigma(t)dW_p(t) \\ d\sigma^2(t) &= \theta[\omega - \sigma(t)]dt + (2\lambda\theta)^{1/2}dW_\sigma(t). \end{aligned} \tag{3}$$

[1]In this term the index i^* runs over all n^* trading days in the month m.

[2]In this equation $W_p(t)$ and $W_\sigma(t)$ are Wiener processes which are continuous time counterparts of random walks. Broadly speaking, the terms $dW_p(t)$ and $dW_\sigma(t)$ are therefore continuous time white noise error terms.

If the price process generated by equation 3 is sampled at discrete and equally spaced points p_t, the discrete process follows an exact GARCH(1,1) model:

$$\begin{aligned} \Delta \ln p(t) &= r_t = \sigma_t z_t \\ \sigma_t^2 &= \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2, \end{aligned} \tag{4}$$

with parameters related to the parameters of the GARCH diffusion (equation 3) in a specific manner (Drost and Werker (1996)). In equation 3, $\sigma^2(t)$ is the instantaneous volatility. It is the volatility relevant for a small (in theory, infinitesimal) interval around time t. If the average volatility over a larger interval is of interest, integrated volatility

$$\sigma_{\Delta,t}^2 = \int_t^{t+\Delta t} \sigma^2(u) du, \tag{5}$$

is the right concept to use. The instantaneous volatility is related to the conditional variance while the integrated volatility is related to the unconditional variance. It has been shown that the rolling sample volatility estimator (equation 1) is a consistent estimator for instantaneous volatility (Andreou and Ghysels (2002b)) while the realised volatility estimator (equation 2) is a consistent estimator for integrated volatility (Barndorff-Nielsen and Shepard (2002)). The main advantage of these non-parametric volatility estimators is that they function independently of a specific model such as the GARCH diffusion (equation 3). Both measures are valid for more general stochastic processes.

Parametric volatility measures are an alternative. The most often used parametric models are stochastic volatility models and GARCH type models.[3] In the paper we use a GARCH(1,1) model because it is flexible enough to describe the most important stylised facts of our asset return data. The GARCH(1,1) model actually used

$$\begin{aligned} r_t &= \mu + \phi r_{t-1} + \sigma_t z_t \\ \sigma_t^2 &= \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2, \end{aligned} \tag{6}$$

[3]The parametric GARCH models can also be interpreted in a non-parametric manner. This interpretation considers a GARCH model as a filter for a general stochastic process. See Anderson, Bollerslev, and Diebold (2002). However, this interpretation is not used in this paper.

is slightly more general than equation 4 and allows for a drift and serial correlation in the return process r_t. The main advantage of parametric models over non-parametric volatility measures is that they allow the volatility process to be interpreted in greater detail. If, for example, a non-parametric volatility measure shows an increase in the (average) volatility after a certain point in time, this may be attributable to different changes of the parameters of an underlying parametric model. The unconditional variance of a GARCH(1,1) process is given by:

$$\sigma^2 = \frac{\omega}{1-\alpha-\beta}, \tag{7}$$

and an increase in the volatility can be caused either by an increase in ω or $\alpha+\beta$.[4] The interpretations of these two possibilities are rather different. If an increase in ω is the reason for the higher overall volatility, the volatility clustering is not effected. If, instead, a larger $\alpha+\beta$ is the reason for the higher volatility, the volatility persistence also increases. This has different consequences for capital market participants. A higher volatility persistence implies not only a higher volatility but also a stronger volatility clustering. High volatility trading days are more likely to be followed by further high volatility trading days. In addition, a higher volatility persistence causes an increase in the fatness of the tails of the unconditional distribution of the returns. A higher volatility persistence implies a higher kurtosis of the unconditional distribution of a GARCH(1,1) process given by (Franses and van Dijk (2000)):

$$K = \frac{3(1-(\alpha+\beta)^2)}{1-(\alpha+\beta)^2-2\alpha^2}. \tag{8}$$

3 Data

The DAX comprises the 30 largest and most actively traded listed German companies. The index capitalisation captures nearly 60% of overall stock market capitalisation.[5] Its order-book turnover accounts for 87% of total order-book turnover of

[4] $\alpha+\beta<1$. In the following we will call $\alpha+\beta$ the volatility persistence.

[5] Since 24 June 2002 the DAX has been free float weighted and makes up around 50% of the market capitalisation of all domestic equities.

domestic equities on all German exchanges and for 90% on the electronic trading platform XETRA.[6] We use the DAX price index calculated as a Laspeyres-type index on the basis of the daily closing prices of the 30 constituents. The index and firm level prices were obtained from the Deutsche Börse AG. In the price series of the constituents we deal with stock split-ups, mergers, and company exchanges by using chaining and adjustment factors. Using the compound series of the particular actual index constituents avoids the issue of survivorship bias.[7] Our sample runs from 31 December 1987, the base date of the DAX, to 31 December 2002.

We calculate daily weights for the index constituents using a centered rolling OLS regression with a 40-day window and HP-filtered them with $\lambda = 10^9$. The recalculated return series from the weighted returns of the 30 constituents shows a correlation of 0.979 with the original index returns. When analysing the rolling sample estimator with a window width of 21-days, the recalculated series from the weighted individual returns behave much as the original DAX return series.[8]

4 Structural break in volatility

To assess whether there is a change in the structure of the stock market volatility, a good place to start is with a non-parametric volatility measure. Figure 4 on page 13 shows the rolling sample volatility of the DAX returns for a 21-day window. The figure suggests, that average volatility is higher in the last quarter of the sample. Formal testing puts these results on a sound statistical basis. In this paper we use a test on breaks in the dynamics of general ARCH(∞) models proposed by Kokoszka and Leipus (1999, 2000) and discussed extensively by Andreou and Ghysels (2002a).

[6]Source: Deutsche Börse AG. Figures are for December 2002.

[7]The coefficient of variation shows a higher value for compound series although ANOVA indicates no statistically significant difference.

[8]In addition, the actual weights capturing the ratio of shares of a company to overall shares on the base date adjusted for share splits, subscription rights and company exchanges are highly correlated with our estimated weights (0.98 for daily weights and 0.96 for monthly weights). Since actual daily and monthly weights could not be obtained for the full sample period, correlations could be calculated only for sub-samples.

The test is based on a recursively computed sum of squared returns (R_k):

$$R_k = \left(1/\sqrt{T} \sum_{j=1}^{k} r_j^2 - k/(T\sqrt{T}) \sum_{j=1}^{T} r_j^2 \right), \tag{9}$$

where $0 < k < T$, and belongs to the category of CUSUM (cumulated sum of squares) type tests. Using R_k it is possible to construct a test with the null hypotheses of no change against the alternative of a change in the volatility dynamics at an unknown change point. The test statistic:

$$\max_{1 \leq j \leq T} |R_j|/\hat{\sigma}, \tag{10}$$

where $\hat{\sigma}$ is an estimator of $\sigma = \sqrt{\sum_{j=-\infty}^{\infty} \mathrm{Cov}(r_j, r_0)}$, behaves asymptotically like a Kolmogorov-Smirnov-type distribution (Andreou and Ghysels, 2002a). An autocorrelation and heteroscedasticity consistent estimator $\hat{\sigma}$ is necessary to carry out this test and we use the Vector Autoregression Heteroscedasticity and Autocorrelation Consistent (VARHAC) estimator, as recommended by Andreou and Ghysels (2002a).

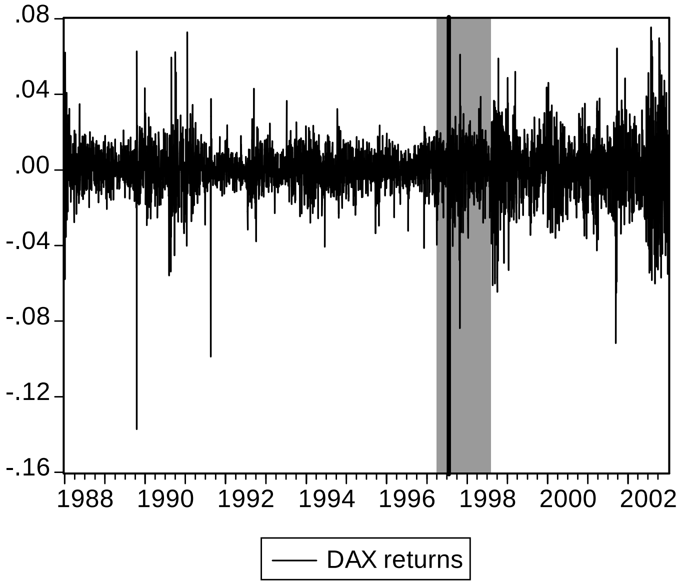
Apart from the question of whether there is a break in the volatility dynamics at all, it is interesting to estimate the break date. A consistent estimator of the breakpoint is:

$$\hat{k} = \min \left(k : |R_k| = \max_{1 \leq j \leq T} |R_j| \right). \tag{11}$$

To get an impression about the estimation uncertainty of the break date, we have implemented confidence intervals based on a wild-bootstrap procedure similar to a method recently proposed by Goncalves and Kilian (2002) in a different context. The test statistic for the break test (equation 10) calculated for the DAX log returns takes a value of 1.61 and therefore shows a break which is significant at the 5% level.[9] The estimated break date is 17 July 1997. Because, owing to estimation uncertainties, the break date is not known precisely, it is futile to ask what exactly happened on 17 July 1997. For this reason it is necessary to calculate confidence intervals, allowing for an assessment of other possible break dates. In Figure 1, the DAX returns

[9]The asymptotical critical value at the 5% significance level is 1.36. See Andreou and Ghysels (2002a).

Figure 1: DAX returns with volatility breakpoint

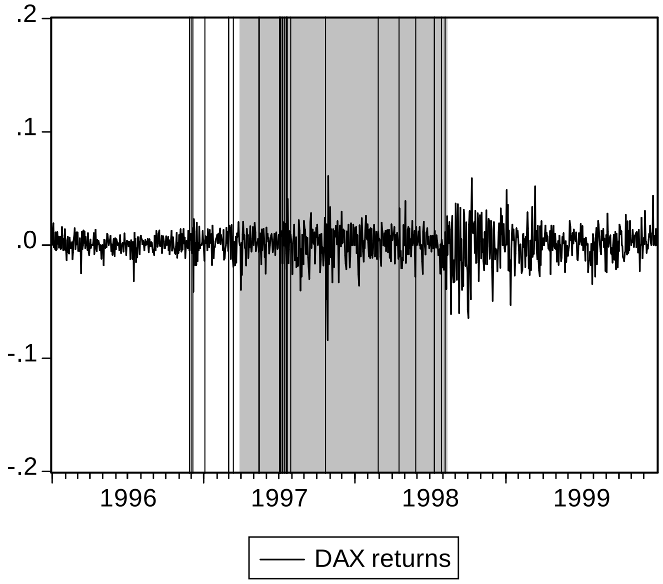


are plotted and the bold vertical line in 1997 shows the estimated breakpoint. The shaded area is the 95% confidence band around the point estimate.[10] It is interesting to note that the confidence band is asymmetric. It is therefore unlikely that the break occurred much before the beginning of 1997, although the break may possibly have taken place in 1998. This provides important pointers when attempting to find reasons for the break in volatility. The DAX is a compound series of 30 stocks and it is therefore interesting to analyse potential volatility breaks in the underlying stock prices. The vertical lines in Figure 2 on page 9 show the point estimates of the individual stock prices and the shaded area depicts again the confidence band for the DAX breakpoint. With the exception of one stock[11] all individual break dates are close to the DAX break date. Indeed, most of the breakpoints of the individual series are within the confidence interval for the DAX. This is rather surprising because the

[10]The lower limit of the confidence band is 27 March 1997 and the upper limit is 17 August 1998.

[11]The estimated breakpoint for one of the series is in 1993 (see Table A.1 in the Appendix) and is not shown in Figure 2.

Figure 2: Volatility breakpoints for individual stock returns



construction of the confidence interval for the DAX does not use information about underlying stock returns and most of these returns enter the DAX only with a small weight. This excludes the possibility of the break date of the DAX beeing a statistical artefact.

Once the break in the volatility of the German stock market index DAX has been identified, it is extremely relevant to analyse the structure of the volatility process before and after the break. The easiest way to do this is to estimate a GARCH model for the pre-break and the post-break period. Table 1 shows the estimated GARCH parameters. It is immediately apparent that the overall (unconditional) variance is much higher in the post-break period (3.50 as opposed to 1.29). This variance corresponds to equation 7. The reason for this is not an increase in the volatility level ω (equation 6) but an increase in the volatility persistence ($\alpha + \beta$). This finding is important. Not only is the overall volatility higher after the break; there is also an increased probability of volatility clustering. This also has implications for the kurtosis of the unconditional distribution of the stock returns. The kurtosis (calculated by equation 8) of the DAX returns ranges around 3 before the break and

Table 1: Pre-break and post-break GARCH estimates for the DAX index

Pre-break period					
ω	α	β	Persistence ($\alpha + \beta$)	Variance	Kurtosis
0.09	0.12	0.82	0.93	1.29	3.81
Post-break period					
ω	α	β	Persistence ($\alpha + \beta$)	Variance	Kurtosis
0.07	0.10	0.88	0.98	3.50	6.06

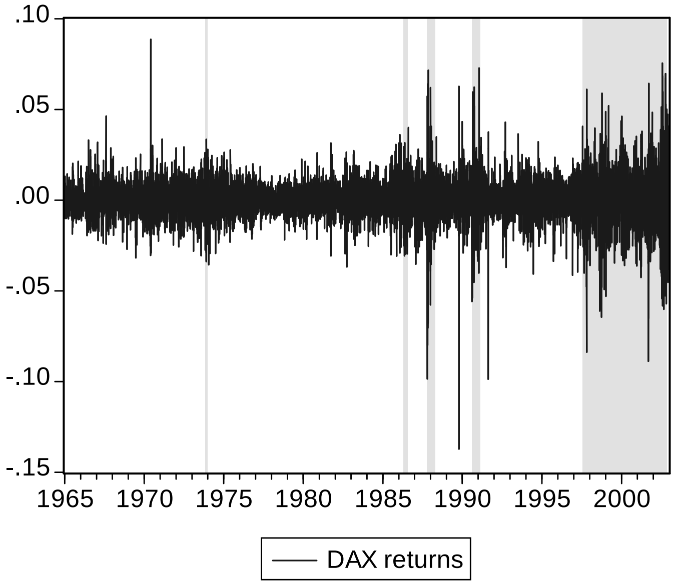
does not rule out the possibility of normally distributed log returns. After the break the kurtosis is about 6 and indicates an excess kurtosis of the returns. Table A.2 in the Appendix summarises the same calculations for all constituents of the DAX. The results are comparable to that of the index. For all series with a break in the variance dynamics, the unconditional variance is higher after the break.[12] For most of the DAX constituents the persistence and the kurtosis is therefore higher after the break. Interestingly, for some of the series the volatility level ω of the GARCH volatility equation (ω in equation 6) is higher after the break, a phenomenon which is not seen in the GARCH parameters for the index.

Given that there is a break in the volatility of the DAX stock market index, it is interesting to view this result from a long-term perspective. The DAX has been in existence since 1988 only, but we can use a recalculated stock price index which goes back to 1965.[13] For this time horizon we have estimated a Markov switching

[12] Series No 14 is an exception. For this series an IGARCH process would seem to be appropriate before and after the break, and the unconditional variance and kurtosis are therefore infinite in both periods.

[13] This series comprises the Hardy-Index, which is chained in 1981 to the Börsenzeitungsindex, which is chained to the DAX in 1988. The historical indices contain the equally weighted share prices of the largest German stocks. Since share price returns seem to be scale-dependent, the historical data may well present a distorted picture of the volatility of the stock market. In addition, it is only since 1988 that the German stock market index has been extensively used as a benchmark for investors, leading to different trading patterns for single stocks.

Figure 3: High volatility regimes of the German stock market



model for the log returns. In the model, two regimes are allowed and the intercept and the variance of the stock returns can switch between two values.[14] On the basis of this model, regime probabilities can be calculated for each day; the probabilities for a high volatility regime are shown in Figure A.1 in the Appendix. If we find that the stock market follows the high volatility regime for a few days only, we have no grounds to speak of a break in the volatility regime. To detect volatility regimes we therefore use a heuristic classification procedure. If the stock market volatility switches to another regime and the new regime lasts for a certain period of time, say one quarter, we detect a change in the volatility regime. It can switch back to the former regime if it also stays there for at least one quarter. Using this classification procedure, five high-volatility regimes can be identified; they are shown in Figure 3 as shaded areas. The first high volatility regime lasts from October 1973 to January 1974, the second from April 1986 to August 1986, the third from October 1987 to

[14]The estimations are performed using the Ox package MSVAR written by Hans Martin Krolzig (http://www.econ.ox.ac.uk/research/hendry/krolzig/) and the Ox programming language by Jurgen Doornik (http://www.nuff.ox.ac.uk/users/doornik/).

May 1988, the fourth from August 1990 to March 1991, and the fifth from July 1997 up to at least the end of 2002. The starting point of the last high volatility regime coincides perfectly with our estimated break date. This is surprising because the volatility break test and the Markov switching model are very different methods. However, the coincidence of the starting point of the most recent high volatility period demonstrates the robustness of the results. Interestingly, all high volatility periods apart from the one starting in July 1997 last less than half a year. Indeed, if we use a six-month criterium for the regime classification instead of one quarter, only the last period is found to be a high volatility regime. The 1997 break in the DAX seems to be an isolated occurrence, even when the German stock market is viewed from a broader historical perspective.

5 Volatility decomposition

Further investigations into changes in stock market volatility set out to detect underlying causes of the estimated structural break.

Looking first at the rolling 21-day window of squared returns, we calculate this non-parametric measure of volatility separately for the market return[15] and a compound series comprising the weighted sum of each individual firm's squared returns. The series are referred to as market volatility and aggregate volatility respectively. Figure 4 and Figure 5 on page 13 show distinctively different volatility behaviour from 1997 onwards. Taking aggregate firm volatility as the overall volatility of of the individual companies, it can be divided into a market and a firm-specific or idiosyncratic component. The idiosyncratic volatility part—the difference between aggregate volatility and market volatility—copies the result of the CUSUM breakpoint test. The idiosyncratic volatility level has increased fivefold since 1997 whereas market volatility has risen only by the factor of 2.7. A more complex method of volatility decomposition is described in the following paragraphs.

[15]Unless otherwise stated, the market return denotes the return of the recalculated DAX index comprising the weighted sum of its constituents returns.

Figure 4: Moving-window volatility

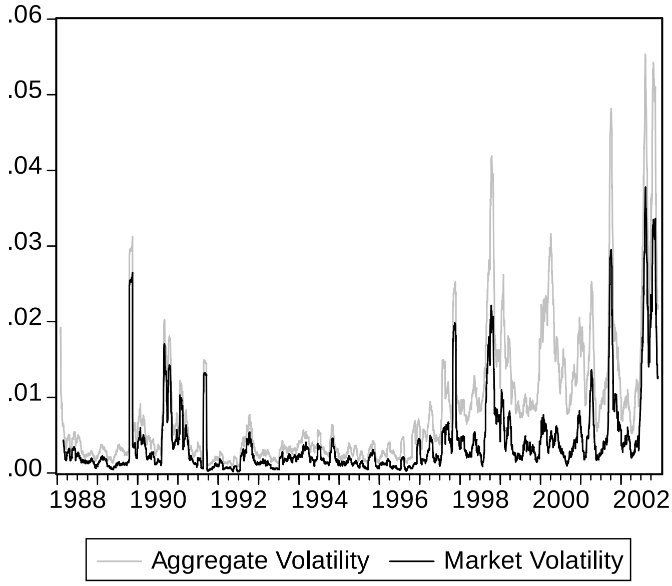
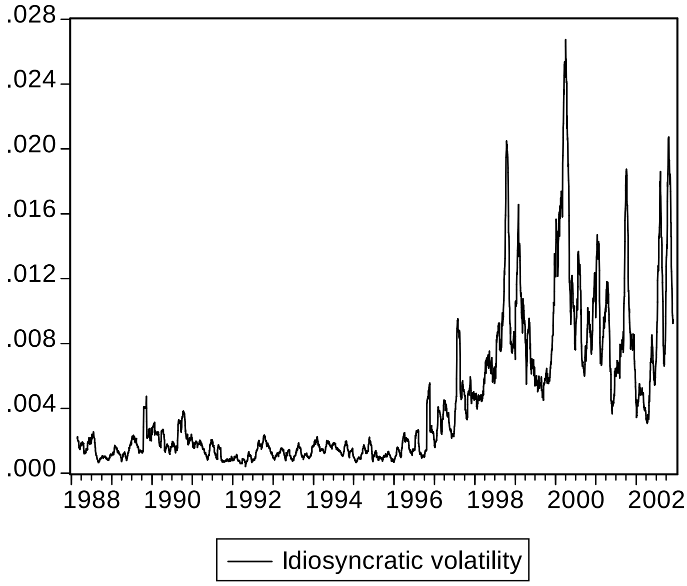


Figure 5: Moving-window idiosyncratic volatility



The idiosyncratic volatility of any one stock is unobservable. On the basis of the CAPM, the idiosyncratic or unsystematic return as well as the volatility of an individual company is measured relative to the systematic return or volatility of a firm. We follow Campbell, Lettau, Malkiel, and Xu (2001) in the decomposition, although we merely derive a company-specific and not an industry-specific component.

Let us denote the simple excess return of a firm $i = (1, ..., 30)$ in period t as $R_{i,t}$. This can be decomposed into an idiosyncratic component $R^I_{i,t}$ and the systematic excess return $\beta_i R^M_t$. β_i is the beta of firm i with respect to the market return and we assume that the sum of the different betas and the sum of the weights equals unity:

$$\sum_{i=1}^{30} w_{i,t} = 1 \qquad \sum_{i=1}^{30} \beta_i = 1. \tag{12}$$

Note that all returns are excess returns, ie returns exceeding the return of a safe interest rate,[16] to allow for interpretation of volatility as risk. If w_i is the weight of a firm i in the index, ie the market portfolio, the excess return on the market portfolio will be defined as:

$$R^M_t = \sum_{i=1}^{30} w_{i,t} R_{i,t}. \tag{13}$$

The return and variance decomposition for a typical stock yields:

$$R_{i,t} = \beta_i R^M_t + R^I_{i,t}, \tag{14}$$

$$Var(R_{i,t}) = \beta_i^2 Var(R^M_t) + Var(R^I_{i,t}) + 2\beta_i Cov(R^M_t, R^I_{i,t}). \tag{15}$$

Given equation 12 and our calculation of the market portfolio with the same weighting scheme the covariances and betas aggregate out when the weighted average of variances across companies is taken:

$$\sum_{i=1}^{30} w_{i,t} Var(R_{i,t}) = Var(R^M_t) + \sum_{i=1}^{30} w_{i,t} Var(R^I_{i,t}). \tag{16}$$

Inserting equation 13 gives:

$$\sum_{i=1}^{30} w_{i,t} Var(R_{i,t}) = Var(\sum_{i=1}^{30} w_{i,t} R_{i,t}) + \sum_{i=1}^{30} (Var R^I_{i,t}). \tag{17}$$

[16]The safe interest rate is the three-month Euribor, which replaced the three-month FIBOR, which replaced the short-term interest rate offered on the Frankfurt banking place.

Using daily returns, d, we construct volatility estimators at monthly intervals, t. To estimate the variance components (equation 16), we use the squared time series variation of the individual return component within each month.[17]

Denoting the estimators for market volatility as $\sum_{d\in t}(R_d^M)^2 = \hat{v}_t^M$, for aggregate volatility as $\sum_{i=1}^{30} w_{i,t} \sum_{d\in t}(R_{i,d})^2 = \hat{v}_t^A$ and the idiosyncratic volatility component as $\sum_{i=1}^{30} w_{i,t} \sum_{d\in t}(R_{i,d}^I)^2 = \hat{v}_t^I$, we can calculate the idiosyncratic volatility or unsystematic risk as:[18]

$$\hat{v}_t^I = \hat{v}_t^A - \hat{v}_t^M. \tag{18}$$

Figure 6 shows the aggregate volatility of a typical German blue chip stock and its two components. From 1997 onwards, the increase in overall volatility is clearly more attributable to a higher idiosyncratic risk component. The increase in the latter is more than twice that of the market volatility component. Although the market return is derived from the weighted returns of individual companies, the differences in the behaviour of idiosyncratic and market volatility can be reconciled by declining correlations among individual company returns. Declining correlations allow the volatility of the market portfolio to remain fairly stable or to show no more than a small increase even if there is a pronounced increase in the volatility of each individual stock. The sub-sample before 1997 shows an equally weighted average of pairwise correlations across the 30 constituents of 0.49, whereas the sub-sample from 1997 onwards exhibits only an average of 0.34.[19]

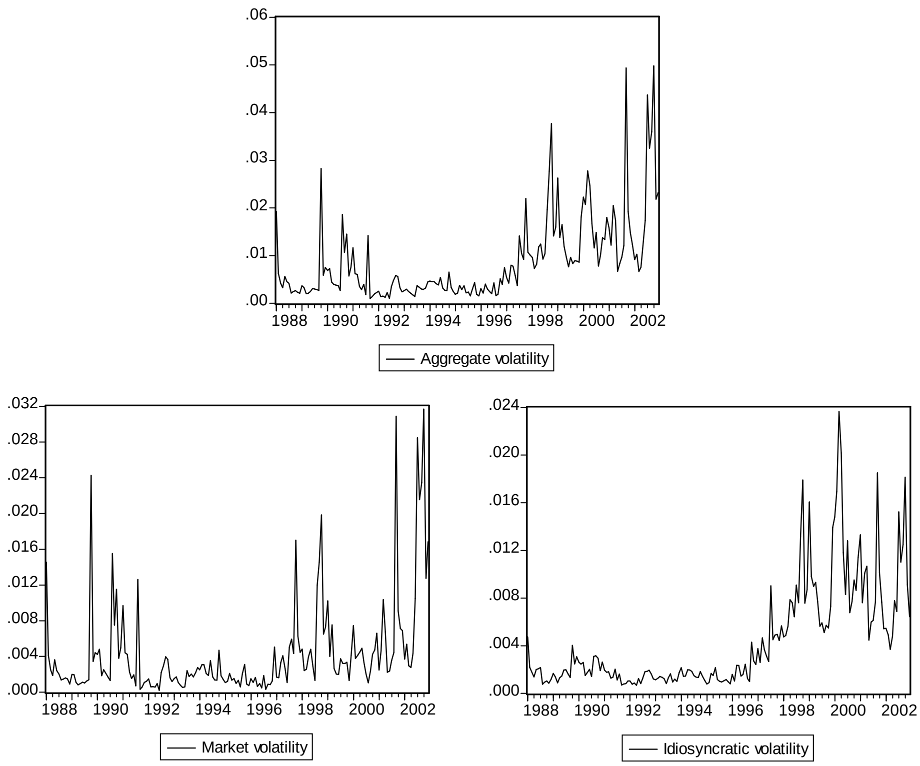
The implications are twofold. On the one hand, with higher idiosyncratic volatility, portfolio diversification becomes more beneficial since unsystematic risk can be eliminated if a mixture of different stocks are held. On the other hand, if, on account of wealth constraints, it is not possible to hold a well-diversified portfolio, increasing idiosyncratic volatility can overcompensate for the effects of declining correlations

[17]By using this measure of volatility instead of variances, we avoid the additional noise that comes from estimating the mean of the time series each month.

[18]A similar representation is used by Xu and Malkiel (2003).

[19]The correlation dynamics is documented by calculating the equally weighted average of all pairwise correlations for each month using the last 12-months daily observations. Nevertheless, correlation figures increase towards the end of the sample.

Figure 6: Volatility decomposition



among individual stocks and can put the portfolio at greater risk. Accordingly, in recent years private households in Germany have shown greater interest in already diversified investments in mutual funds than for direct investments in shares. The number of fund owners nearly quadrupled between 1997 and 2002 whereas the number of direct shareholders has not quite doubled (Deutsches Aktieninstitut (2002)).

6 What causes the shift in volatility?

For some years attempts have been made to determine what causes stock return volatility to be time varying. A recent overview of studies which focus mainly on the US market is given by Beltratti and Morana (2002), Schwert (2002), and Campbell, Lettau, Malkiel, and Xu (2001). Explanatory factors cover the volatility of macroeconomic and financial variables (Officer (1973), Schwert (1989)), the effect of news (Andersen and Bollerslev (1997), Funke and Matsuda (2002)) and firm-specific causes (Schwert (2002), Dennis and Strickland (2002)).

We restrict ourselves to endeavouring to explain the shift in volatility in Germany. As this shift appears in nearly every return series of the DAX and its constituents at around the same time we do not look for industry-specific or company-specific causes.[20] US stock indices are used to test whether volatility can be adequately explained by international spillovers. As another potential driving factor we test for the ratio of shares controlled by institutional investors to total market capitalisation. We then try to link uncertainty about the future net value of the DAX to the volatility of a discount factor as proxied by different interest rates.

First, it is important to test whether the volatility of the German stock market is driven by international factors only. We regressed the log returns of the DAX against the contemporaneous and lagged log returns of the S&P 100 and the Dow Jones Composite 65. The estimation results are shown in Tables A.4 and A.5 in

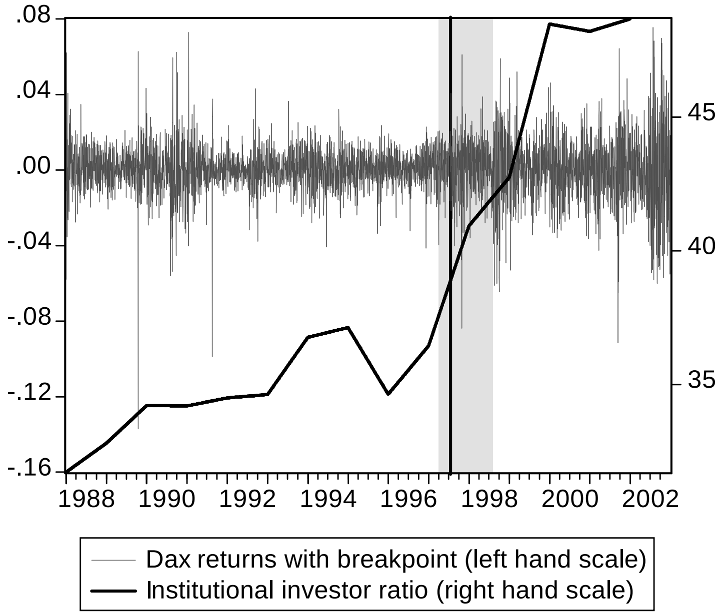
[20] A principal component analysis of the volatility series of the constituents of the DAX shows no significantly different behaviour of shares of different industries, eg financial shares or tech stocks. A common underlying factor is identified as driving large parts of the volatility development.

the Appendix. In both cases the R^2 is over 20%, which is quite a high figure for a regression analysis of daily log returns. A considerable proportion of the daily movements of the DAX can therefore be explained by the US stock market. However, an analysis of the residuals of the regressions of the DAX on the US stocks shows a significant break in the volatility at exactly the same break date as that on the DAX. The S&P 100 and the Dow Jones Composite 65 therefore fail to provide an explanation for the shift in volatility. Consequently, the increase in volatility of the DAX after 1997 cannot be explained by international influences alone.

Our aggregate institutional ownership indicator comprises the holdings of institutional investors at domestic credit institutions in relation to the total value of domestic shares in circulation, both at nominal values. Institutional investors are investment companies, insurance companies, other corporate enterprises and non-residents; most non-residents are clearing institutions and foreign banks. Data is collected from the Bundesbank's capital market statistics and the annual securities deposits statistics.[21] We interpolated the time series linearly to obtain data points on a daily basis. In Figure 7 the DAX returns and the institutional investor indicator (dashed line) are shown. The bold vertical line is again the volatility break date and the shaded area the confidence interval for the breakpoint. The figure suggests that the sharp increase of the institutional investors ratio coincides with the volatility break date. However, a more formal procedure is needed to test the relationship between the DAX volatility and the institutional investors. If our institutional investor variable was included as additional regressor (besides the lagged squared returns and the lagged variance) in the variance equation of our GARCH (1,1) model on the DAX returns, we found institutional ownership to be significant at the 95% level (see Table A.3 in the Appendix). To avoid running a spurious regression since both time series are upward sloping, we included an additional trend in the variance equation. However, the trend is not significant and hence does not explain the shift in

[21]Security deposits comprise around three-quarters of overall domestic shares. The remaining quarter consists mainly of cross equity holdings among companies. Data from the security deposits statistics is used up to 2001.

Figure 7: Dax returns and institutional investors



variances.

Why should the number of institutional investors explain increasing volatility of stock returns and even a growing persistence of volatility? Institutional investors manage large amounts of assets, they have instruments at hand with which to react to every item of news, and transaction costs do not hinder adjustment reactions. This leads to an immediate adjustment to a new efficient share price equilibrium. Nonetheless, herding can trigger the clustering of price movements (Froot, Scharfstein, and Stein (1992)). The evaluation of fund managers based on relative instead of absolute performance, momentum trading strategies and the existence of positive feedback trading—a rational agent will purchase more stocks than justified by his private information because he knows there are positive feedback traders—can induce a clustering of trading activities and abnormal returns.[22] There has been weak evidence from studies using the amount of institutional ownership of companies (Dennis and Strickland (2002), Xu and Malkiel (2003)) or data on investors port-

[22] A recent survey about the behaviour of investment fund managers in Germany by Arnswald (2001) gives some evidence for herding behaviour among fund managers.

folios and transactions (Froot, O'Connell, and Seasholes (2001), Borensztein and Gelos (2003)) to show that herding and volatility go together and that volatility induced by institutional investors is not limited to single days. Yet, no clear-cut explanation has been given as to why the time horizon for volatility clustering extends over several months.

When qualifying the interpretation of institutional investors as driving force for volatility, one should note, that the institutional investor variable might be endogenous itself. In the previous discussion we have implicitly assumed that our institutional investor variable is given exogenously. This need not necessarily be the case. The increase in the market volatility could also have caused an increase in the number of institutional investors trading on the market, because they supply their customers with additional hedging possibilities. We cannot rule out such a possibility in any case. However, institutional investors became increasingly more important at least two years before 1997, ie the lower bound of our confidence interval of the breakpoint (see Figure 7). The growing number of institutional investors is therefore probably a cause for the break in volatility in the sense of Granger-causality.

In present value models, changes in the volatility of either future dividend payouts or discount rates cause changes in the volatility of stock returns. Dividend changes are not sufficient to explain share price movements (Shiller (2000), Delong and Becht (1992)); we therefore look at a discount factor as proxied by interest rates as explanatory factor. Since daily changes in government bond yields and short-term interest rates are available, it is advisable to employ the same technique to test for volatility shifts as for the index return series. The CUSUM-type estimator gives the time at which there is maximal sample evidence for a break in variances. In Table 2 the volatility break tests for interest rates on different maturities are collected. No break can be detected for the 3-month money market rate.[23] The breakpoints for the volatility of one-year and ten-year government bond redemption yields[24] are in 1995 and 1994 respectively and the volatility is higher after the break for both series.

[23]The short-term interest rate series is the same as for the safe interest rate. See section 5.

[24]Data is taken from the Bundesbank's capital markets statistics.

Table 2: Test for a break in the volatility of interest rates

Maturity	Test value	Lower bound	Break date	Upper bound
3 months	1.191		No break	
1 year	2.143	17/01/1994	29/03/1995	09/02/1999
10 years	1.698	12/01/1994	03/02/1994	21/08/1998

These breakpoints seem to be too early to be related to the break in the volatility of the DAX in 1997. However, if the wide confidence intervals are taken into account, the breaks in the volatility of the interest rates may help to explain the break in the stock market volatility. It should be noted however, that the whole argumentation is based on a partial equilibrium analysis. The interest rates and their volatility are considered as exogenous. In a general equilibrium approach both, the stock market prices and the interest rates should be explained simultaneously.

7 Outlook

We found firm evidence of a structural break in volatility on the German stock market in 1997. One possible explanation for the increase in volatility is the growing influence of institutional investors.

Whereas the increase in overall volatility can be seen using non-parametric measures, parametric measures help to relate the volatility shift to an increased persistence of volatility and accordingly to fatter tails of the return distribution. Decomposing the realised volatility we see that market volatility increased to a far lesser extent than idiosyncratic or firm-specific volatility. These results put the spotlight on portfolio diversification as a mean of eliminating unsystematic risk but they also highlight the considerable increase in risk incurred by narrow investments in portfolios which are not well diversified. Companies with large (cross) holdings, in particular, may therefore be more exposed to default risks. Nevertheless, market participants are becoming increasingly aware of the risk stemming from increased volatility and demonstrate greater willingness to deal with volatility risks, as the recent development of a market for volatility derivatives has shown.[25]

Will the state of high volatility persist? From a historical perspective high volatility periods in the US have typically been followed by lower volatility periods as shown by the decrease after the 1920s or, more recently, the volatility downswing after the stock market crash in 1987 (Delong and Becht (1992)). In the long run volatility is not trending but rather exhibits breaks or different regimes. Our Markov switching analysis of German stock market volatility since 1965 shows that the current high volatility period is exceptionally long. The 1997 break in volatility may therefore be a permanent one.

Since at a first glance we find no evidence of a different volatility behaviour in different industries and branches within the DAX, it might be interesting to look at spillover effects between different markets, eg the NEMAX and the DAX. This would help to clarify the underlying causes of volatility shifts. Of course, there is a range of possible factors affecting volatility which could provide fruitful areas for future research. Another important research agenda is general equilibrium modelling. Up to now the focus in general equilibrium models is on first moments and is by construction not able to explain second moments such as variance or volatility. Yet, some very recent developments in higher-order approximation of computable general equilibrium models open the possibility to investigate the origins of volatility and volatility clustering in a general equilibrium context.

[25] The not (yet) institutionalised market consists mainly of bank dealers.

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A Appendix

Table A.1: Estimated breakpoints

time series	label	test value	lower limit	break date	upper limit
1	ALV	1.61	28.01.1997	3.07.1997	19.08.1998
2	BAS	2.54	27.06.1996	27.11.1996	15.10.1997
3	BAY	2.20	5.11.1996	2.12.1996	23.10.1997
4	BMW	2.75	29.11.1996	13.03.1997	24.10.1997
5	HVM	1.94	9.07.1997	10.07.1997	20.05.1998
6	BHW-ADS	3.06	4.12.1996	18.07.1997	17.10.1997
7	CBK	1.65	6.03.1997	7.07.1997	30.09.1997
8	CONT-MUV	1.72	2.04.1997	3.07.1997	3.02.1998
9	DCX	1.86	27.02.1997	22.10.1997	26.05.1998
10	DGS-ALT	2.54	22.11.1996	14.05.1997	17.10.1997
11	DBC-SAP	2.96	17.10.1996	29.07.1998	25.08.1998
12	DBK	2.19	24.03.1997	21.07.1997	5.08.1998
13	DRB-MLP	1.63	7.07.1997	13.07.1998	1.05.2002
14	FDN-MET-DTE	2.20	4.11.1993	3.12.1993	3.09.1998
15	HEN	2.07	12.04.1996	5.12.1996	27.08.1997
16	HOE-FME	2.36	29.11.1996	3.03.1997	23.10.1997
17	KAR-DPW	2.30	15.11.1996	15.05.1997	25.06.1998
18	KFH-MEO	2.23	26.02.1997	4.07.1997	22.10.1997
19	LIN	2.37	3.01.1997	3.01.1997	21.07.1997

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Time series	Label	Test value	Lower limit	Break date	Upper limit
20	LHA	1.30	No break	No break	No break
21	MAN	1.69	12.08.1991	22.10.1997	23.07.1998
22	MMN-EPC-DB1	1.60	20.10.1997	26.02.1998	26.08.1998
23	NIX-PRS-TUI	1.82	16.01.1990	17.04.1998	19.08.1998
24	RWE	2.50	8.10.1996	22.07.1997	9.09.1997
25	SCH	2.14	15.11.1996	15.07.1997	23.10.1997
26	SIE	2.06	23.06.1997	18.07.1997	17.07.1998
27	THY	2.33	28.01.1997	7.08.1998	4.09.1998
28	VEB-EON	2.20	21.02.1997	30.07.1997	15.06.1998
29	VIA-IFX	1.47	1.05.1998	28.05.1998	29.06.2000
30	VOW	1.92	26.11.1996	3.03.1997	23.10.1997

Table A.2: GARCH parameters for pre-break and post-break periods

		Pre-break period				Post-break period			
Time series	Label	Omega	Persistence	Variance	Kurtosis	Omega	Persistence	Variance	Kurtosis
1	ALV	0.10	0.95	2.03	3.49	0.36	0.95	7.90	5.94
2	BAS	0.28	0.83	1.68	3.17	0.29	0.93	4.07	3.48
3	BAY	0.22	0.86	1.62	3.56	0.19	0.96	5.08	3.24
4	BMW	0.19	0.92	2.36	4.74	0.29	0.96	7.46	3.66
5	HVM	0.45	0.78	2.06	3.54	0.37	0.96	8.93	6.27
6	BHW-ADS	0.53	0.74	2.02	3.19	0.47	0.92	6.03	3.34
7	CBK	0.05	0.98	2.05	3.49	0.14	0.98	8.72	+.Inf
8	CONT-MUV	0.07	0.97	2.60	3.22	0.22	0.98	9.87	9.37
9	DCX	0.05	0.98	2.24	3.54	0.21	0.96	5.90	4.06
10	DGS-ALT	0.58	0.76	2.44	3.18	0.25	0.96	5.59	3.49
11	DBC-SAP	1.57	0.65	4.45	3.07	1.57	0.91	16.66	4.26
12	DBK	0.03	0.98	1.68	3.29	0.41	0.94	6.61	3.90
13	DRB-MLP	0.01	0.99	2.01	3.43	0.63	0.98	30.15	+.Inf
14	FDN-MET-DTE	0.03	1.00	+.Inf	+.Inf	0.04	1.00	+.Inf	+.Inf
15	HEN	0.39	0.76	1.60	3.20	0.11	0.98	5.46	5.25
16	HOE-FME	0.27	0.87	2.04	3.88	0.06	0.99	8.95	4.25
17	KAR-DPW	1.65	0.24	2.18	3.33	0.36	0.95	6.59	3.93
18	KFH-MEO	0.42	0.82	2.42	3.33	0.34	0.95	6.39	3.63

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		pre-break period				post-break period			
time series	label	omega	persistence	variance	kurtosis	omega	persistence	variance	kurtosis
19	LIN	0.26	0.82	1.47	3.33	0.09	0.98	5.13	4.00
20	LHA	0.10	0.98	5.03	3.44	No break	No break	No break	No break
21	MAN	0.23	0.92	2.79	3.41	0.09	0.99	7.50	4.50
22	MMN-EPC-DB1	0.29	0.90	2.95	3.73	0.35	0.98	14.32	3.70
23	NIX-PRS-TUI	0.40	0.90	3.79	8.52	0.26	0.96	6.44	3.60
24	RWE	0.01	1.00	2.03	3.56	0.09	0.98	5.74	7.83
25	SCH	0.12	0.93	1.69	3.49	0.33	0.93	4.56	3.71
26	SIE	0.05	0.97	1.52	3.43	0.29	0.96	8.20	3.53
27	THY	0.30	0.88	2.51	3.39	0.10	0.99	11.00	7.56
28	VEB-EON	0.09	0.96	2.06	4.76	0.10	0.98	5.24	4.23
29	VIA-IFX	0.14	0.95	2.72	5.78	0.19	0.99	15.24	6.27
30	VOW	0.15	0.94	2.71	3.33	0.24	0.96	6.15	3.61

Table A.3: GARCH model with investor variable

Dependent Variable: DAX (log returns) Method: ML - ARCH (BHHH)
Sample(adjusted): 4/01/1988 31/12/2001 Included observations: 3651
after adjusting endpoints Convergence achieved after 52 iterations
Bollerslev-Wooldrige robust standard errors & covariance

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.057291	0.018710	3.062151	0.0022
DAX(-1)	0.037008	0.020263	1.826436	0.0678
	Variance Equation			
C	-0.355811	0.133311	-2.669027	0.0076
ARCH(1)	0.109048	0.033070	3.297489	0.0010
GARCH(1)	0.829841	0.038344	21.64185	0.0000
INVESTOR	0.014221	0.005673	2.506882	0.0122
TREND	-4.63E-05	3.02E-05	-1.533982	0.1250

Table A.4: DAX returns explained by S&P 100

Dependent Variable: DAX (log returns) Method: Least Squares
Sample(adjusted): 7/01/1988 31/12/2002 Included observations: 3909
after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-9.37E-05	0.000199	-0.471154	0.6376
SP100	0.487479	0.018369	26.53758	0.0000
SP100(-1)	0.384014	0.018356	20.92004	0.0000
SP100(-2)	-0.036437	0.018355	-1.985178	0.0472
SP100(-3)	0.037065	0.018342	2.020793	0.0434

R-squared	0.224122	Mean dependent var	0.000190
Adjusted R-squared	0.223327	S.D. dependent var	0.014088
S.E. of regression	0.012415	Akaike info criterion	-5.938496
Sum squared resid	0.601761	Schwarz criterion	-5.930475
Log likelihood	11611.79	F-statistic	281.9304
Durbin-Watson stat	2.297557	Prob(F-statistic)	0.000000

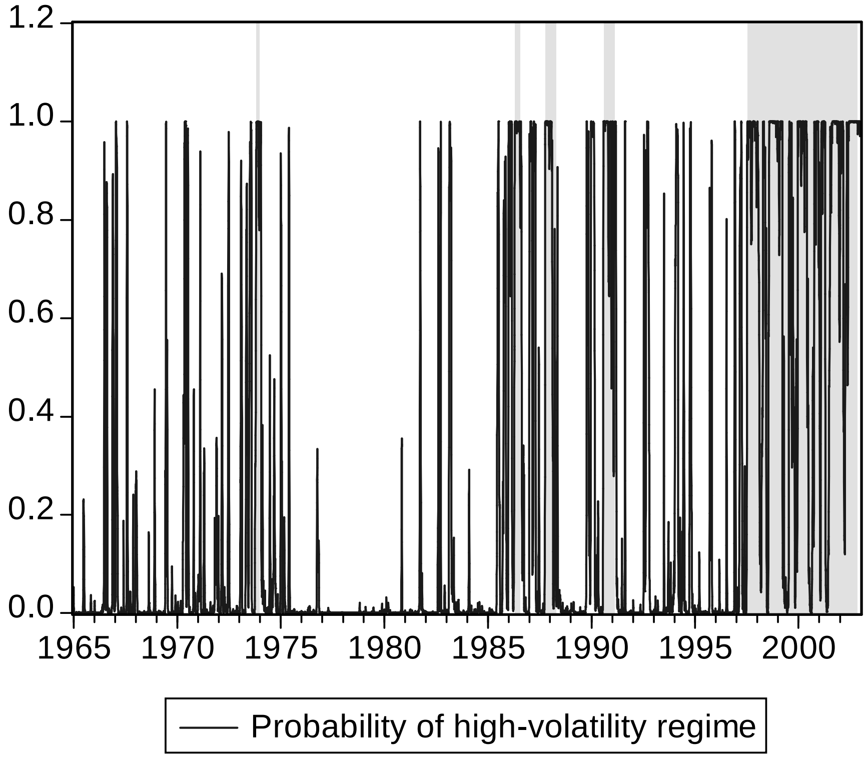
Table A.5: DAX returns explained by Dow Jones Comp 65

Dependent Variable: DAX (log returns) Method: Least Squares
Sample(adjusted): 7/01/1988 31/12/2002 Included observations: 3909
after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-7.40E-05	0.000200	-0.369859	0.7115
DOW	0.555288	0.021219	26.16991	0.0000
DOW(-1)	0.381840	0.021236	17.98085	0.0000
DOW(-2)	-0.090035	0.021235	-4.239915	0.0000
DOW(-3)	0.045386	0.021185	2.142342	0.0322

R-squared	0.214598	Mean dependent var	0.000190
Adjusted R-squared	0.213794	S.D. dependent var	0.014088
S.E. of regression	0.012491	Akaike info criterion	-5.926296
Sum squared resid	0.609148	Schwarz criterion	-5.918274
Log likelihood	11587.94	F-statistic	266.6763
Durbin-Watson stat	2.259029	Prob(F-statistic)	0.000000

Figure A.1: Markov switching volatility regimes



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