Comovement in International Equity Markets: a Sectoral View

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Abstract

We investigate shifts in correlation patterns among international equity returns at the market level as well as the industry level. We develop a novel bivariate GARCH model for equity returns with a smoothly time-varying correlation and then derive a Lagrange Multiplier statistic to test the constant-correlation hypothesis directly. Applying the test to weekly data from Germany, Japan, the UK and the US in the period 1980-2000, we find that correlations among the German, UK and US stock markets have doubled, whereas Japanese correlations have remained the same. Both dates of change and speeds of adjustment vary widely across countries and sectors.

JEL classification: C22, G15

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1 Introduction

Over the past twenty years, the importance of the domestic stock market in many industrialized economies has grown sharply, while at the same time the degree of comovement among international equity markets seems to have increased. As a result, national economies are more frequently affected by disturbances originating in foreign stock markets, and these disturbances also tend to have more far-reaching consequences. This is a widely-held view among financial market participants, the media, academics and policy makers. It is argued that financial integration has been spurred by improved electronic communications, the world-wide liberalization of capital controls, financial innovation, as well as growing political and economic integration. However, it is unclear whether correlations among equity returns across countries really have increased. It is conceivable that this idea just stems from a biased reading of the data. Discussions of stock market developments in the media may exaggerate the importance of infrequent, large, but simultaneously occurring changes in international stock returns. While such dramatic changes may seem to offer strong anecdotal evidence for greater comovement, a careful empirical investigation into this issue would need to take into account the behavior of returns during the entire sample period.

An accurate assessment of the degree of comovement among international equity markets is important for several reasons. For investors, the design of a well-diversified portfolio crucially depends on a correct understanding of how closely international stock market returns are correlated. Changes in international correlation patterns call for an adjustment of portfolios. Policy makers are interested in correlations among equity markets because of their implications for the stability of the global financial system. The preparation of monetary policy is also affected by international stock market developments, due to the international propagation of shocks via equity markets, the wealth channel and confidence effects. The global trend towards a greater role of the stock market in the economy has made this kind of spillovers more important.

The academic literature on comovement among international equity markets is voluminous. Although there seems to be general agreement that correlations between equity markets are not constant over time, it is less clear whether correlations are actually trending upward[1]. For instance, Roll (1989), surveying a number of papers published in the 1980s, concludes that the increase in international stock return correlations in the 1980s compared to the 1970s is only of a small magnitude. Similarly, King *et al.* (1994) find little support for a trend increase in correlations among stock markets for the 1970-90 period. They conclude that authors who argue that markets have become increasingly integrated

[1]For a comprehensive survey of the literature on comovement among international equity markets, see Karolyi and Stulz (2001).

on the basis of data immediately around the crash in 1987 might confuse a transitory (ie. around the crash) with a permanent increase in correlations[2]. In contrast, Longin and Solnik (1995), who explicitly model the conditional multivariate distribution of international equity returns, are able to show that, for the period 1960-90, correlations between stock returns in the US and in France, Switzerland, Japan, and the UK, respectively, have increased significantly. Furthermore, Rangvid (2001) conducts a recursive common stochastic trends analysis and is able to show that there is increasing convergence (in levels) among European stock markets. Last, Goetzmann *et al.* (2001) find that international equity correlations change dramatically through time, with peaks in the late 19^{th} Century, the Great Depression, and the late 20^{th} Century.

Empirical tests for changes in correlation among equity returns usually involve some sort of two-step approach, where in the first step correlations are calculated over either fixed or moving subsamples, and in the second step the presence of level shifts or trends is assessed. These tests may suffer from two statistical deficiencies. First, Boyer *et al.* (1999) show that changes in correlations over time or across regimes cannot be detected reliably by splitting a sample according to the realized values of the data. Tests of changes in correlations are therefore often severely biased; see also Corsetti *et al.* (2001) and Forbes and Rigobon (2002). Put differently, it is not possible to assess the presence of an upward trend in correlations by looking at the (trending) behavior of subsample estimates of correlations. Instead, Boyer *et al.* (1999) argue, one should start with formulating a data-coherent model of the data generating process that includes the possibility of structural change, estimate the model's parameters, and then decide whether correlations have actually changed. A second statistical deficiency, which pertains particularly to the sample-splitting approach to testing for a change in correlation, is that such a test will lack power if the selected subsamples do not closely match the true correlation regimes.

In this paper we attempt to find out whether there has been a structural increase in the correlations among the stock markets of the US, the UK, Japan and Germany in the period 1980-2000. We seek to contribute to the existing literature in two ways. The first contribution is a novel procedure for evaluating structural change that avoids the weaknesses discussed above. We introduce a multivariate GARCH model with smoothly time-varying correlations, and derive a new test for constant correlation, building on the Lagrange Multiplier test developed by Tse (2000). Our set-up allows us not only to endogenously determine the date of change, but also whether the transition to the new regime was abrupt or gradual.

The second contribution of the paper is the focus on equity returns at the industry

[2]Corsetti *et al.* (2001) argue that the correlation between stock market returns is not necessarily larger during crisis periods than during tranquil periods. Longin and Solnik (2001) investigate the relationship between equity market correlations and volatility.

level, in addition to those at the aggregate level. We distinguish ten sectors. The analysis of industry data enables us to investigate whether shifts in correlations are a broad-based phenomenon across industries. It might be the case that a specific group of sectors drives the movement towards greater international interdependence of stock returns. This part of the paper is related to the strand of the literature that explores whether differences in comovement of equity returns can be attributed to differences in industrial structure; see Griffin and Karolyi (1998), Heston and Rouwenhorst (1994) and Roll (1992).

The remainder of this paper is organized as follows. Section 2 discusses the data. Section 3 introduces the new multivariate GARCH model and develops the test for correlation constancy. Section 4 presents the empirical results. Section 5 contains a summary and some concluding remarks. Details on estimation and simulation evidence on the test for correlation constancy can be found in Appendices A and B, respectively.

2 Data

We use weekly returns on stock indices for Germany, Japan, the United Kingdom, and the United States, comprising the financial centers of the three main time-zones. For each country we consider both the market index and ten industry stock indices: basic industries, cyclical consumer goods, cyclical services, financials, general industries, information technology, noncyclical consumer goods, noncyclical services, resources, and utilities. This industry classification follows the Financial Times Actuaries Standards[3]. This disaggregation into ten sectors is sufficient to adequately capture the major differences among industries, while at the same time keeping the computational burden within reasonable limits. All data are from Datastream, and we refer to the manual *Datastream Global Equity Indices* for further details. Weekly returns are calculated from daily price indices (closing values), as weekly log first differences from Thursday to Thursday, multiplied by one hundred. We use weekly data to avoid spurious spillover effects due to non-synchronous trading hours[4]. Furthermore, from the perspective of a policy maker concerned with financial stability, correlations at a high frequency are more relevant than correlations over long horizons[5]. The stock price indices are not corrected for dividend payments, so as to

[3]These data have recently been used by, among others, Brooks and Catao (2000) and Dahlquist and Sällström (2001).

[4]Burns *et al.* (1998) show that aggregation to weekly returns largely avoids the problems caused by non-synchronous trading hours. We have screened our data on potential problems in this regard. First, we looked whether current returns in one market can be predicted by lagged returns in markets that close later in the day. This was rejected for all country-sector combinations. Second, although we found that correlations based on monthly returns tend to be greater than those based on weekly returns, this cannot be attributed to the non-synchronous trading hours problem. The difference between the two correlations is quite small for correlations involving Japan, which should be most affected by this problem, whereas the biggest differences were for correlations between Germany and the UK, for which the problem is minor.

[5]Monthly correlations display the same trending behavior as weekly correlations. Using monthly returns in the period 1960-90, Longin and Solnik (1995) found that correlations between the US stock market and

more closely match price developments as they are perceived in the financial press and by policy makers. For the same reason, we use returns denominated in local currency[6]. The sample starts on 3 January 1980 and ends on 22 June 2000, which gives 1065 weekly observations[7].

- insert Table 1 about here -

Table 1 contains some descriptive statistics. The sample mean of the weekly returns is fairly small. On an annual basis, the average return on the market index was about 14% for the UK and the US, 12% for Germany and only 7% for Japan. Stocks of the technology sectors performed much better than the market in all countries, especially in Germany. The next four columns show the standard deviation of the returns as a measure of volatility. As expected, returns on sectoral indices are more volatile than the return on the corresponding market index, as the latter represents a more diversified portfolio. Volatility varies substantially across sectors. Technology stocks were very volatile in all countries, which is not surprising in view of the high returns, while utilities stocks are relatively stable. The mean and standard deviation for the Japanese market index appear to be at odds with the conventional risk-return trade-off: investors in the Japanese stock market received the lowest return, but ran the highest risk.

Next, the table presents Richardson and Smith's (1994) robust test for first order autocorrelation. Statistically significant autocorrelation in the return series is detected only in a limited number of cases. Consequently, we do not include an AR correction in the mean equations. Results on Engle's ARCH test (allowing for five lags), which are presented in the last four columns of Table 1, suggest that second moments are heavily autocorrelated with long lags, pointing towards an ARCH parameterization for the second moments. Consequently, we model the conditional variances in our multivariate GARCH model to be presented in the next section as GARCH(1,1) processes, as the empirical literature has found that this specification adequately captures the persistence in second moments of high frequency stock returns.

- insert Figure 1 about here -

To get a visual impression of the trend behavior of the correlations among the returns, Figure 1 provides kernel-smoothed estimates[8] of the correlation between the market index

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a number of other stock markets had increased.

[6] Goetzmann *et al.* (2001) find that correlation estimates based on total returns are very close to those based on capital gains. As a check on robustness we have also computed our LM test using returns denominated in a common currency (dollar) and obtained quantitatively similar results. This can be explained by the fact that stock return volatility exceeds exchange rate volatility by a wide margin. These results are available from the authors upon request.

[7] Exceptions are the time series for utilities in the UK, resources in Germany, and information technology in Germany, which start in December 1986, January 1985, and November 1988, respectively.

[8] A Gaussian kernel has been used, which provides unconditional estimates of the correlations.

returns of the US and the UK, the US and Germany, the US and Japan, and the UK and Germany, respectively[9]. With the exception of the correlation between the US and Japan, all correlations have greatly increased between 1980 and 2000. However, there appear to be marked differences in speed and timing of change. For instance, the German-UK correlation starts increasing around 1985, whereas the German-US correlations only starts increasing around 1995. Moreover it is not clear whether these correlation changes are statistically significant. In the next section, we introduce a multivariate GARCH model that enables us to rigorously test whether correlations have indeed changed, and which also provides us with a time profile of the correlations.

3 Modelling Time-Varying Correlations

3.1 Representation and Estimation

Consider a bivariate observed time series of stock returns $\{y_t\}$, $t = 1, \ldots, n$, with two elements each, so that $y_t = (y_{1,t}, y_{2,t})'$, the stochastic properties of which are assumed to be described by the following model

$$
\begin{aligned}
y_t &= \mu_{t-1} + \varepsilon_t, && (1)\\
\mu_{t-1} &= \mathrm{E}[y_t|\Psi_{t-1}], && (2)\\
\varepsilon_t|\Psi_{t-1} &\sim \mathcal{N}(0, H_t), && (3)
\end{aligned}
$$

where Ψ_{t-1} is the information set consisting of all relevant information up to and including time $t-1$, and $\mathcal{N}$ denotes the bivariate normal distribution. The conditional covariance matrix of ε_t, H_t, is assumed to follow a time-varying structure given by

$$
\begin{aligned}
H_t &= \mathrm{E}[\varepsilon_t\varepsilon_t'|\Psi_{t-1}], && (4)\\
h_{11,t} &= \omega_1 + \alpha_1\varepsilon_{1,t-1}^2 + \beta_1 h_{11,t-1}, && (5)\\
h_{22,t} &= \omega_2 + \alpha_2\varepsilon_{2,t-1}^2 + \beta_2 h_{22,t-1}, && (6)\\
h_{12,t} &= \rho_t(h_{11,t}h_{22,t})^{1/2}, && (7)\\
\rho_t &= \rho_0(1 - G(s_t;\gamma,c)) + \rho_1 G(s_t;\gamma,c), && (8)
\end{aligned}
$$

where, in order to keep the analysis tractable, we have assumed that the conditional variances $h_{11,t}$ and $h_{22,t}$ both follow a GARCH(1,1) specification[10]. Following Lin and Teräsvirta (1994), we allow for a smooth transition between two correlation regimes. Let $G(s_t;\gamma,c)$ be the logistic function

$$
G(s_t;\gamma,c) = \frac{1}{1+\exp(-\gamma(s_t-c))}, \qquad \gamma > 0, \qquad (9)
$$

[9] The smoothing parameter is fixed at 0.10.

[10] This choice is motivated by the fact that the GARCH(1,1) model is able to capture many stylized facts for stock returns, such as volatility clustering and fat-tailedness, reasonably well; see Franses and Van Dijk (2000, chapter 4).

where s_t is the transition variable, and γ and c determine the smoothness and location, respectively, of the transition between the two correlation regimes[11] [12]. As we want to describe dominant, long-run trends in correlations among stock returns, we allow for one change in correlation regime and specify the transition variable as a function of time: $s_t = t/n$[13]. Note that the conditional correlation at time t partly depends on t/n and c, which strictly speaking are not part of the information set at $t-1$. For this reason, our empirical model should be interpreted as a parsimonious description of conditional correlation developments within the sample[14].

Our Smooth-Transition Correlation GARCH (STC-GARCH) model is able to capture a wide variety of patterns of change. If ρ_0 and ρ_1 differ, correlations move monotonically upward or downward, but the pace of change may vary strongly over time[15]. The change between correlation regimes is abrupt for large values of γ, while the transition can be made arbitrarily gradual for small values of γ[16]. Obviously, for $\rho_0 < \rho_1$ an increase in correlation will be observed, whereas for $\rho_0 > \rho_1$ a decrease is obtained. Bollerslev's (1990) constant correlations model shows up as a special case of the STC-GARCH model by setting either $\rho_0 = \rho_1$ or $\gamma = 0$[17].

- insert Figure 2 about here -

To illustrate the range of feasible adjustment patterns, Figure 2 shows the shape of the transition function $G(t; \gamma, c)$ for three different values of γ and two values of c. If the change takes place in the middle of the sample, the transition function resembles a straight line for $\gamma = 1$, an S-shape for $\gamma = 5$ and a step-function for $\gamma = 100$. It is a gently rising curve if c is small and $\gamma = 1$.

Assuming normality, the log-likelihood of the observation at time t is given by (ignoring

[11] As the transition function $G(s_t; \gamma, c)$ is bounded between zero and one, and assuming that ρ_0 and ρ_1 are between -1 and +1, the correlation ρ_t will be between -1 and +1 as well.

[12] In the paper, we will occasionally refer to c loosely as 'the break data', although strictly speaking the correlation only gradually changes around c.

[13] In practice, we scale $(t/n - c)$ by $\sigma_{t/n}$, the standard deviation of the transition function t/n, to make estimates of γ comparable across different sample sizes. In principle, any variable can act as a transition variable. For instance, Longin and Solnik (1995) consider specifications in which the conditional correlation is predictable based on past values of the US dividend yield and interest rate.

[14] See Lundbergh *et al.* (2003) for an application of this approach to the AR model.

[15] Extending the model to more than two correlation regimes, which would open up the possibility of non-monotonic change over the sample, is beyond the scope of the present paper, which focuses on dominant trends.

[16] Note that if $\gamma \to \infty$, the transition between ρ_0 and ρ_1 becomes a step at $t = cn$.

[17] In the majority of multivariate GARCH models, the covariance matrix is specified directly; see Kroner and Ng (1998) for a recent survey. Notable exceptions are Engle and Sheppard (2001) and Tse and Tsui (1998), who postulate the conditional correlation matrix to follow an autoregressive moving average process. Suitable restrictions are then imposed in order to guarantee that the conditional correlation matrix is always positive definite.

the constant term)

$$l_t(\theta) = -\frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1}\varepsilon_t, \tag{10}$$

where θ is the vector of all the parameters to be estimated. The log-likelihood for the whole sample from time 1 to n, $L(\theta)$, is given by

$$L(\theta) = \sum_{t=1}^{n} l_t(\theta). \tag{11}$$

This log-likelihood is maximized with respect to all parameters simultaneously, employing numerical derivatives of the log-likelihood. Robust standard errors of the parameter estimates are computed using the procedure proposed by Bollerslev and Wooldridge (1992). Estimation issues, in particular the choice of starting values, are dealt with in detail in Appendix A.

3.2 Testing

Before considering a model with time-varying parameters, one should assess whether allowing for time-varying parameters really improves the model's ability to track the time-series properties of the data over a fixed parameter version of the model. Here we will employ a Lagrange Multiplier (LM) test to discriminate between the constant correlation GARCH model and the STC-GARCH model. As discussed above, the constant correlation GARCH model can be obtained from the STC-GARCH by either putting γ equal to zero, or imposing $\rho_0 = \rho_1$. This illustrates that any test of the constant correlation hypothesis in the STC-GARCH model will suffer from unidentified nuisance parameters under the null hypothesis, which is typical for tests of structural change[18]. We will deal with this problem by following the Taylor-approximation approach advocated by Luukkonen *et al.* (1988) in the context of smooth transition autoregressive models.

Following the literature, the constant correlation hypothesis can be expressed formally as $\mathrm{H}_0 : \gamma = 0$, and we develop an LM test of this null hypothesis against the alternative hypothesis $\mathrm{H}_a : \gamma > 0$, which implies time-varying correlation. To circumvent the nuisance parameter problem[19], we replace the logistic transition function in the STC-GARCH model by a first-order Taylor approximation to the logistic function around $\gamma = 0$, that is,

$$\begin{aligned} G(t;\gamma,c) &= G(t;0,c) + \gamma\frac{\partial G(t;\gamma,c)}{\partial\gamma}|_{\gamma=0} + R, \\ &= \frac{1}{2} + \gamma\frac{1}{4}(t-c) + R, \end{aligned} \tag{12}$$

where R denotes the approximation error, which is of order γ^2. It follows that under the null hypothesis, the remainder R equals zero, and hence does not affect the distribution

[18]We refer to Hansen (1996) for a general treatment of the issue of unidentified nuisance parameters in econometric tests.

[19]We refer to Luukonen *et al.* (1988) for a detailed account of this method.

theory for the LM test. Following Tse (2000), we assume that within a neighborhood of $\gamma = 0$, the optimal properties of the LM test hold under some regularity conditions as provided by, among others, Godfrey (1988). If we plug the above Taylor approximation into the STC-GARCH model, we obtain after some algebraic manipulations an auxiliary STC-GARCH model in which the time-varying correlation reads

$$\rho_t = \tilde{\rho} + \tilde{\gamma} t, \tag{13}$$

where $\tilde{\rho} = \frac{1}{2}(\rho_0 + \rho_1) + \frac{1}{4}c\gamma(\rho_0 - \rho_1)$ and $\tilde{\gamma} = \gamma\frac{1}{4}t(\rho_1 - \rho_0)$. Hence, it follows that testing the null hypothesis $\mathrm{H}_0 : \gamma = 0$ in the STC-GARCH model is equivalent to testing the null hypothesis $\mathrm{H}_0' : \tilde{\gamma} = 0$ in the auxiliary STC-GARCH model. The latter hypothesis can be tested using the outer product form of the LM test, which is defined as

$$\mathrm{LM} = \mathbf{1}'\hat{s}(\hat{s}'\hat{s})^{-1}\hat{s}'\mathbf{1}, \tag{14}$$

where $\mathbf{1}$ is the $n \times 1$ vector of ones and $\hat{s}$ is the score function of the auxiliary STC-GARCH model evaluated at the parameter estimates under the null hypothesis $\mathrm{H}_0' : \tilde{\gamma} = 0$, which is asymptotically distributed as χ_1^2 (as we test only one linear restriction). An analytic expression for the score function of the constant correlation GARCH model can be found in Tse (2000), and this expression can be easily extended to the auxiliary STC-GARCH model. Appendix B presents the details of the score function and also some Monte Carlo evidence on the size and power of our LM test in small samples, which appear to be quite satisfactory. As it is well-known that stock returns have fat-tailed distributions and that conditional variances may react differently to negative and positive innovations, we also checked the size of the test if the true error-terms are t distributed instead of Gaussian, or if the true specification of the conditional variances contains leverage-effects as in Glosten *et al.* (1993). We find that in both cases the empirical rejection frequency is still close to the nominal size.

4 Empirical Results

In this section, we apply the LM test to investigate whether a structural change has occurred in the correlations among the stock markets of Germany, Japan, the UK and the US. Subsequently, we estimate the STC-GARCH model to determine the date and speed of these changes. Before doing this, we first have a look at the full-sample cross-section of correlations.

4.1 Cross-section of correlations

Table 2 shows the correlations for the six possible country pairs, for the aggregate index as well as the industry indices. A number of observations stand out.

- insert Table 2 about here -

First, with one exception, correlations at the aggregate level are larger than those at the sectoral level. This suggests that stock returns contain a significant global component shared by all sectors in all countries and that the variance of the specific component unique to a industry-country combination is relatively large. This has profound implications for portfolio allocation[20]. Based on decompositions of changes in equity returns into country-specific and sector-specific shocks, some authors have argued that the latter have become more important than the former; see Beckers *et al.* (1996), Heston and Rouwenhorst (1995), and Cavaglia *et al.* (2000). One may therefore hold the view that the exact location of investment is no longer important[21]. However, Table 2 shows that cross-country correlations at the industry level can be fairly low, suggesting that neglecting locational aspects in the investment strategy may be suboptimal.

Second, these differences in correlation patterns at the aggregate and sectoral levels have also implications for policy makers. As long as shocks are concentrated in a particular sector of the economy, spillovers to other countries are less likely than at the aggregate level. Policy makers concerned with global financial stability should thus monitor equity returns at the aggregate level.

Third, measured over the full sample, correlations for the IT sector are comparatively low. This is a bit surprising since it is especially returns in this sector of the economy that have more or less simultaneously become increasingly 'wacky' in the second half of the 1990s (see Schwert 2001), giving the impression that this sector has been hit by a series of global sector-specific shocks. The combination of low correlation and high volatility, however, indicates it is more likely that it is country-specific sectoral shocks that drive the returns of IT stocks.

Fourth, correlations with respect to Japan are low at around 0.30, suggesting that the Japanese equity market is comparatively disconnected from global market developments. In contrast, the US and UK markets exhibit a much higher degree of comovement (0.52), while the German stock market correlations are around 0.40.

4.2 Have correlations changed?

To address this question, we apply the methodology developed in Section 3. In particular, motivated by the summary statistics presented in Table 1, we assume that all equity

[20] In interpreting Table 2,we assume the Capital Asset Pricing Model applies. Hence, covariances fully determine equity returns, and because in our model the variances of equity returns over long horizons are equal to the unconditional variances, and thus constant, correlations are critical for portfolio allocation.

[21] Blitz *et al.* (2000) argue that the decision to include a stock into a worldwide portfolio should depend more on the sector outlook than on the expectations for a country or region.

returns have a constant mean and that time-varying variances follow a GARCH(1,1) specification[22].

- insert Table 3 about here -

Table 3 shows the LM statistics. Under the null hypothesis, the LM statistic is asymptotically χ^2 distributed with one degree of freedom. Note that the LM test does not discriminate between an increase and a decrease in correlation. The STC-GARCH model has to be estimated to determine whether the correlation has gone up or down. The evidence on structural change can be summarized as follows.

First, there is strong evidence that correlations between the Japanese equity market on the one hand, and the German, UK and US equity markets on the other hand, have not changed at all. Looking at the tests at the sectoral level, we see that the no change hypothesis also gets broad support from the industry data. The LM test indicates structural change in only five cases. In 18 out of 30 cases the LM statistic is even below one, its expected value under the null. The weak link between the Japanese stock market and the other stock markets is thus a pervasive characteristic, both across sectors and across time. This may reflect the severe financial problems of the Japanese economy.

Second, the experience of the other three countries is quite different. The hypothesis that correlation patterns among Germany, the UK and the US have not changed at the market level is rejected at very low marginal significance levels for all country pairs. The empirical evidence for structural change is most convincing for the correlation between the UK and US stock markets, as eight out of ten sectors experienced a change in correlation. For the country pairs Germany-UK and Germany-US we find statistically significant changes in correlation for four industries.

Third, the results for the industry level data demonstrate that it is impossible to identify a group of sectors to which the observed correlation increase among the Germany, UK and US market indices can be attributed. In other words, the tendency towards greater comovement of equity returns among these three countries is not confined to certain sectors in the economy. For example, for both the Germany-US link and the Germany-UK link we find that four sectors exhibited a correlation shift. However, the four sectors involved, save one, differ in each case. Cyclical services is the only sector that contributed to all correlation changes at the aggregate level among Germany, the UK and the US[23]. Only the utilities industry does not take part in the trend towards greater integration,

[22] Results from diagnostic tests, which are available upon request, indicate that the GARCH(1,1) specification is appropriate in general. Standardized residuals are found to have unit variance, Engle's LM statistic shows there is little evidence of remaining linear dependence, and Lundbergh and Teräsvirta's (1999) LM statistics support the constancy of the GARCH parameters.

[23] For basic industries and noncyclical services correlations changed for four country pairs, but for two of them the change did not register at the aggregate level. Moreover, two of the changes in the basic industries correlations are declines; see Table 4.

as the no change hypothesis can be easily maintained in all cases. Returns on utilities shares were hardly correlated throughout the entire sample period, which can be explained by the sheltered nature of the utilities business. Most sectors experienced cross-country correlation shifts for two of the three bilateral stock market linkages among Germany, the UK and the US. Information technology shares only played a part in the shift of the UK-US correlation.

4.3 When did correlations change, and how quickly?

We estimate the STC-GARCH model, described by eqs. (1)-(9), for those cases for which the LM test detected structural change at the 5 percent level. Table 4 presents the estimates of the parameters of the transition function (9) and the correlations that define the old and new regimes[24]. ρ_0 and ρ_1 are the correlations in the old and new regime, respectively. γ determines the shape of the transition curve, while c determines its inflection point[25]. c defines the middle of the transition period and is expressed as a fraction of the sample size. Under the heading 'date' we report the month which corresponds to c. To get a sense of the length of the transition period we also report the start and end date of the symmetric time interval around c during which 80% of the total projected change (equal to $\rho_1 - \rho_0$) took place. As Figure 2 shows, it is possible that ρ_0 and/or ρ_1 will not be observed within the sample period, for example because of a slow transition after a break early in the sample. For this reason we also present the estimated correlation at the beginning and the end of the sample, which are obtained by putting s_t equal to zero and one, respectively.

- insert Table 4 about here -

- insert Figure 3 about here -

The global picture that emerges from Table 4 is that in the early 1980s correlations among the stock markets of Germany, Japan, the UK and the US were all about 0.30. In the late 1990s this was still true for Japan, but correlations among Germany, the UK and the US had more than doubled. This conclusion is supported by the analysis at the industry level. Among Germany, the UK and the US, 16 sectoral correlations went up and 14 were unchanged, whereas 25 sectoral correlations remained the same for Japan. The dates of change and the lengths of the transition periods vary a great deal across national

[24]To save space we do not report estimates of the GARCH parameters, which are highly significant and confirm the well-established fact that conditional second moments are highly persistent for high frequency stock returns. Results from Engle's LM statistic for remaining ARCH and Lundbergh and Teräsvirta's LM statistics for parameter constancy indicate that the univariate GARCH(1,1) specifications are adequate. The full set of estimation and test results is available from the authors upon request.

[25]If the transition function looks like a step-function, γ becomes very large and ill-determined. In these cases, we have fixed γ at an upper bound equal to 400.

markets and industries. This finding suggests that the tendency toward greater stock market interdependence is not solely driven by global developments, but that country- and industry-specific factors played a significant role as well. From a methodological vantage point, the finding of large differences in date and pace of structural change illustrates the advantages of having a testing procedure that endogenously determines change points.

We now briefly discuss the results for the correlation patterns among Germany, the UK and the US. As to stock market linkages between the UK and the US, the estimates point to a continuous and very gradual rise of the total market correlation from 0.30 in 1980 to 0.63 in 2000. Change was relatively rapid in the years around 1983[26]. Eight out of ten industry correlations display a structural break, and all of them are increases. Time-patterns of structural change vary widely across sectors, but the larger part of the changes was accomplished in the 1980s. The greater degree of comovement of the UK and US equity markets is thus a broad-based phenomenon.

The correlation between the German and UK markets has more than tripled, from 0.21 to 0.66. The transition phase comprises the years 1986-94. In this case too, all of the industry correlation changes are found to be increases. Looking at the dates and speeds of the sectoral correlation transitions, all sectors seem to have contributed to the correlation shift at the market level. The financial and the noncyclical services sectors appear to be the main drivers, as the main periods of change for these sectors overlap with the period 1986-94. Both the noncyclical consumers goods sector and cyclical services sector show a break in 1987, in the early years of the transition phase.

Turning to the case of Germany and the US, we find that for the market index the correlation occurs late in the sample, but that the transition is swift. 80% of the change is effected within a time-span of 2.5 years (between April 1995 and September 1997). The correlation is estimated to have doubled from 0.33 to 0.63. The estimation results at the industry level show that all correlation changes involve increases. Inspection of the dating of the changes, however, reveals that no single sector can be held responsible for the correlation shift at the aggregate level. Two sectoral correlations display an abrupt hike in 1987, while the other two sectors went through a very gradual change.

Finally, regarding the correlations involving Japan, the verdict of the LM test was that there was no evidence for correlation changes at the market level and only limited evidene at the industry level. The estimation results of the STC-GARCH throw some light on this result. In contrast to the results for Germany, the UK and the US, we find that in two out of the five cases the sectoral correlation has decreased. The apparent constancy of the Japanse correlations at the aggregate level thus not only reflects the fact that just a few

[26] Note that the estimated correlation at the start of the sample is much higher than ρ_0, which implies that much of the lower half of the S-curve falls outside the sample. The estimate of c means that only 16% of the observations are drawn from the low correlation regime. The asymmetric shape of the transition function within the sample explains why the estimate of ρ_0 is much more inaccurate than that of ρ_1.

sectoral correlations have changed, but also that those few changes include both increases and decreases.

5 Summary and Conclusions

In this paper, we focus on two important questions regarding the correlation among international equity returns. First, has there has been a structural increase in the degree of comovement among the world's most important stock markets – Germany, Japan, the UK and the US – over the past twenty years? And if so, at what moment did the change occur, and how long was the transition phase? Second, is the higher degree of comovement a broad-based phenomenon across industries, or is it possible to identify a group of sectors that appears to drive the process of deepening international stock market integration?

To answer the two questions, we formulate a novel bivariate GARCH model for international equity returns with a smoothly time-varying correlation, and then derive a Lagrange Multiplier (LM) statistic to test the constant-correlation hypothesis directly. Our procedure avoids the statistical deficiencies which often afflict other approaches in the literature, since both the date of change and the speed of the transition are endogenous. We apply the LM test to the stock market linkages among Germany, Japan, the UK and the US, using weekly stock prices for the market index and ten industry indices between January 1980 and June 2000.

Our main findings can be summarized as follows. Correlations among the German, UK and US stock markets have more than doubled, from around 0.30 to around 0.65 between 1980 and 2000. By contrast, correlations between the Japanese stock market and the other three markets have remained unchanged at 0.30 in this period. Correlation behavior at the aggregate level broadly reflects similar behavior at the industry level. Among Germany, the UK and the US, cross-country industry correlations have either gone up or remained the same, while for Japan the sectoral correlations overwhelmingly have not changed. There is no empirical evidence for the notion that a specific group of sectors plays a dominant part in the process of growing stock market integration. In short, we thus find a statistically significant broad-based increase in stock market comovement among Germany, the UK and the US, while the trend towards stock market integration seems to have bypassed Japan.

Our estimation results point to a great variety in timing and speed of the correlation shifts across the bilateral stock market linkages, both at the market level and the industry level. For instance, the correlation between the returns on the market indices of the UK and the US gradually rose throughout the sample period, while that between the German and US markets increased sharply in the second half of the 1990s. This finding suggests that the structural shift towards a greater degree of comovement among international stock markets is not solely governed by global factors (such as advances in information technology, financial innovation and greater trade interdependence), but that country- and industry-specific factors also have a substantial impact. Relevant country-specific factors may be differences in transaction costs across exchanges and differences in information costs as a result of differences in listing requirements and accounting standards.

The implications of our research for investors are that optimal portfolios have changed as a result of the correlation shifts. Because the correlations among the German, UK and US stock markets have greatly increased, whereas the correlations between Japanese stock market and the other three stock markets have not, the weight of Japanese stocks in the optimal portfolio has tended to increase over time at the expense of German, UK and US stocks[27]. For policy makers, significantly higher correlations mean that equity market disturbances in one country are more likely to be transmitted to other countries, which may have adverse consequences for the stability of the global financial system. International stock market spillovers have also become more significant as the link between stock market and real economy has intensified, for example because of greater share holdings by households.

Our finding of widely varying dates and speeds of structural change is a strong reminder that a flexible approach to modelling structural change really pays dividends. This is an important lesson for future research. However, our methodology still contains some important restrictive elements, in particular the strict monotonicity of correlation change. Relaxing these restrictions is an interesting topic for future research. Within our basic set-up, monotonicity can be replaced by richer time-patterns in two ways. The first one is the introduction of more than two correlation regimes, which allows hump-shaped patterns. The second one is not to use time as the transition variable, but a measure of interdependence, for instance international trade patterns. As such variables may not be necessarily monotonic, this also introduces the possibility of non-monotonic change. An additional advantage of this approach is that it may shed some light on the underlying causes of long-run changes in the degree of stock market comovement. Finally, a natural extension of our analysis is to estimate a single multivariate STC-GARCH model instead of a series of bivariate STC-GARCH models.

A Estimation Details

Starting values for the maximization algorithm are chosen as follows. First, initial estimates of μ_{t-1} are obtained by OLS. Then, using the estimated residuals $\hat{\varepsilon}_t$, univariate GARCH(1,1) models are estimated, yielding initial estimates of conditional variance parameters and estimates of the scaled residuals. Last, starting values for ρ_0 and ρ_1 are obtained by putting them equal to the sample correlation over the first 10% and last 10% of the scaled residuals, respectively. c is fixed

[27]Note that our analysis can only permit tentative conclusions regarding portfolio choice, as we consider only a subset of the stock markets in the world and we disregard exchange rate movements, which also matter to investors. However, our results for returns denominated in dollars imply that for American investors the latter issue does not appear to be of overriding importance (see footnote 6).

at 0.5, and γ is selected such as to connect the initial estimates of ρ_0 and ρ_1 by means of a straight line.

The implementation of the LM test requires estimates of the score function of the auxiliary model under the null hypothesis of constant correlation. Analytic expressions for the first partial derivatives of $l_t(\theta)$ with respect to the model parameters ω_1, α_1, β_1, ω_2, α_2, β_2, and $\tilde{\rho}$ can be found in Tse (2000), and are reproduced here for convenience. Using his results, it is straightforward to obtain the partial derivative of $l_t(\theta)$ with respect to $\tilde{\gamma}$.

$$
\begin{aligned}
\frac{\partial l_t}{\omega_i} &= \frac{(\eta^*_{i,t}\eta_{i,t} - 1)d_{i,t}}{2h_{ii,t}}, \\
\frac{\partial l_t}{\alpha_i} &= \frac{(\eta^*_{i,t}\eta_{i,t} - 1)e_{i,t}}{2h_{ii,t}}, \\
\frac{\partial l_t}{\beta_i} &= \frac{(\eta^*_{i,t}\eta_{i,t} - 1)f_{i,t}}{2h_{ii,t}}, \\
\frac{\partial l_t}{\tilde{\rho}} &= \eta^*_{i,t}\eta^*_{j,t} - \rho^t, \\
\frac{\partial l_t}{\tilde{\gamma}} &= (\eta^*_{i,t}\eta^*_{j,t} - \rho^t)t,
\end{aligned}
$$

for $i = 1, 2$, and where $\eta_t = (\eta_{1,t}, \eta_{2,t})'$ denote the scaled residuals, and $\eta^*_t = (\eta^*_{1,t}, \eta^*_{2,t})'$ denote the scaled residuals premultiplied by the inverse of the correlation matrix $\Gamma_t = (1\ \rho_t, \rho_t\ 1)'$. Last, ρ^t indicates the upper right element of the inverse of the correlation matrix. $d_{i,t}$, $e_{i,t}$ and $f_{i,t}$ represent the derivates of the $h_{ii,t}$ with respect to ω_i, α_i, and β_i, respectively, which must be obtained recursively as shown by Tse.

B Simulation Evidence

This appendix presents some simulation evidence on the behavior of the LM test in small samples. Generally speaking, the size and power of the test appears to be satisfactory.

Size

In the simulations, we generate 2000 series of length $n+100$ from the constant correlation bivariate GARCH model, which is obtained from the STC-GARCH model in Section 3 by putting γ equal to zero. Starting values for the lagged residuals are set equal to zero, while lagged conditional variances are set equal to the unconditional variance. The first 100 observations of each series are discarded, giving an effective sample size of n, where $n = 200, 500, 1000$ and 2000. To save space, we only present results for parameterizations for which $\alpha_1 = \alpha_2 = \alpha$, $\beta_1 = \beta_2 = \beta$, and $\omega_1 = \omega_2 = \omega$. ω is fixed at 0.10. The parameters α and β are varied among $\{0.10, 0.40\}$ and $\{0.50, 0.80\}$, respectively. Because equity returns tend to be positively correlated, we only consider positive values for the correlation coefficient, $\rho = \{0.20, 0.80\}$ under the null hypothesis.

- insert Table 5 about here -

The percentage of replications for which the null hypothesis of a constant correlation is falsely rejected at the 1, 5, and 10% significance levels is reported in Table 5. The single most important conclusion that emerges from this table is that for samples of size 1000 or larger, the size of the LMt statistic is in most cases fairly close to the theoretical value.

- insert Table 6 about here -

To examine the effects of nonnormality on the size of the LM test, we conducted some further Monte Carlo experiments. We considered experiments in which the disturbances were t distributed with 8 and 12 degrees of freedom, respectively. Also, we allowed for leverage effects in the conditional variances, following Glosten *et al.* (1993). To be precise, we changed equations (5) and (6) into:

$$h_{11,t} = \omega_1 + \alpha_1 \varepsilon^2_{1,t-1} + \delta_1 \varepsilon^2_{1,t-1} I[\varepsilon_{1,t-1} < 0] + \beta_1 h_{11,t-1}, \quad (15)$$

$$h_{22,t} = \omega_2 + \alpha_2 \varepsilon^2_{2,t-1} + \delta_2 \varepsilon^2_{2,t-1} I[\varepsilon_{2,t-1} < 0] + \beta_2 h_{22,t-1}, \quad (16)$$

where $I(A)$ is an indicator function with $I[A] = 1$ if event A occurs and $I[A] = 0$ otherwise. Table 6, which is based on 1000 simulations, shows that in all cases, the LM test does not over-reject strongly. Put differently, the empirical size of the LM test is close to its theoretical size, even if the model is (slightly) misspecified.

Power

To assess the power of the LM test in small samples, we generate 1000 series on length $n+100$ from the STC-GARCH model. The first 100 observations are generated with ρ_t put equal to ρ_0, and are subsequently discarded, yielding an effective sample size of n, where $n = 500, 1000$. The model parameters are chosen as follows: $\omega = 0.10$, $\alpha = 0.10$, $\beta = 0.80$, $(\rho_0, \rho_1) = \{(0.20, 0.40), (0.20, 0.60), (0.40, 0.60)\}$, $c = \{0.50, 0.80\}$, and $\gamma = \{1, 10, 100\}$. Table 7 presents the power of the LM test at a nominal size of 5%. Two observations stand out. First, power is increasing in both γ and $\rho_1 - \rho_0$. Second, power decreases if c is shifted towards either end of the unit interval.

- insert Table 7 about here -

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Table 1: Summary Statistics[1]

	mean				standard deviation			
sector	GER	JAP	UK	US	GER	JAP	UK	US
market index	0.22	0.13	0.26	0.26	2.23	2.44	2.13	2.08
basic industries	0.17	0.07	0.16	0.17	2.42	2.83	2.51	2.68
cyclical consumer goods	0.12	0.13	0.13	0.17	2.92	2.75	3.40	2.65
cyclical services	0.18	0.11	0.25	0.29	2.67	2.36	2.35	2.56
financials	0.24	0.13	0.27	0.28	2.65	3.35	2.49	2.60
general industries	0.19	0.12	0.22	0.27	2.38	2.78	2.69	2.44
information technology	0.79	0.22	0.32	0.33	5.38	3.77	3.93	3.25
noncyclical consumer goods	0.20	0.15	0.30	0.30	2.05	2.34	2.51	2.24
noncyclical services	0.28	0.31	0.38	0.24	3.49	3.88	2.91	2.14
resources	0.03	−0.05	0.22	0.16	3.24	3.67	2.97	2.71
utilities	0.16	0.08	0.21	0.13	1.42	3.17	2.54	1.75
	first order autocorrelation				ARCH(5)			
sector	GER	JAP	UK	US	GER	JAP	UK	US
market index	1.54	0.14	0.57	0.02	129.43	126.64	40.19	64.97
basic industries	0.15	0.17	5.32*	4.64*	69.91	118.20	73.38	38.79
cyclical consumer goods	0.30	0.04	2.63	1.19	89.73	105.37	108.91	21.27
cyclical services	0.71	0.16	2.05	1.29	64.52	133.31	46.58	93.50
financials	8.55**	0.38	0.59	1.55	122.39	98.52	71.89	56.14
general industries	1.40	0.25	3.80†	0.63	102.96	133.05	46.40	72.96
information technology	1.36	0.59	4.59*	0.16	33.82	115.45	73.78	51.80
noncyclical consumer goods	1.79	0.04	0.01	0.04	75.86	157.38	45.58	53.86
noncyclical services	0.40	0.01	0.41	2.08	85.45	78.90	34.89	36.96
resources	0.09	1.12	0.08	4.42*	34.44	40.67	55.94	73.40
utilities	0.55	0.25	0.29	0.27	53.74	114.98	9.29	19.59

[1] In the case of the test for first order autocorrelation, †, ∗, ∗∗ denote significance at the 10, 5 and 1 percent level, respectively. This test is robust in case of heteroskedasticity (Richardson and Smith 1994, fn. 3). ARCH(5) denotes Engle's LM test for ARCH, allowing for five lags. Save the utilities sector in the UK, the ARCH(5) is highly statistically significant.

Table 2: Correlations[1]

sector	GER-US	JAP-US	UK-US	GER-UK	JAP-UK	GER-JAP
market index	0.41	0.31	0.52	0.44	0.30	0.29
basic industries	0.37	0.26	0.51	0.36	0.22	0.24
cyclical consumer goods	0.31	0.29	0.30	0.28	0.22	0.27
cyclical services	0.30	0.23	0.38	0.31	0.26	0.22
financials	0.32	0.19	0.47	0.39	0.21	0.16
general industries	0.37	0.30	0.37	0.29	0.25	0.30
information technology	0.28	0.27	0.23	0.21	0.22	0.17
noncyclical consumer goods	0.30	0.21	0.46	0.33	0.20	0.18
noncyclical services	0.21	0.15	0.29	0.26	0.17	0.12
resources	0.05	0.17	0.57	0.09	0.13	0.12
utilities	0.10	0.12	0.24	0.12	0.17	0.05

[1] Full sample estimate of correlation based on bivariate constant correlation GARCH model.

Table 3: LM statistics[1]

sector	GER-US	JAP-US	UK-US	GER-UK	JAP-UK	GER-JAP
market index	14.115**	1.356	22.367**	51.848**	0.024	0.049
basic industries	6.156*	2.574	6.294*	2.480	4.980*	5.426*
cyclical consumer goods	9.775**	2.231	0.610	1.493	0.035	3.089†
cyclical services	9.155**	0.057	9.942**	21.329**	1.190	0.539
financials	0.111	0.207	8.486**	8.821**	0.082	0.302
general industries	8.370**	0.040	3.916*	3.203†	0.704	0.487
information technology	2.289	1.399	26.382**	0.110	4.587*	0.632
noncyclical consumer goods	2.293	0.006	19.222**	4.501*	0.006	0.379
noncyclical services	1.967	4.027*	5.543*	30.034**	0.334	5.421*
resources	0.606	0.410	5.256*	0.210	0.015	0.399
utilities	2.607	0.698	2.033	0.111	1.200	1.182

[1] †, ∗, ∗∗ denote signifance at the 10, 5, and 1 percent level, respectively.

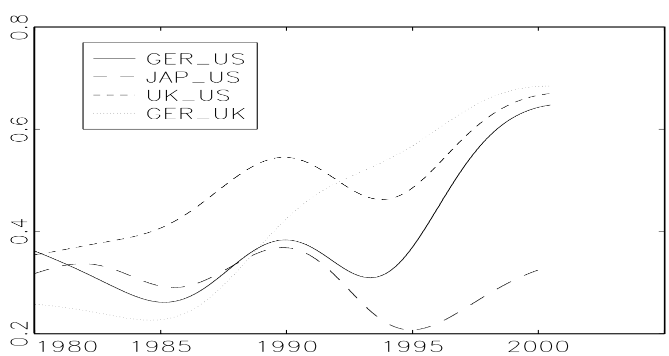

Figure 1: Kernel-smoothed estimates of correlations between market index returns.

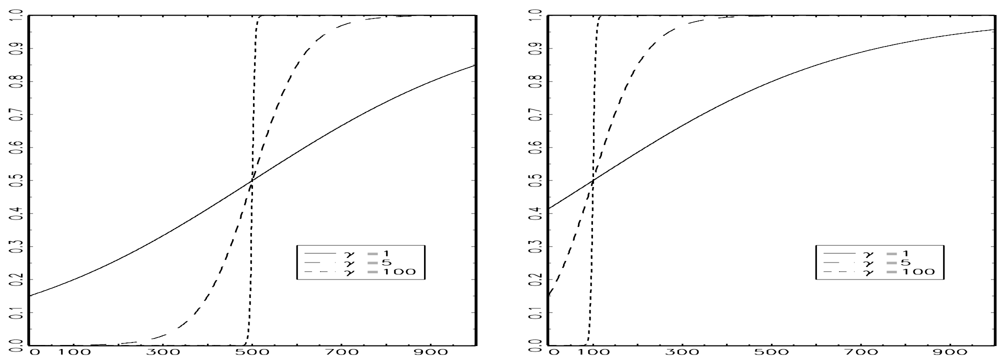

Figure 2: Shape of the transition function $G(t; \gamma, c)$ for three different values of γ. In the left pane, c equals 0.5, whereas in the right pane, c is 0.1.

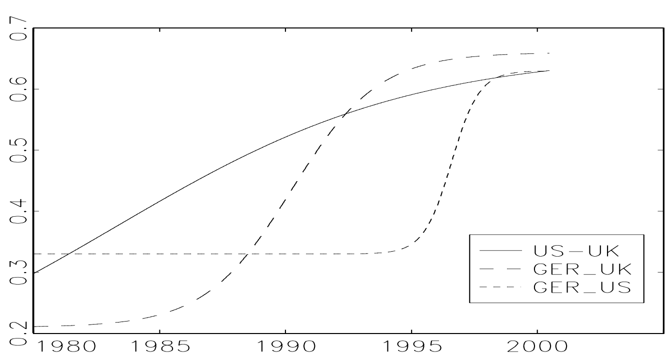

Figure 3: Shape of the estimated conditional correlation ρ_t (see equation (8)) for the UK-US, the UK-Germany, and the US-Germany, respectively.

Table 4: Estimates of STC-GARCH model[1]

sector	$\hat{\gamma}$	$\hat{c}$		date	start trans.	end trans.	$\hat{\rho}_0$		$\hat{\rho}_1$		$\hat{\rho}_{1980:1}$	$\hat{\rho}_{2000:6}$
						United Kingdom-United States						
market index	1.00	0.16	(1.40)	1983:4	.	.	0.09	(1.49)	0.66	(0.19)	0.30	0.63
basic industries	5.78	0.19	(0.08)	1983:12	.	1986:3	0.29	(0.14)	0.56	(0.04)	0.30	0.56
cyclical consumer goods						*no change*						
cyclical services	400.00	0.31	(0.00)	1986:5	1986:5	1986:5	0.22	(0.05)	0.46	(0.04)	0.22	0.46
financials	1.02	0.50	(0.83)	1990:2	.	.	0.34	(0.54)	0.59	(0.45)	0.38	0.55
general industries	400.00	0.38	(0.01)	1987:9	1987:9	1987:9	0.22	(0.05)	0.44	(0.03)	0.22	0.44
information technology	0.33	0.09	(18.02)	1981:11	.	.	-0.86	(28.17)	0.93	(10.06)	-0.01	0.46
noncyclical consumer goods	3.09	0.18	(0.15)	1983:10	.	1988:3	0.08	(0.31)	0.56	(0.04)	0.14	0.56
noncyclical services	0.90	0.47	(1.07)	1989:8	.	.	0.14	(0.94)	0.44	(0.81)	0.19	0.39
resources	0.23	0.11	(62.51)	1982:4	.	.	0.10	(41.40)	0.91	(21.72)	0.49	0.64
utilities						*no change*						
						Germany-United Kingdom						
market index	3.43	0.50	(0.06)	1990:4	1986:7	1994:1	0.21	(0.07)	0.66	(0.04)	0.21	0.66
basic industries						*no change*						
cyclical consumer goods						*no change*						
cyclical services	400.00	0.37	(0.00)	1987:8	1987:8	1987:8	0.09	(0.06)	0.45	(0.04)	0.09	0.45
financials	6.08	0.44	(0.08)	1988:12	1986:11	1991:1	0.24	(0.05)	0.49	(0.05)	0.24	0.49
general industries						*no change*						
information technology						*no change*						
noncyclical consumer goods	400.00	0.38	(0.00)	1987:9	1987:9	1987:9	0.16	(0.05)	0.43	(0.04)	0.16	0.43
noncyclical services	1.78	0.93	(0.59)	1999:1	1990:2	.	0.11	(0.07)	1.00	(1.65)	0.11	0.65
resources						*no change*						
utilities						*no change*						

[1] The table presents maximum likelihood estimates of part of the parameters of the STC-GARCH model in (1)-(9); remaining parameter estimates are available upon request. 'date' is the month that corresponds to c, the inflection point of the transition curve. 'start trans.' and 'end trans.' present an interval around 'date' in which 80% of the projected change in correlation from ρ_0 to ρ_1 took place. If the start or the end of this intervals falls outside the sample, a . is reported. $\hat{\rho}_{1980:1}$ and $\hat{\rho}_{2000:6}$ denote the estimated correlation at the start and the end of the sample, respectively. Robust standard errors are reported in parentheses.

Table 4: Estimates of STC-GARCH model *continued*[1]

sector	$\hat{\gamma}$	$\hat{c}$		date	start trans.	end trans.	$\hat{\rho}_0$		$\hat{\rho}_1$		$\hat{\rho}_{1980:1}$	$\hat{\rho}_{2000:6}$
						Germany-United States						
market index	10.70	0.81	(0.04)	1996:7	1995:4	1997:9	0.33	(0.04)	0.63	(0.07)	0.33	0.63
basic industries	400.00	0.36	(0.00)	1987:4	1987:4	1987:4	0.21	(0.05)	0.44	(0.04)	0.21	0.44
cyclical consumer goods	0.42	0.46	(3.60)	1989:5	.	.	−0.14	(8.51)	0.73	(7.27)	0.16	0.46
cyclical services	400.00	0.35	(0.00)	1987:2	1987:2	1987:2	0.12	(0.06)	0.40	(0.04)	0.12	0.40
financials						*no change*						
general industries	1.31	0.70	(0.85)	1994:5	1984:5	.	0.26	(0.18)	0.57	(0.68)	0.27	0.51
information technology						*no change*						
noncyclical consumer goods						*no change*						
noncyclical services						*no change*						
resources						*no change*						
utilities						*no change*						
						Japan-United States						
market index						*no change*						
basic industries						*no change*						
cyclical consumer goods						*no change*						
cyclical services						*no change*						
financials						*no change*						
general industries						*no change*						
information technology						*no change*						
noncyclical consumer goods						*no change*						
noncyclical services	4.89	0.16	(0.08)	1983:5	1980:9	1985:12	−0.24	(0.21)	0.20	(0.04)	−0.22	0.20
resources						*no change*						
utilities						*no change*						

[1] See previous page.

Table 4: Estimates of STC-GARCH model *continued*[1]

sector	$\hat{\gamma}$	$\hat{c}$		date	start trans.	end trans.	$\hat{\rho}_0$		$\hat{\rho}_1$		$\hat{\rho}_{1980:1}$	$\hat{\rho}_{2000:6}$
						Japan-United Kingdom						
market index						*no change*						
basic industries	400.00	0.62	(0.02)	1992:9	1992:9	1992:9	0.29	(0.04)	0.10	(0.05)	0.29	0.10
cyclical consumer goods						*no change*						
cyclical services						*no change*						
financials						*no change*						
general industries						*no change*						
information technology	0.21	0.45	(20.48)	1989:2	.	.	−0.37	(55.18)	0.79	(49.75)	0.11	0.33
noncyclical consumer goods						*no change*						
noncyclical services						*no change*						
resources						*no change*						
utilities						*no change*						
						Germany-Japan						
market index						*no change*						
basic industries	1.62	0.50	(0.38)	1990:3	1982:3	1998:4	0.37	(0.16)	0.13	(0.20)	0.35	0.15
cyclical consumer goods						*no change*						
cyclical services						*no change*						
financials						*no change*						
general industries						*no change*						
information technology						*no change*						
noncyclical consumer goods						*no change*						
noncyclical services	400.00	0.37	(0.01)	1987:9	1987:9	1987:9	−0.01	(0.04)	0.18	(0.04)	−0.01	0.18
resources						*no change*						
utilities						*no change*						

[1] See previous page.

Table 5: LM-test: small sample size[1]

ω	α	β	ρ	n	10%	5%	1%
0.10	0.10	0.80	0.80	200	0.15	0.08	0.02
				500	0.13	0.07	0.02
				1000	0.11	0.05	0.01
				2000	0.10	0.05	0.01
0.10	0.10	0.80	0.20	200	0.13	0.08	0.02
				500	0.13	0.07	0.01
				1000	0.12	0.06	0.01
				2000	0.12	0.06	0.01
0.10	0.40	0.50	0.80	200	0.13	0.07	0.02
				500	0.12	0.06	0.02
				1000	0.11	0.06	0.01
				2000	0.11	0.05	0.01
0.10	0.40	0.50	0.20	200	0.14	0.08	0.02
				500	0.11	0.06	0.01
				1000	0.11	0.06	0.01
				2000	0.10	0.05	0.01

[1] The Table reports rejection frequencies of the null hypothesis of correlation constancy by the LM test introduced in equation (14). Artificial time series are generated from a bivariate constant correlation GARCH(1,1) model with Gaussian disturbances. The table is based on 2000 replications.

Table 6: LM-test: small sample size when residuals are non-normal or variances feature 'leverage' effect[1]

ω	δ	α	β	ρ	k	n	10%	5%	1%
0.10	0.16	0.02	0.80	0.80	8	500	0.16	0.10	0.03
						1000	0.16	0.09	0.02
0.10	0.16	0.02	0.80	0.20	8	500	0.15	0.08	0.03
						1000	0.12	0.05	0.01
0.10	0.16	0.02	0.80	0.80	8	500	0.18	0.10	0.03
						1000	0.16	0.08	0.02
0.10	0.16	0.02	0.80	0.20	8	500	0.13	0.07	0.02
						1000	0.12	0.08	0.02
0.10	0.16	0.02	0.80	0.80	12	500	0.15	0.09	0.03
						1000	0.15	0.07	0.02
0.10	0.16	0.02	0.80	0.20	12	500	0.14	0.08	0.03
						1000	0.12	0.05	0.01
0.10	0.16	0.02	0.80	0.80	12	500	0.15	0.09	0.03
						1000	0.15	0.08	0.02
0.10	0.16	0.02	0.80	0.20	12	500	0.14	0.08	0.02
						1000	0.11	0.07	0.01
0.10	0.16	0.02	0.80	0.80	∞	500	0.14	0.09	0.02
						1000	0.13	0.07	0.01
0.10	0.16	0.02	0.80	0.20	∞	500	0.11	0.06	0.01
						1000	0.13	0.08	0.02
0.10	0.16	0.02	0.80	0.80	∞	500	0.14	0.09	0.02
						1000	0.12	0.06	0.01
0.10	0.16	0.02	0.80	0.20	∞	500	0.12	0.06	0.02
						1000	0.12	0.07	0.02

[1] The Table reports rejection frequencies of the null hypothesis of correlation constancy by the LM test introduced in equation (14). Artificial time series are generated from a bivariate constant correlation GARCH(1,1) with t_k-distributed disturbances and/or leverage effects in the conditional variances, cf. equations (15)-(16). k denotes the degrees of freedom of the t distribution, where $k = 8, 12$. $k = \infty$ means that the residuals are sampled from the Gaussian distribution. The Table is based on 1000 replications.

Table 7: LM-test: small sample power at nominal size of 5%[1]

ω	α	β	ρ_0	ρ_1	γ	c	n	
0.10	0.10	0.80	0.20	0.40	100.00	0.50	500	0.64
							1000	0.90
0.10	0.10	0.80	0.20	0.40	100.00	0.80	500	0.30
							1000	0.53
0.10	0.10	0.80	0.20	0.40	10.00	0.50	500	0.62
							1000	0.89
0.10	0.10	0.80	0.20	0.40	10.00	0.80	500	0.29
							1000	0.52
0.10	0.10	0.80	0.20	0.40	1.00	0.50	500	0.23
							1000	0.36
0.10	0.10	0.80	0.20	0.40	1.00	0.80	500	0.17
							1000	0.27
0.10	0.10	0.80	0.20	0.60	100.00	0.50	500	1.00
							1000	1.00
0.10	0.10	0.80	0.20	0.60	100.00	0.80	500	0.87
							1000	0.99
0.10	0.10	0.80	0.20	0.60	10.00	0.50	500	1.00
							1000	1.00
0.10	0.10	0.80	0.20	0.60	10.00	0.80	500	0.86
							1000	0.98
0.10	0.10	0.80	0.20	0.60	1.00	0.50	500	0.74
							1000	0.95
0.10	0.10	0.80	0.20	0.60	1.00	0.80	500	0.52
							1000	0.83
0.10	0.10	0.80	0.20	0.80	100.00	0.50	500	1.00
							1000	1.00
0.10	0.10	0.80	0.20	0.80	100.00	0.80	500	1.00
							1000	1.00
0.10	0.10	0.80	0.20	0.80	10.00	0.50	500	1.00
							1000	1.00
0.10	0.10	0.80	0.20	0.80	10.00	0.80	500	1.00
							1000	1.00
0.10	0.10	0.80	0.20	0.80	1.00	0.50	500	0.99
							1000	1.00
0.10	0.10	0.80	0.20	0.80	1.00	0.80	500	0.91
							1000	0.99

[1] The Table reports rejection frequencies of the null hypothesis of correlation constancy by the LM test introduced in equation (14). Artificial time series are generated by the STC-GARCH model (1)-(9). The table is based on 1000 replications.