What Drives Correlation Between Stock Market Returns? International Evidence

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Abstract

This paper proposes to model time-varying conditional correlation as a function of conditional volatilities and possible additional explanatory variables via logit-type regression. The advantage of this approach is that it allows us to study the contributions of internal national market volatilities, external world market volatility, and some other factors to the correlation between stock market returns. Empirical investigation of the incremental effect of volatility on correlation is reported for a number of stock markets in North America, Asia, and Europe. Our results reveal that time-varying correlations between stock markets are primarily dependent on national and world market volatilities. Weaker evidence is found that correlations are driven by market downturns. Also, we find that correlations have been increasing between national markets in recent years.

Key words: Conditional correlation, volatility, logit, GARCH.

JEL classification: C21; C22; C51; G10; G15

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I. Introduction

Numerous studies demonstrate that contemporaneous correlations between international stock markets' returns are unstable over time (see Makridakis and Wheelwright (1974), Knif and Pynnonen (1999), and Koch and Koch (1991)). In this regard, it is well known that correlations among international markets tend to increase when stock returns fall precipitously (see King and Wadhwani (1990), Lin, Engle, and Ito (1994), Longin and Solnik (1995), Karolyi and Stulz (1996), Solnik, Boucrelle, and Fur (1996), Ramchand and Susmel (1998), Chesnay and Jondeau (2001), Ang and Bekaert (2002), Dennis, Mayhew, and Stivers (2005), Baele (2005), Silvennoinen and Teräsvirta (2005), and others). Extending these findings to domestic markets, studies by Ang and Chen (2002) and Silvennoinen and Teräsvirta (2005) find asymmetries in correlations between individual U.S. stocks and the aggregate U.S. market also.

Only a few studies have sought to examine the sources of time-varying correlation. For example, based on a switching ARCH model and weekly data, Ramchand and Susmel (1998) find that correlations between the U.S. and other world markets are 2 to 3.5 times higher when the U.S. market is in a high volatility state (or regime) as compared to a low volatility state. These results suggest that volatility is a major driver of correlation. However, applying extreme value theory, Longin and Solnik (2001) argue that correlation is not related to market volatility (large absolute returns) per se but to the market trend. Using monthly data, they find that in international markets, especially in the case of negative returns, correlations tend to increase and hence the negative tail-distribution deviates considerably from the normal distribution. Consequently, they infer that correlation tends to increase in bear markets but not in bull markets. Also, they infer that conditional correlation is mainly affected by market trend rather than volatility in periods of extreme returns. Thus, the limited empirical evidence on the question of what drives time-varying correlation is mixed.

In this paper we attempt to contribute further evidence on the sources of correlation between stock returns. Unlike the aforementioned studies that examine changing correlation across either various sub-periods, conditional or extreme value correlation, or correlation under different volatility regimes, we model the dependence of the correlation *directly* on the level of prevailing uncertainty, which is measured in terms of volatilities and other potential risk factors. Starting from the definition of correlation, we derive an explicit logit functional relation between time-varying conditional correlation and conditional volatilities plus possible additional explanatory variables. Importantly, this model enables us to comparatively investigate how time-varying correlation is affected by internal volatilities (i.e., volatility terms included in the correlation definition), external volatilities (i.e., volatility terms not included in the correlation definition), and other factors such as market trend.

We collect daily returns for markets in North America (United States), Asia (Japan), and Europe (United Kingdom, France, Germany, Switzerland, the Netherlands, Denmark, Sweden, Norway, and Finland), in addition to the Financial Times world index (FTAW) as a proxy for the world market. Although preliminary analyses for the period 1990-2005 appear to suggest that volatilities and correlations are significantly higher when world markets are down trending (i.e., a bear market) as in some earlier studies cited above, more structured analyses using our logit regression model reveal that this effect is secondary in importance to volatility as a driver of correlation. For the sample period 1990 to 2005, we find that time-varying correlations between stock market returns are primarily explained by internal national market volatilities and external world market volatilities. Moreover, in terms of economic significance, we find that large increases in volatility can substantially change correlations. Down trends in world markets are significant at times but have a relatively weaker relationship than volatility to correlations between stock market returns. We also document that correlations have been increasing between national markets from 1990 to 2005, which means that the increasing correlation found by Longin and Solnik (1995) for the period 1960 to 1990 has continued in recent years. This trend is likely attributable to increasing financial market integration of national stock markets around the world. We conclude from these findings that national market and world market volatility are the major drivers of time-varying correlation between international stock markets, and that down trending markets in some cases plays a role in explaining contemporaneous correlation also.

The rest of the paper is organized as follows. The next section discusses the methodology, including model development and estimation. Section 3 describes the sample data. Section 4 presents the empirical results, and Section 5 concludes.

2. Methodology

This section deals with the relationship of correlation to time-varying volatility as well as to the underlying volatility regime. In the GARCH literature time-varying correlation is considered to be a kind of clustering phenomenon in the same manner as volatility clustering. This approach has the fundamental shortcoming of not identifying the sources of changing volatility and changing correlation. The focus is on a description of the process, rather than explicitly understanding what explains changes in correlation, such as the magnitude of risk or other factors. In this paper we model the degree of correlation as a function of the magnitude of local and global uncertainties and other factors. In this way we attempt to identify potential drivers of changing correlations.

A. Modeling Correlation and Volatility

By definition, the conditional correlation of (return) series u_t and v_t is defined as:

$$\rho_t(u,v) = \frac{\text{cov}_t(u,v)}{\sqrt{\text{var}_t(u)\,\text{var}_t(v)}}\,, \tag{1}$$

where the subscript denotes the predicted entity given information up to time point $t-1$, e.g., $\text{var}_t(u) = E_{t-1}[u_t - E_{t-1}(u_t)]^2 = E\left[(u_t - E(u_t \mid \Psi_{t-1}))^2 \mid \Psi_{t-1}\right]$ with Ψ_{t-1} indicating the available information up to time $t-1$. In terms of the covariance, we have:

$$\text{cov}_t(u,v) = \rho_t(u,v)\sqrt{\text{var}_t(u)}\sqrt{\text{var}_t(v)}\,. \tag{2}$$

In the simple case when the correlation is time invariant, we see from equation (2) that the time-varying covariance must change in a fixed proportion to the product of the time-varying standard deviations. In this case asymmetries in volatilities reflect asymmetries in the covariance as well. Consequently, it may be difficult to infer on the basis of the covariance whether the dependence per se between the series is time-varying or due simply to the fixed relation between the volatilities and covariance determined by the time invariant correlation.

In order to avoid this problem, we investigate the time variability in the covariation allowing also correlation to be time varying (rather than constant). For this purpose we define as an instrumental tool a "generalized conditional covariance"

$$\text{cov}_{t,a,b}(u,v) = c_t\sigma_{1,t}^a\sigma_{2,t}^b\,, \tag{3}$$

where $\sigma_{1,t} = \sqrt{\text{var}_t(u)}$, $\sigma_{2,t} = \sqrt{\text{var}_t(v)}$, and c_t is a coefficient which may be time-varying and may depend on some additional variables. With $a = b = 1$ and $c_t = \rho_t(u,v)$, equation (3) coincides with the usual covariance. In equation (3) parameters *a* and *b* determine the importance of each standard deviation's relative contribution to the covariance. For example, if both *a* and *b* are larger than one, the correlation must increase as a function of the volatilities.

To focus on the correlation, we divide both sides of equation (3) by the conditional standard deviations to get

$$\rho_t(u,v) = c_t \sigma_{1,t}^{\tilde{a}} \sigma_{2,t}^{\tilde{b}}, \tag{4}$$

where $\tilde{a} = a - 1$ and $\tilde{b} = b - 1$. If the correlation is independent of the level of volatilities, we should have $\tilde{a} = \tilde{b} = 0$. Given estimates of the correlations and standard deviations, we could in principle estimate equation (4) with non-linear techniques. However, technical difficulties may arise because the left-hand-side is restricted by definition between –1 and +1, whereas the right-hand-side is not restricted in an econometric specification. To linearize the problem and make both sides unrestricted, we adopt the Fisher *z*-transformation (or a generalized logit transformation) such that

$$\frac{1}{2}\log\left(\frac{1+\rho_t}{1-\rho_t}\right) = \omega_t + \gamma_1 \log \sigma_{1,t} + \gamma_2 \log \sigma_{2,t}, \tag{5}$$

in which both sides are balanced in the sense that they can assume all real values. A similar transformation is utilized in Christodoulakis and Satchell (2002). Using the Taylor approximation (in the vicinity of zero), we have $0.5\log\left((1+\rho_t)/(1-\rho_t)\right) \approx \rho_t$. Thus, the γ coefficients have a straightforward interpretation: as volatility increases by 1%, the correlation should change by $0.01 \times \gamma$.[1] The intercept term parameter ω_t may include other variables, such as world volatility, global market trend, etc. If the correlation is neither dependent on the internal volatilities nor some external factors, coefficients γ_1 and γ_2 should be zeros, and ω_t should be a constant. A positive sign on the γ-coefficient indicates increasing correlation with the internal volatilities. We call this effect *convergence* because of the implied more pronounced co-movement. A negative coefficient sign would suggest that the internal volatility reflects local intra-market shocks that have no external impact and hence would reduce the co-movement in returns. We call this effect *divergence*.

To further investigate the properties of the above correlation model, we take the inverse transformation of equation (5), which gives

$$\rho_t = \frac{e^{2\omega_t + 2\gamma_1 \log\sigma_{1,t} + 2\gamma_2 \log\sigma_{2,t}} - 1}{e^{2\omega_t + 2\gamma_1 \log\sigma_{1,t} + 2\gamma_2 \log\sigma_{2,t}} + 1} = \frac{\sigma_{1,t}^{2\gamma_1}\sigma_{2,t}^{2\gamma_2}e^{2\omega_t} - 1}{\sigma_{1,t}^{2\gamma_1}\sigma_{2,t}^{2\gamma_2}e^{2\omega_t} + 1}. \tag{6}$$

It is immediately obvious that $|\rho_t| < 1$ for all real values of the variables. Consider next the asymmetry of correlation observed in several empirical studies (Longin and Solnik (2001), Ang and Chen (2002), and others). From equations (5) and (6) it is obvious that asymmetry in volatility affects correlation. For example, suppose that the volatility follows an asymmetric GARCH (or threshold GARCH, TGARCH, Zakoïan (1994)) process such that

$$\sigma_t^2 = \alpha_0 + \alpha_1 w_{t-1}^2 + \alpha_2 w_{t-1}^2 I_{t-1} + \beta\sigma_{t-1}^2, \tag{7}$$

where I_{t-1} is an indicator function equal to one if $w_{t-1} < 0$, and zero otherwise. Volatility asymmetry is captured in equation (7) by α_2, where positive α_2 indicates the presence of leverage.

Because equation (5) is a monotonic transformation of the correlation in equation (6), we can utilize it in detecting the effect of leverage on correlation. The impact of leverage depends on the sign of the γ coefficients. For example, if $\gamma_1 < 0$ (i.e., a diverging volatility effect as discussed above), and given the usual case in which the contemporaneous correlation is positive, an increase in internal volatility induces a reduction in the co-movements of the returns. Hence, in the presence of leverage, a negative shock further increases the volatility and, in turn, decreases the correlation. The opposite is true if the corresponding γ coefficient is positive. Thus, the way asymmetries in local market risks are reflected in mutual correlations depend on whether convergence or divergence due to the volatility increase prevails between the markets. In the presence of leverage, the former increases the correlation and the latter decreases it.

B. Estimation of the Model

In equation (5) the volatilities $\sigma_{u,t}$ and $\sigma_{v,t}$ are internal in the sense that they are contained in the basic definition of the correlation. Additionally, by structuring ω_t further we may consider it as a function of additional explanatory variables, such as volatilities of other series which can serve as additional risk components in the correlation. To investigate the influences of general market volatility and market trend effects on correlation (Longin and Solnik (2001)), we incorporate the world index volatility and indicator variables of world bullish and bearish markets into the correlation equation. Also, to isolate these factors' independent effects on correlation, it may be important to allow some additional covariates, such as the time trend discussed above, to eliminate confounding effects in the estimation. Hence, our final regression takes the general form

$$z_t = \mathbf{x}_t^{'}\boldsymbol{\beta} + \mathbf{c}_t^{'}\boldsymbol{\eta}, \qquad (8)$$

where $z_t = \log[(1+\rho_t)/(1-\rho_t)]$, $\mathbf{x}_t$ is a vector including the constant term, log volatilities, and market trend (bullish/bearish), and $\mathbf{c}_t$ includes possible additional covariates (e.g., seasonal effects akin to day-of-week, turn-of-month, January effects, and ARMA terms).

As already discussed, we have $|\rho_t| < 1$ for all real values of z_t. This implies that the conditional covariance matrix of bivariate return vector $\mathbf{u}_t = (u_t, v_t)'$,

$$\operatorname{cov}_{t-1}(\mathbf{r}_t) = \Sigma_t = \begin{pmatrix} \sigma_{1,t}^2 & \rho_t\sigma_{1,t}\sigma_{2,t} \\ \rho_t\sigma_{1,t}\sigma_{2,t} & \sigma_{2,t}^2 \end{pmatrix} = \mathbf{D}_t^{1/2}\mathbf{R}_t\mathbf{D}_t^{1/2}, \qquad (9)$$

is positive definite, where

$$\mathbf{D}_t^{1/2} = \begin{pmatrix} \sigma_{1,t} & 0 \\ 0 & \sigma_{2,t} \end{pmatrix} \text{ and } \mathbf{R}_t = \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix}. \qquad (10)$$

As shown in Appendix A, since the positive definiteness of the covariance matrix is not guaranteed except in the bivariate case, our analyses are based solely on this case. Assuming conditional normality of the return vector and ignoring the constant terms, we can write the log likelihood as $\ell = \sum_t \ell_t$, where ℓ_t are the (conditional) likelihoods of the single observations given by

$$\ell_t = -\frac{1}{2}\log|\Sigma_t| - \frac{1}{2}\boldsymbol{\varepsilon}_t{}'\Sigma_t^{-1}\boldsymbol{\varepsilon}_t, \tag{11}$$

where $\boldsymbol{\varepsilon}_t = \mathbf{u}_t - E_{t-1}[\mathbf{u}_t]$, and the prime denotes transposition. Following Engle (2002), and using the right-hand presentation of the covariance matrix in equation (9), we can decompose the log likelihood as

$$\ell_t = \left(-\frac{1}{2}\log|\mathbf{D}_t| - \frac{1}{2}\boldsymbol{\varepsilon}_t{}'\mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t\right) + \left(-\frac{1}{2}\log|\mathbf{R}_t| - \frac{1}{2}\mathbf{w}_t{}'\mathbf{R}_t^{-1}\mathbf{w}_t\right) + \frac{1}{2}\mathbf{w}_t{}'\mathbf{w}_t, \tag{12}$$

where $\mathbf{w}_t = \mathbf{D}_t^{-1/2}\boldsymbol{\varepsilon}_t = (\varepsilon_{1,t}/\sigma_{1,t}, \varepsilon_{2,t}/\sigma_{2,t})'$ are independent variables with zero means and unit variances. Hence, the last term can be ignored again as a constant from the likelihood. As in Engle (2002), we have

$$\ell_{V,t} = -\frac{1}{2}\log|\mathbf{D}_t| - \frac{1}{2}\boldsymbol{\varepsilon}_t{}'\mathbf{D}_t^{-1}\boldsymbol{\varepsilon}_t, \tag{13}$$

and

$$\ell_{C,t} = -\frac{1}{2}\log|\mathbf{R}_t| - \frac{1}{2}\mathbf{w}_t{}'\mathbf{R}_t^{-1}\mathbf{w}_t \tag{14}$$

so that the log likelihood decomposes into the volatility part and correlation such that

$$\ell_{VC,t} = \ell_{V,t} + \ell_{C,t}. \tag{15}$$

Because D_t is a diagonal matrix, equation (13) is the sum of individual volatility likelihoods. Making the reasonable assumption that the volatility parameters do not depend on the correlation parameters, the properties of maximum likelihood (ML) estimates imply that under standard regularity conditions the estimates resulting from the volatility part will be consistent. Using these volatility parameters in the correlation likelihood, and solving the

ML estimates of the remaining parameters in the correlation function, again (by the properties of the ML) yields consistent estimates for these parameters (for a thorough discussion of two-step estimation, see Newey and McFadden (1994)).

Decomposition of equation (15) and the above discussion suggests that two-step estimation can be expected to produce estimates as accurate as the single step estimation based on likelihoods given in equation (11). The two-step procedure simplifies the estimation task and is particularly useful in high dimensional problems. However, as already mentioned, we focus here on only the bivariate case because the positive definiteness of the correlation matrix cannot be guaranteed in general. Even in this case, two-step estimation based on likelihoods in equation (15) is preferred.

An alternative to the normal distribution is the *t*-distribution, for which the single observation log likelihood becomes

$$\ell_{m,t} = -\frac{1}{2}\log\left[\frac{(\pi v)^m \Gamma^2[v/2]}{\Gamma^2[(v+m)/2]}\right] - \frac{1}{2}\log|\Sigma_t| - \frac{v+m}{2}\log\left(1 + \frac{\boldsymbol{\varepsilon}_t'\Sigma_t^{-1}\boldsymbol{\varepsilon}_t}{v}\right), \tag{16}$$

where $\Gamma[\cdot]$ is the Gamma function, m is the number of variables, and v is the degrees of freedom. In the bivariate case with $m = 2$, because $\Gamma[x] = (x-1)\Gamma[x-1]$, we have $\Gamma[(v+2)/2] = (v/2)\Gamma[v/2]$, and the first term on the right-hand-side of equation (16) reduces to $-\log(2\pi)$ and can be dropped out from the likelihood. However, it is obvious that, unless the degrees of freedom parameter v is known, the *t*-log likelihood in equation (16) does not decompose contrary to the normal likelihood.

Finally, diagnostic statistics to check the adequacy of the correlation model are derived in Appendix B.

3. Data

We utilize daily close-to-close stock index returns for twelve national markets, including stock exchanges in the United States (S&P500), Japan (Nikkei 225), UK (FT100), United Kingdom (FT100), Germany (DAX), Switzerland (SSMI), France (CAC40), the Netherlands (AEX General), Denmark (KFX), Sweden (Stockholm General), Norway (OSE All Share), and Finland (HEX All Share), in addition to the Financial Times world index (FTAW). The sample series starts January 2, 1990 and ends January 31, 2005. Index quotations for national holidays are replaced by the index value of the previous trading day yielding N = 3,992 daily observations. Data is obtained mainly from the websites for Yahoo (finance.yahoo.com) and Global Financial Data Inc. (www.globalfindata.com) where complete descriptions of the indices can be found.

Previous studies on the relationship between correlation, volatility, and market trends use weekly or monthly data, rather than daily data. As observed in standard textbooks (e.g., Ingersoll (1985) and Campel, Lo, and MacKinlay (1997)), higher sampling frequency is associated with more accurate (contemporaneous) correlation and volatility estimates. This is due to the fact that, unlike mean return estimation for which the sampling frequency is unimportant, lower frequency data smooths variation between adjacent observations resulting in smoothed estimates of correlation and volatility that discard important information. However, the benefits of more frequent sampling must be balanced against other problems, commonly called microstructure issues, which arise particularly in the case of intraday data. Consequently, we prefer daily data for the estimation of contemporaneous correlation and time-varying volatilities.

The daily index returns are defined by log-differences as

$$r_t = 100 \times \log(I_t / I_{t-1}) \,, \tag{17}$$

where log is the natural logarithm, and I_t is the index value of day *t*. Table 1 reports sample statistics for the returns. Generally, the sample period is characterized by a small positive daily mean return between 0.02% to 0.04% for all other markets but Japan, where the average return is negative -0.031% due to the long stock market downturn there. All the markets exhibit slight negative skewness and strong kurtosis, as well as highly statistically significant squared return autocorrelations (volatility clustering). Additionally, besides the small Nordic markets, Switzerland and the world market index have slight though statistically significant return autocorrelations.

Table 2 reports estimated contemporaneous correlation coefficients for the sample period. All the correlations are positive ranging from 0.117 (US/Japan) to 0.803 (France/Netherlands). The overall average correlation is 0.475. Japan has the lowest correlations with the other markets, with an average of 0.224. These lower correlations are partially explained by the non-overlapping trading hours of Asian markets with the European and North American markets. France and Netherlands have the highest average correlations of 0.575 and 0.593, respectively, with the other markets. The major European markets of UK, Germany, France, Switzerland, and the Netherlands have the highest correlations with values ranging from 0.663 to 0.803. The small Nordic markets of Sweden, Denmark, Finland, and Norway are also fairly highly correlated with one another as well as with the major European markets, with correlations ranging from 0.438 (Denmark/Finland) to 0.639 (Sweden/Finland).

To gain further insight into the nature of the cross-county correlations, we divided the sample into global up and down markets according to the slope of the trend in the world market index. The trend is defined here as the slope of the Exponentially Weighted Moving Average (EWMA), or

(18) $$\text{trend}_t = w\,(\text{world index})_t + (1-w)\,\text{trend}_{t-1}$$

with weight $w = 0.05$ (i.e., 5% weight on the previous observation). The world markets are considered down (bear market) when $\text{trend}_t < \text{trend}_{t-1}$, and up (bull market) otherwise. Another possibility could be to define pairwise bull/bear markets in a similar manner; however, this approach would be exposed to a selection bias. That is, we first define regimes in which the markets are behaving alike and then measure whether the markets during these periods are more alike than on average in the sample period. To avoid this selection bias we employ the trend of global markets to define bull and bear markets. For further discussion of the selection bias and relative consequences to correlation of different value regimes of the variables affecting correlation, see Forbes and Rigobon (1998), Boyer, Gibson, and Loretan (1999), and Longin and Solnik (2001).

Table 3 reports the estimated correlations for the down trending and up trending periods in panels A and B, respectively. On average the correlations are 0.09 (24%) larger in the down markets than in the up markets. The Swiss market correlations increase on average the most in absolute terms (0.122) in down markets, while the Japanese correlation increases the most in relative terms with an increase from 0.161 on average in up markets to 0.244 on average in down markets (or about a 50% increase in down markets).

Most of the other differences are statistically significant[2], with the exception of correlations between US/Japan, US/UK, US/France, US/Netherlands, and US/Finland. The non-overlapping opening hours of markets in different parts of the world may have an impact on these results.

We also calculated other sample statistics for these two market directions. To conserve space the results are not reported here but are available from the authors upon request. In summary, the results show that volatility was on average more than 40% higher in the down markets, and the difference in each case was highly statistically significant. The smallest increase in volatility during the down market was 31% for Norway, and the largest was over 50% for France. For the US the increase was about 50% also.

Table 4 reports the individual TGARCH specifications as given in equation (7) for the return volatilities over the whole sample period (with mean-returns modeled using an ARMA if needed to account for possible autocorrelation). Panel A of Table 4 indicates that in several cases the return series are autocorrelated. No discernible autocorrelation is found in the US, Japan, UK, Germany, and the Netherlands series. Nevertheless, in most cases the asymmetric GARCH effect is clearly present, except for Finland. From the diagnostic statistics in panel C of Table 4, we see that there is possibly left behind some longer lag autocorrelation in some return series (e.g., in France and the US), albeit small in magnitude (e.g., for France the largest autocorrelation for lags 1 to 5 is -0.038, and for the US it is -0.037). Hence, autocorrelation will not have any material impact on the TGARCH estimation, which is important here. Again, according to the diagnostics in panel C of Table 4, the asymmetric TGARCH captures fairly well the clustering volatility. With respect to the squared residuals, the first order autocorrelation is borderline significant in the cases of Japan and Norway with corresponding autocorrelations of -0.034 and 0.029, respectively, which again are quite small. For France, Norway, and Finland we removed one or two obvious outliers; however, the estimation results were not changed, with the exception of the kurtosis estimate. As such, we retained all observations in our correlation estimations.

IV. Empirical Results

This section reports estimation results for the logit regression models. We have enhanced the basic model in equations (5) to (10) by including log world volatility, world down trend dummy defined by the sign of the slope of (18), and trend. We present estimation results for European markets and leading world markets. For the European markets there is no problem of non-overlapping trading hours that arises when using daily data to compute correlations among leading markets in different parts of the world. For this reason we use daily returns for analyses of European markets and weekly returns for the world leading markets that span different continents and daylight time zones. As mentioned earlier, higher frequency observations tend to yield more precise estimates for correlations and volatilities. Consequently, forthcoming discussion begins with and places more emphasis on the European markets' daily return results than the leading world markets' weekly return results.

A. European Markets

We break the European markets into two parts: (1) major European markets, and (2) Nordic markets. The reason for this bifurcation is that the Nordic markets form a fairly homogenous group and are considerably smaller in volume and market capitalization than the other European markets in our sample. For example, each of the Nordic countries is only about 1/6th (1/20th) in market capitalization relative to the smallest major European market of Switzerland (largest European market of the UK) in the sample. It also provides an opportunity to investigate whether the dependence structure among smaller markets and larger markets differ from each other.

1. Major European Markets

As noted in Solnik, Boucrelle, and Fur (1996, p. 23), the volatilities themselves tend to be highly correlated with one another, thereby causing multicollinearity in regressions of national and world volatilities on correlation coefficients. This proved to be the case in our study as well. The average correlation of the log TGARCH volatilities between the major European markets was 0.84, with a minimum of 0.76 (UK/Switzerland) and maximum of 0.92 (Germany/Netherlands). The correlations with the world market volatility were generally close to 0.80. It is obvious that there is much overlapping information in the volatilities; hence, when including all the volatility series into the equation, the results manifested the typical symptoms of multicollinearity. One symptom was the significance of volatility variables when included in the model one at a time but insignificance of volatility variables when they are all included in the regression model (e.g., the case of UK/Germany). Another symptom was both positive and negative signs for estimated volatility coefficients (e.g., in each Swiss correlation the Swiss volatility was positive and highly significant, while the other country had a highly significant negative coefficient, which was also true for the Germany/France equation). Because of the high degree of overlapping information, identification of each volatility's marginal contribution becomes extremely unreliable. Thus, we can only infer whether volatility per se is an important driver of correlations relative to other factors. We do this by running the separate regressions with each volatility variable (in combination with the world down trend dummy and time trend in the equation). The results for these separate (logit) regressions for pairwise countries denoted country(1)/country(2) are reported in Table 5, with country 1's volatility in Panel A, country 2's volatility in Panel B, and world volatility in Panel C.

Panels A and B of Table 5 show that in almost all cases the national volatilities are statistically significant with positive signs. In 8-out-of-10 cases (9-out-of-10 cases) the estimated coefficients for log σ_1 (log σ_2) are significant. An exception here is the Germany/France correlation, in which neither of the national volatilities is significant. Also, in the case of France/Netherlands correlations, the French volatility is not significant. Panel C of Table 5 shows that in 10-out-of-10 cases the world volatility is highly statistically significant with positive sign, with the possible exception of the borderline significance in the UK/French equation.

The world down trend dummy is statistically significant in a number of equations but not as frequently as the volatility variables. In Panels A, B, and C of Table 5, world down trend is significant in 6-out-of-10 cases, 4-out-of-10 cases, and 1-out-of-10 cases, respectively. Hence, when national volatilities are in the model, world down trend is a fairly significant explanatory variable. But when world volatility is in the model, the down trend dummy becomes insignificant for the most part, with the exception of the Germany/Switzerland equation.

Finally, notice that the time trend is highly statistically significant in all equations, excluding Germany/Switzerland. This suggests that the mutual correlations between European markets have been increasing over the last 15 years.

We infer that national and world volatilities are the major drivers of changes in correlation over time (i.e., convergence), and that world down trend is significant but of lesser importance. To get some intuition about the magnitude of the impact of volatility increases on the correlations, we can interpret the estimated regression coefficients as discussed earlier. For example, in Panel C of Table 5, the regression coefficients vary from 0.209 (UK/France) to 0.601 (France/Netherlands). From Table 1 on average world volatility is about 13%. If world volatility increased by 10% (or by 1.3 percentage points to 14.4 %), the model would predict the UK/France correlation to increase by 0.02 and the France/Netherlands correlation by 0.06. Other correlations would increase by amounts in between these values. Importantly, these magnitudes have economic significance in the sense that larger increases in volatility can substantially change the correlation.

According to the diagnostic statistics reported in the two last lines in each panel, empirically there are no differences between the models. In terms of the Q-test, which measures the remaining correlation in the products $z_1 z_2$ of the (Cholesky) standardized residuals, the only statistically significant cases are Germany/Netherlands and France/Netherlands. However, the individual autocorrelations of the residual cross-products are of magnitude 0.05 or smaller, which are negligible compared to the autocorrelations in the range of 0.18 to 0.28 for the cross-products of the original returns series. Thus, although statistically significant, these results are not economically meaningful. The QM-statistics measure adequateness in a broad sense by taking into account other possible serial dependencies. There are dependencies (other than time-varying correlation) left behind in many of the models when lags are accumulated up to the fifth order. However, the Q-statistics indicate that these possible dependencies are likely from other sources than time-varying correlation. Accordingly, the overall results and in particular the Q-statistics indicate that the model performs quite well in capturing time-varying correlations.

2. Small Nordic Markets

Table 6 reports the correlation equation results for the four Nordic markets of Sweden, Denmark, Finland, and Norway. These markets are considerably smaller in volume and market capitalization than the major European markets (i.e., capitalization below 10% of the UK). Summarizing the volatility findings: in 3-out-of-6 cases (viz., Sweden/Denmark, Sweden/Finland, and Sweden/Norway) the national market volatilities of the first country are significant, in 4-out-of-6 cases (viz., Sweden/Finland, Sweden/Norway, Denmark/Norway, and Finland/Norway) the national market volatilities for the second country are significant, and in 6-out-of-6 cases the world market volatility is significant. With only the exception of the Sweden/Norway correlation, the trend results indicate that the correlations between Nordic countries have been significantly increasing over the sample period. Finally, with only the exception of the Sweden/Norway correlation, the world down trend is not statistically significant. We infer that, to a greater extent than in the major European markets, the major driver behind time-varying correlations among small Nordic countries' stock market returns is market volatility in general and world market volatility in particular. When world market volatility increases, Nordic countries' stock markets tend to move increasingly in the same direction and, hence, increase mutual contemporaneous correlations. Notice that the marginal effect of world volatility is somewhat more pronounced in the correlations of these small European markets than the larger European markets discussed above. Panel C of

Table 6 shows that the world volatility's marginal effect on the correlations ranges from 0.353 (Sweden/Norway) to 0.669 (Sweden/Denmark). Again, these estimated coefficients can be interpreted to mean that, if the world volatility increases by 10% (i.e, from its average of 13% by about 1.3 percentage points to 14.4%), the correlations among Nordic markets are expected to increase by 0.04 for Sweden/Norway and 0.07 for Sweden/Denmark. As we found for major European markets, large volatility shocks have economic significance. Finally, world down trend has a weaker effect than in the major European markets, due in all likelihood to the dominance of world volatility as the most important factor explaining contemporaneous correlations.

The diagnostic statistics in the lower portion of Table 6 suggest that the models capture the time series dependencies in the data. The only exception is the Finnish/Norwegian correlation, where the general QM statistics indicate dependencies in the residuals. However, as in the case of the major European countries, we infer from the Q-statistics that these potential dependencies are attributable to influences other than time-varying correlation.

B. Leading World Markets

As already mentioned, correlations based on daily returns between regions (North America/Europe, North America/Asia, and Europe/Asia) are prone to some degree to the problem of (largely) non-overlapping trading hours. Information generated in Europe and the US is impounded in Asian returns the next day. By contrast, Asian information is fully available in the US on a given trading day after being filtered through the European markets. The same is mainly true of the relationship between the US and Europe, where US information arrives in Europe the next day after being processed in the Asian markets.

Due to this timing problem, we initially lagged US market daily returns one day relative to European and Japanese returns, and lagged European market daily returns one day relative to Japanese returns (see Hamao, Masulis and Ng (1990) and Bessler and Yang (2003)). In all cases the estimated coefficients for $\log\sigma_1$ were positive and those for $\log\sigma_2$ were negative. At first glance this appears to be divergence but another potential explanation is the use of lagged observations due to nonoverlapping trading hours (i.e., $\log\sigma_2$ is computed one day later than $\log\sigma_1$). We tested this possibility by not lagging the data series (i.e., the data is lagged the other way with $\log\sigma_1$ computed on the same day but later in time than $\log\sigma_2$). Now the estimated coefficients for $\log\sigma_1$ became negative and those for $\log\sigma_2$ became positive. We further tested how lagged observations affect the estimated coefficients for $\log\sigma_1$ and $\log\sigma_2$ by using the European data series. We lagged the German market returns relative to other countries' returns and in every case the other country had a negative volatility coefficient. These results suggest that contemporaneous correlations between stock markets are difficult to study when nonoverlapping trading hours exist. Importantly, the implication for our study is that the contemporaneous correlation results for the European countries are more reliable than those for leading world markets.

To mitigate the problem of nonoverlapping trading hours, we opted to run the analyses of leading world markets using weekly returns. Table 7 reports the results of correlation regressions between the leading major markets in the world, including the US, UK, Germany, and Japan.[2] Notice that national volatilities and the world volatility variable are generally significant for US/UK and US/Germany correlations[3] but not significant in the correlations of Japan with the US, UK, and Germany. A plausible explanation for the latter finding is the chronic economic stagnation and financial market turmoil in Japan throughout the 1990's that affected its correlations with other leading markets.

World down trend is significant for US/UK and UK/Japan correlations. Thus, as in the European market results, market down trend is significant in explaining changes in correlation over time.

Finally, the time trend variable is significant for the US/UK, US/Germany, and Germany/Japan correlations but not for US/Japan and UK/Japan correlations. We infer that correlations between leading markets have been generally increasing in our sample period, with the exception of the unique case of Japan.

The diagnostic statistics in the lower panel of Table 7 again suggest that the models capture the time variation in the series. The QM-statistic is only borderline significant in the US/Germany correlation. In all other cases except Germany/Japan, the Q-statistics are far from significance. A closer look at the autocorrelations of the cross-products of the Cholesky standardized residuals of the Germany/Japan case revealed that in each case the autocorrelation at lag 3 is about 0.12, which explains the significance of the Q-statistics. However, it is likely that this long lagged dependence between markets in different parts of the world is simply a random result.

5. Conclusion

This paper focused on the dependence of contemporaneous return correlation between stock market returns in different countries on volatilities of both internal national markets and external world markets. Starting with the definition of correlation, our main contribution was to propose an explicit model to investigate the contribution of the level of volatility and other variables with respect to mutual correlations between stock market returns. More specifically, we directly modeled time-varying conditional correlation as a function of internal national market and external world market volatilities in addition to other explanatory variables via logit-type regression.

The markets in our study were: North America -- US (S&P500); Asia -- Japan (Nikkei225); and Europe – United Kingdom (FT500), France (CAC40), Germany (DAX), Switzerland (SSMI), the Netherlands (AEX General), Denmark (KFX), Sweden (Stockholm All Share), Norway (OSE All Share), and Finland (HEX All Share). Considering the small Nordic markets (Finland, Denmark, Norway and Sweden) as its own group provided an opportunity to investigate whether the correlations between small markets behave differently than those between larger markets. We also included in our analyses the Financial Times world index (FTAW) as a proxy for world market volatility. Initial empirical analyses of stock market returns using daily data in the sample period 1990-2005 confirmed that correlation is more pronounced when the world market index is trending down. However, further structured analyses based on our logit-type regression model using daily data lead us to conclude that the major determinants of time-varying correlations between stock market returns are national market and world market volatilities (i.e., the convergence effect). After controlling for the general increasing trend in the correlations, the world volatility was especially pronounced in the small Nordic market equations. Moreover, in terms of economic significance, we found that large increases in volatility can substantially change correlations. These results support earlier studies that find mutual correlations tend to increase when volatility is high (Solnik, Boucrelle, and Fur (1996), Ramchand and Susmel (1998), Dennis, Mayhew, and Stivers (2005), Baele (2005), and others). We also find that correlations between stock market returns in different countries increase during worldwide bearish markets (Longin and Solnik (2001), Ang and Chen (2002), and others), but this relationship was weaker in magnitude than volatility. Further results showed that most of the stock market correlations between countries have been increasing from 1990 to 2005. Hence, the increase in market correlations reported by Longin and Solnik (1995) for the period 1960 to 1990 has continued in recent years. This trend likely is due to increasing global capital flows and coincident financial market integration. Finally, we found that contemporaneous correlation results using daily returns for the European countries with overlapping trading hours were more reliable than those for the leading world markets with nonoverlapping trading hours.

Future research is recommended on what drives contemporaneous correlation between stocks in individual domestic markets. In this instance there is no problem of nonoverlapping trading hours. As cited earlier, Ang and Chen (2002) use monthly returns to investigate correlations between different segments of domestic U.S. stocks and the aggregate U.S. market. Following their study, small and large stocks, value and growth stocks, past loser and winner stocks, stocks in different industries, etc. are possible cases to examine to gain insight into the functional relationship between the contemporaneous correlation of these different segments' returns and potential determinants, including their respective volatilities, domestic market volatility, market trends, and other variables.

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Footnotes

1. This is because, if $y = a \log x$, then $\frac{dy}{dx} = a\frac{1}{x}$. Consequently, $\frac{\Delta y}{\Delta x} \approx a\frac{1}{x}$ or

$\Delta y \approx a\frac{\Delta x}{x} = 0.01a\frac{100\Delta x}{x}$. Thus, a 1 percentage change in *x* amounts approximately to a

0.01*a* change in *y*.

2. The test statistic is $t = (z_1 - z_2)\sqrt{T-3}$, where *T* is the total sample size, and

$z_i = \frac{1}{2}\log\left(\frac{1+\hat{\rho}_i}{1-\hat{\rho}_i}\right)$, i = 1, 2 are the Fisher transformations. Under the null hypothesis of

equality of population correlations, the *t*-statistic is asymptotically N(0,1)

distributed.

3. Panel C of Table 7 shows that the world volatility's marginal effect on the correlations for US/UK and US/Germany are 1.121 and 0.769, respectively. If the world volatility increased by 10%, the correlations among these markets would be expected to increase by 0.12 and 0.08, respectively.

APPENDIX A. Positive definiteness of the correlation matrix

As discussed in section II, a necessary and sufficient condition for the covariance matrix to be positive definite in the bivariate case is that $|\rho_t| < 1$, which is always the case for equation (6). Unfortunately, in the general case with three or more variables, there are no simple rules to guarantee the positive definiteness of the covariance matrix. The difficulty is easily demonstrated with a simple example of three series, denoted 1, 2, and 3, with correlations ρ_{21}, ρ_{31}, and ρ_{32}. If $\rho_{31} = 0$ and $\rho_{21} = \pm\sqrt{1-\rho_{32}^2}$, the correlation matrix is singular, and even negative definite if $|\rho_{21}| > \sqrt{1-\rho_{32}^2}$. Thus, in the general case without strong restrictions on the correlations, we cannot guarantee the positive definiteness.

A simplified case that guarantees positive definiteness has found some popularity in portfolio optimization is the "constant correlation model" or "overall mean correlation model" (e.g., Elton and Gruber (1973)), which we will refer to as the uniform contemporaneous correlation model. That is, for all pairs *i* and *j* of stocks, the time *t* correlations are the same, i.e., $\rho_{ij,t} = \rho_t$. As such, the correlation matrix simplifies to $\mathbf{R}_t = (1-\rho_t)\mathbf{I} + \rho_t \boldsymbol{\iota}\boldsymbol{\iota}'$, where $\mathbf{I}$ is an $m \times m$ the identity matrix, and $\boldsymbol{\iota}$ is a *m*-vector of ones with *m* the dimension (number of return series) of the correlation matrix. Though extremely simple, the uniform correlation model has proven to perform surprisingly well in portfolio diversification relative to more general models. Essentially this model means that, while the correlations are time-varying cross-sectionally, the best estimate of the pair-wise correlations is the grand mean, and the deviations of the single pair-wise correlations are zero-mean deviations from the grand mean. In this simple case a necessary and sufficient condition for the positive definiteness of the correlation matrix is $-\frac{1}{m-1} < \rho_t < 1$, which is usually met, because stocks are on average positively correlated. Finally, we should note that, because

$\sigma_{ij,t} = \rho_t \sigma_{i,t} \sigma_{j,t}$, the covariances need not be the same across pairs. An implication of this is that, if one applies the single index model, the uniform correlation model leads to a restricted beta with $\beta_{i,t} = \sigma_{i,t} \rho_t / \sigma_{m,t}$, where $\sigma_{m,t}$ is the volatility of the market index. Thus, the beta varies cross-sectionally only as a function of the volatilities.

APPENDIX B. Residual testing

Given the conditional variances h_{it}, $i = 1,2$, with $\varepsilon_{it} \mid \Psi_{t-1} \sim N(0, h_t)$, we have

$$w_{it} = \frac{\varepsilon_{it}}{\sqrt{h_{it}}} \sim \text{NID}(0,1), \tag{B.1}$$

(i.e., the standardized residuals are independent standard normal random variables). Accordingly, a standard tool to test the adequacy of the conditional variance specification is to check the autocorrelations of the squared standardized residuals of the form (B.1). A popular Portmanteau testing tool is the Ljung and Box (1979) *Q*-statistic. Another tool is the ARCH-test introduced by Engle (1982).

Although w_{it} are serially independent, the joint distribution of $\mathbf{w}_t = (w_{1t}, w_{2t})'$ need not be, and indeed is not, if the correlation is time-varying. Thus, in order to take into account the serial dependency in the bivariate case, and thereby check the adequacy of the correlation specification, we can utilize the time *t* Cholesky decomposition of the covariance matrix such that

$$\Sigma_t = \mathbf{A}_t \mathbf{A'}_t, \tag{B.2}$$

where $\mathbf{A}_t$ is a (unique) lower triangular matrix with positive diagonal elements. Defining Cholesky-standardized residuals as

$$\mathbf{r}_t = \mathbf{A}_t^{-1} \mathbf{w}_t, \tag{B.3}$$

then

$$\mathbf{r}_t \sim NID(\mathbf{0}, \mathbf{I}), \tag{B.4}$$

where $\boldsymbol{I}$ is the 2×2 identity matrix.

To test the white noisiness of $\mathbf{r}_t$, a multivariate extension of the Ljung-Box type Portmanteau statistic (see Hosking (1980)) can be utilized. The statistic is of the form

$$\mathrm{QM}(s) = T^2 \sum_{j=1}^{s} \frac{1}{T-j} \mathrm{tr}(\mathbf{C}'_{0j}\, \mathbf{C}_{00}^{-1} \mathbf{C}_{0j} \mathbf{C}_{00}^{-1}), \tag{B.5}$$

where

$$C_{ij} = \frac{1}{T} \sum_{t=1}^{T} \hat{\mathbf{r}}_{t-i} \hat{\mathbf{r}}'_{t-j} , \tag{B.6}$$

is the estimated cross autocorrelation matrix of the Cholesky-standardized residuals with $\hat{\mathbf{r}}_u = \mathbf{0}$ for $u \leq 0$, and the hat indicates that the $\mathbf{A}_t$ - matrix in equation (B.2) is computed from the estimated residual covariance matrix. If the (standardized) residuals are white noise, the LB(s) is asymptotically $\chi^2(p^2(s-k))$ -distributed, where p is the number of series (here p = 2), and k is the lag-length in the return vector autoregression (VAR).

The multivariate Ljung-Box statistic is an aggregate test statistic. Significance of the statistic indicates that there is either non-modeled clustering volatility or clustering correlation, or both, in the residuals. To determine whether the time-varying volatility is captured by the fitted model, a simple diagnostic tool is to test the autocorrelation of the cross-products of the Cholesky-standardized residuals with the univariate Ljung-Box statistic.

Table 1
Descriptive Statistics for Daily Stock Index Returns by Country

	US	JPN	UK	GER	SWZ	FRA	NED	DEN	SWE	NOR	FIN	World
Mean (%)	0.031	-0.031	0.018	0.022	0.030	0.017	0.025	0.026	0.030	0.032	0.036	0.017
Volatility (%, pa)	16.129	23.437	16.350	22.888	18.374	21.345	20.789	16.514	20.568	18.576	29.292	13.067
Kurtosis (excess)	3.885	3.366	2.987	3.598	5.046	2.820	4.946	3.068	4.198	5.501	7.121	3.421
Skewness	-0.102	0.199	-0.063	-0.163	-0.244	-0.093	-0.119	-0.261	0.238	-0.341	-0.353	-0.119
Range	12.687	19.662	11.493	17.424	15.761	14.680	17.048	11.228	16.771	18.141	31.966	10.130
Minimum	-7.114	-7.234	-5.589	-9.871	-8.299	-7.678	-7.531	-6.258	-6.894	-9.206	-17.403	-5.053
Maximum	5.573	12.428	5.904	7.553	7.462	7.002	9.517	4.970	9.877	8.934	14.563	5.077
Jarque-Bera (JB)	2465.1	1871.0	1455.2	2125.3	4186.2	1300.9	3994.4	1577.6	2907.4	5006.4	8342.4	1915.0
p-value (JB)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
rho(1)	-0.001	-0.021	0.014	-0.009	0.035	0.018	0.010	0.072	0.087	0.101	0.056	0.177
p-value [rho(1)]	0.926	0.196	0.380	0.590	0.029	0.267	0.538	0.000	0.000	0.000	0.000	0.000
rho(1) [squared return]	0.197	0.096	0.217	0.173	0.230	0.174	0.265	0.244	0.175	0.198	0.143	0.145
p-value [rho(1) sq return]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	3922	3922	3922	3922	3922	3922	3922	3922	3922	3922	3922	3922

Daily index returns in the sample period December 31, 1989 to January 31, 2005 are defined as differences in log-prices, or $r_t = 100 \times \left(\log(I_t) - \log(I_{t-1})\right)$.
Returns for national holidays are replaced by zeros. The sample size (N) is 3,922.

Table 2
Contemporaneous Cross-Market Return Correlations Between Countries

	US	JPN	UK	GER	SWZ	FRA	NED	DEN	SWE	NOR	FIN	World
US	1											
JPN	0.119	1										
UK	0.402	0.249	1									
GER	0.455	0.229	0.663	1								
SWZ	0.377	0.245	0.682	0.713	1							
FRA	0.406	0.235	0.748	0.749	0.717	1						
NED	0.405	0.255	0.760	0.779	0.764	0.803	1					
DEN	0.246	0.225	0.489	0.528	0.512	0.523	0.556	1				
SWE	0.349	0.274	0.609	0.642	0.608	0.663	0.664	0.536	1			
NOR	0.250	0.266	0.514	0.532	0.554	0.524	0.567	0.514	0.588	1		
FIN	0.288	0.199	0.508	0.528	0.458	0.551	0.563	0.438	0.639	0.460	1	
World	0.782	0.472	0.603	0.625	0.565	0.598	0.604	0.419	0.549	0.438	0.442	1
Average[1]	0.360	0.224	0.549	0.568	0.545	0.575	0.593	0.441	0.543	0.462	0.454	0.561

[1] World market is excluded from the marketwide averages.

Daily index returns in the sample period December 31, 1989 to January 31, 2005 are defined as log-differences, or $r_t = 100 \times \left(\log(I_t) - \log(I_{t-1})\right)$.
Returns for national holidays are replaced by zeros. The sample size (N) is 3,922.

Table 3
Contemporaneous Cross-Market Stock Return Correlations When World Markets Are Up and Down Trending

Panel A. Up trending world market returns

	US	JPN	UK	GER	SWZ	FRA	NED	DEN	SWE	NOR	FIN
US	1										
JPN	0.101	1									
UK	0.389	0.179	1								
GER	0.406	0.189	0.594	1							
SWZ	0.341	0.159	0.592	0.631	1						
FRA	0.383	0.173	0.687	0.699	0.619	1					
NED	0.390	0.186	0.682	0.741	0.680	0.749	1				
DEN	0.193	0.150	0.416	0.471	0.416	0.442	0.486	1			
SWE	0.308	0.198	0.538	0.593	0.535	0.591	0.614	0.468	1		
NOR	0.211	0.175	0.429	0.464	0.447	0.436	0.488	0.412	0.502	1	
FIN	0.262	0.126	0.445	0.487	0.397	0.482	0.536	0.381	0.589	0.397	1
Average	0.327	0.161	0.484	0.514	0.467	0.512	0.540	0.372	0.481	0.385	0.403

Table 3, continued

Panel B. Down trending world market returns											
	US	JPN	UK	GER	SWZ	FRA	NED	DEN	SWE	NOR	FIN
US	1										
JPN	0.098	1									
UK	0.392	0.281	1								
GER	0.472	0.231	0.705	1							
SWZ	0.382	0.287	0.737	0.766	1						
FRA	0.406	0.261	0.789	0.780	0.781	1					
NED	0.393	0.279	0.810	0.800	0.815	0.839	1				
DEN	0.262	0.261	0.531	0.557	0.571	0.575	0.596	1			
SWE	0.354	0.306	0.651	0.666	0.650	0.710	0.689	0.574	1		
NOR	0.249	0.312	0.567	0.570	0.624	0.583	0.614	0.584	0.642	1	
FIN	0.282	0.229	0.541	0.543	0.485	0.591	0.567	0.465	0.665	0.491	1
Average	0.361	0.244	0.583	0.594	0.589	0.612	0.617	0.479	0.573	0.503	0.474

Daily index returns in the sample period December 31, 1989 to January 31, 2005 are defined as log-differences, or $r_t = 100 \times \left(\log(I_t) - \log(I_{t-1}) \right)$. Returns for national holidays are replaced by zeros. The sample size (N) is 2,404 in up markets (panel A) and 1,518 in down markets (panel B).

Table 4
Conditional Variance Estimates for Stock Returns by Country

Panel A. Mean equation												
	US	JPN	UK	GER	SWZ	FRA	NED	DEN	SWE	NOR	FIN	World
Constant	0.0272	-0.039	0.015	0.033	0.023	0.009	0.030	0.026	0.051	0.054	0.020	0.011
Standard error	0.0129	0.021	0.013	0.017	0.017	0.018	0.015	0.016	0.018	0.019	0.024	0.013
AR(1)					0.044	0.025		0.112	0.101	0.496	0.140	0.204
Standard error					0.018	0.017		0.018	0.017	0.086	0.018	0.016
Other lags[1]					0.055					-0.363		
Standard error					0.015					0.091		
Panel B. Variance equation												
Constant	0.010	0.050	0.011	0.022	0.057	0.025	0.018	0.037	0.029	0.036	0.019	0.011
Standard error	0.001	0.006	0.002	0.003	0.004	0.004	0.005	0.014	0.008	0.008	0.007	0.001
ARCH(1)	0.006	0.022	0.016	0.032	0.017	0.011	0.039	0.051	0.033	0.059	0.053	0.014
Standard error	0.005	0.005	0.006	0.007	0.006	0.005	0.017	0.018	0.015	0.014	0.013	0.006
ARCH(1) < 0	0.099	0.112	0.074	0.090	0.157	0.089	0.072	0.053	0.114	0.102	0.024	0.123
Standard error	0.008	0.010	0.008	0.009	0.012	0.009	0.022	0.021	0.024	0.026	0.017	0.009
GARCH(1)	0.935	0.902	0.935	0.911	0.855	0.929	0.910	0.887	0.894	0.863	0.930	0.910
Standard error	0.005	0.008	0.006	0.007	0.009	0.006	0.011	0.018	0.011	0.018	0.010	0.007

[1]For Norway the mean model is ARMA(1,1), and for Switzerland AR lags 1 and 4 are used. The standard errors are the robust standard errors described in Bollerslev and Wooldrige (1992).

Table 4, continued

Panel C. Diagnostic statistics												
	US	JPN	UK	GER	SWZ	FRA	NED	DEN	SWE	NOR	FIN	World
Q(1) z	2.458	0.141	3.310	1.543	2.148	0.416	3.305	0.558	1.260	0.270	0.129	5.757
p-value	0.117	0.707	0.069	0.214	0.143	0.519	0.069	0.455	0.262	0.603	0.720	0.016
Q(5) z	11.300	0.859	9.653	6.938	3.828	14.170	9.301	2.719	4.273	3.326	9.333	10.387
p-value	0.046	0.973	0.086	0.225	0.281	0.007	0.098	0.606	0.370	0.344	0.053	0.034
Q(1) z^2	2.456	4.616	0.425	3.011	0.546	0.213	1.928	2.925	1.043	3.933	1.828	0.549
p-value	0.117	0.032	0.515	0.083	0.460	0.644	0.165	0.087	0.307	0.047	0.176	0.459
Q(5) z^2	4.371	6.562	2.883	6.782	0.725	5.234	2.959	4.531	1.465	4.191	2.090	0.863
p-value	0.497	0.255	0.718	0.237	0.867	0.264	0.706	0.339	0.833	0.242	0.719	0.930
Skewness	-0.363	-0.029	-0.112	-0.130	-0.609	-0.141	-0.458	-0.442	-0.066	-0.064	-0.093	-0.232
p-value	0.000	0.459	0.004	0.001	0.000	0.000	0.000	0.000	0.092	0.100	0.018	0.000
Excess kurtosis	1.917	1.844	1.112	1.122	5.856	0.639	2.500	4.121	2.347	1.426	3.729	1.896
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
JB-residuals	686.5	556.3	210.4	216.9	5845.8	79.7	1158.7	2903.1	902.7	335.1	2278.0	622.9
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	3922	3922	3922	3922	3922	3921	3922	3922	3922	3921	3920	3922

This table gives the individual ARMA-TGARCH specifications as given in equation (7). The sample period of daily observations covers January 2, 1990 to January 31, 2005 of log daily returns, or $r_t = 100 \times \left(\log(I_t) - \log(I_{t-1})\right)$. Returns for national holidays are replaced by zeros.

Table 5
Logit Regression Results for Major European Markets

	Dependent variable: Logit transformation of time-varying correlation between countries 1 and 2, or $\log\left[(1+\rho_{12,t})/(1-\rho_{12,t})\right]$														
	UK(1)/GER(2)			UK(1)/FRA(2)			UK(1)/SWZ(2)			UK(1)/NED(2)			GER(1)/FRA(2)		
Independent variables	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val
Panel A. Country 1 volatility alone															
Constant	0.773	0.076	0.000	1.284	0.087	0.000	1.002	0.083	0.000	1.491	0.100	0.000	0.924	0.084	0.000
Log σ_1	0.339	0.109	0.002	0.421	0.119	0.000	0.229	0.115	0.047	0.679	0.120	0.000	0.137	0.089	0.126
World down trend	0.174	0.125	0.163	0.083	0.153	0.586	0.352	0.149	0.018	0.260	0.131	0.047	0.095	0.125	0.445
Time trend(x 1,000)	0.632	0.061	0.000	0.515	0.059	0.000	0.415	0.058	0.000	0.285	0.073	0.000	0.834	0.064	0.000
Diagnostic statistics	Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val	
QM(5)	25.088	0.068		46.026	0.000		31.239	0.013		38.455	0.001		49.188	0.000	
Q(5) z_1z_2	3.555	0.615		1.616	0.899		6.784	0.237		3.502	0.623		2.962	0.706	
Panel B. Country 2 volatility alone															
Constant	0.742	0.071	0.000	1.118	0.076	0.000	1.043	0.076	0.000	1.459	0.020	0.000	0.876	0.078	0.000
Log σ_2	0.352	0.112	0.002	0.294	0.141	0.038	0.655	0.119	0.000	0.636	0.080	0.000	-0.075	0.165	0.651
World down trend	0.071	0.070	0.307	0.152	0.157	0.332	0.231	0.152	0.129	0.288	0.130	0.027	0.186	0.166	0.262
Time trend(x 1,000)	0.571	0.065	0.000	0.564	0.061	0.000	0.383	0.058	0.000	0.214	0.024	0.000	0.905	0.066	0.000
Diagnostic statistics															
QM(5)	24.22	0.085		47.53	0.000		29.76	0.019		36.86	0.002		49.42	0.000	
Q(5) z_1z_2	2.59	0.763		1.76	0.882		2.86	0.722		3.75	0.587		2.85	0.723	
Panel C. World volatility alone															
Constant	0.805	0.108	0.000	1.238	0.103	0.000	1.055	0.110	0.000	1.538	0.124	0.000	1.188	0.103	0.000
Log world volatility	0.287	0.115	0.013	0.209	0.114	0.067	0.250	0.117	0.033	0.530	0.122	0.000	0.406	0.107	0.000
World down trend	0.125	0.146	0.392	0.112	0.159	0.482	0.287	0.176	0.102	0.160	0.148	0.280	-0.126	0.156	0.419
Time trend(x 1,000)	0.665	0.062	0.000	0.577	0.065	0.000	0.433	0.063	0.000	0.356	0.072	0.000	0.780	0.068	0.000
Diagnostic statistics															
QM(5)	24.84	0.073		46.58	0.000		30.94	0.014		37.68	0.002		48.91	0.000	
Q(5) z_1z_2	3.23	0.665		3.68	0.597		6.74	0.240		3.93	0.560		3.45	0.631	

Table 5, continued

	Dependent variable: Logit transformation of time-varying correlation between countries 1 and 2, or $\log\left[(1+\rho_{12,t})/(1-\rho_{12,t})\right]$														
	GER(1)/SWZ(2)			GER(1)/NED(2)			FRA(1)/SWZ(2)			FRA(1)/NED(2)			SWZ(1)/NED(2)		
Independent variables	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val
Panel A. Country 1 volatility alone															
Constant	1.351	0.074	0.000	1.308	0.068	0.000	1.095	0.074	0.000	1.173	0.094	0.000	1.641	0.083	0.000
Log σ_1	0.242	0.123	0.049	0.231	0.069	0.001	0.309	0.181	0.087	0.308	0.281	0.273	0.903	0.119	0.000
World down trend	0.500	0.140	0.000	0.272	0.138	0.049	0.405	0.163	0.013	0.366	0.159	0.021	0.194	0.157	0.218
Time trend(x 1,000)	0.092	0.061	0.135	0.485	0.065	0.000	0.341	0.068	0.000	0.716	0.080	0.000	0.074	0.066	0.262
Diagnostic statistics															
QM(5)	29.39	0.021		19.03	0.267		45.19	0.000		52.17	0.000		30.03	0.018	
Q(5) z_1z_2	4.16	0.526		19.21	0.002		8.09	0.152		14.64	0.012		1.47	0.916	
Panel B. Country 2 volatility alone															
Constant	1.459	0.073	0.000	1.359	0.072	0.000	1.265	0.087	0.000	1.391	0.099	0.000	1.629	0.085	0.000
Log σ_2	0.603	0.130	0.000	0.205	0.098	0.037	0.780	0.143	0.000	0.522	0.102	0.000	0.477	0.100	0.000
World down trend	0.400	0.165	0.015	0.276	0.127	0.030	0.270	0.176	0.126	0.242	0.178	0.174	0.292	0.154	0.058
Time trend(x 1,000)	0.062	0.061	0.305	0.472	0.070	0.000	0.271	0.073	0.000	0.567	0.093	0.000	0.030	0.068	0.663
Diagnostic statistics															
QM(5)	29.60	0.020		18.93	0.273		44.26	0.000		51.39	0.000		28.91	0.025	
Q(5) z_1z_2	3.43	0.634		18.68	0.002		4.37	0.498		17.00	0.005		1.09	0.955	
Panel C. World volatility alone															
Constant	1.561	0.119	0.000	1.503	0.092	0.000	1.380	0.116	0.000	1.561	0.105	0.000	1.756	0.033	0.000
Log world volatility	0.388	0.124	0.002	0.331	0.116	0.004	0.463	0.129	0.000	0.601	0.116	0.000	0.509	0.089	0.000
World down trend	0.358	0.179	0.045	0.025	0.123	0.837	0.209	0.204	0.304	0.078	0.197	0.691	0.152	0.135	0.262
Time trend(x 1,000)	0.089	0.074	0.229	0.503	0.058	0.000	0.307	0.074	0.000	0.649	0.080	0.000	0.119	0.045	0.008
Diagnostic statistics															
QM(5)	29.26	0.022		18.66	0.287		45.28	0.000		50.38	0.000		28.91	0.025	
Q(5) z_1z_2	4.46	0.485		15.00	0.010		7.43	0.190		15.50	0.008		1.20	0.945	

The sample period covers daily observations from January 2, 1990 to January 31, 2005 (N = 3,922). QM(5) is a multivariate Box-Ljung statistics aggregated over lags 1 to 5 (discussed in Appendix B), and Q(5) is the univariate Box-Ljung statistic for the autocorrelation in the cross-products of the Cholesky standardized residuals (derived in Appendix B) aggregated over lags 1 to 5. The time trend estimates are multiplied by 1,000.

Table 6
Logit Regression Results for Nordic Markets

Dependent variable: Logit transformation of time-varying correlation between countries 1 and 2, or $\log\left[(1+\rho_{12,t})/(1-\rho_{12,t})\right]$

Independent variables	SWE(1)/DEN(2)			SWE(1)/FIN(2)			SWE(1)/NOR(2)			DEN(1)/FIN(2)			DEN(1)/NOR(2)			FIN(1)/NOR(2)		
	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val	Coef	Std err	p-val
Panel A: Country 1 volatility alone																		
Constant	0.861	0.098	0.000	0.730	0.073	0.000	1.015	0.072	0.000	0.305	0.092	0.001	0.127	0.087	0.144	0.574	0.081	0.000
Log σ_1	0.423	0.094	0.000	0.483	0.123	0.000	0.288	0.111	0.009	-0.123	0.121	0.311	-0.103	0.142	0.466	0.152	0.121	0.210
World down trend	0.016	0.164	0.924	-0.151	0.193	0.434	0.449	0.151	0.003	-0.171	0.139	0.216	0.103	0.155	0.507	0.233	0.175	0.183
Time trend (x 1,000)	0.152	0.075	0.043	0.594	0.074	0.000	0.086	0.059	0.144	-0.236	0.066	0.000	-0.136	0.068	0.045	0.274	0.092	0.003
Diagnostic statistics	Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val	
QM(5)	23.80	0.094		24.54	0.078		21.74	0.152		28.29	0.029		27.63	0.035		40.45	0.001	
Q(5) z_1z_2	17.68	0.003		28.34	0.000		3.51	0.622		11.57	0.041		1.39	0.925		1.13	0.951	
Panel B: Country 2 volatility alone																		
Constant	0.844	0.093	0.000	0.695	0.081	0.000	0.999	0.079	0.000	0.509	0.082	0.000	0.851	0.092	0.000	0.564	0.095	0.000
Log σ_2	0.264	0.169	0.118	0.265	0.139	0.056	0.418	0.088	0.000	-0.040	0.112	0.721	0.461	0.143	0.001	0.292	0.124	0.018
World down trend	0.156	0.168	0.352	-0.033	0.168	0.845	0.446	0.152	0.003	0.084	0.156	0.588	0.235	0.171	0.170	0.202	0.158	0.201
Time trend (x 1,000)	0.200	0.074	0.007	0.550	0.102	0.000	0.124	0.060	0.039	0.351	0.098	0.000	0.107	0.072	0.137	0.344	0.081	0.000
Diagnostic statistics	Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val	
QM(5)	22.88	0.117		23.99	0.090		21.66	0.155		20.67	0.192		26.29	0.050		41.06	0.001	
Q(5) z_1z_2	18.10	0.003		28.75	0.000		3.15	0.677		24.30	0.000		2.07	0.839		0.65	0.986	
Panel C: World volatility alone																		
Constant	1.215	0.105	0.000	1.021	0.115	0.000	1.187	0.100	0.000	0.803	0.108	0.000	1.090	0.095	0.000	0.853	0.106	0.000
Log world volatility	0.669	0.118	0.000	0.559	0.123	0.000	0.354	0.119	0.003	0.460	0.114	0.000	0.427	0.114	0.000	0.491	0.119	0.000
World down trend	-0.170	0.165	0.303	-0.260	0.197	0.185	0.367	0.145	0.011	-0.185	0.156	0.235	0.113	0.159	0.476	0.003	0.141	0.982
Time trend (x 1,000)	0.104	0.075	0.169	0.570	0.091	0.000	0.078	0.061	0.199	0.253	0.077	0.001	0.044	0.065	0.504	0.267	0.062	0.000
Diagnostic statistics	Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val		Stat	p-val	
QM(5)	23.99	0.090		23.43	0.103		21.79	0.150		20.60	0.194		24.52	0.079		39.82	0.001	
Q(5) z_1z_2	13.85	0.017		27.47	0.000		3.10	0.685		22.56	0.000		2.98	0.703		0.53	0.991	

The sample period covers daily observations from January 2, 1990 to January 31, 2005 (N = 3,922). QM(5) is a multivariate Box-Ljung statistics aggregated over lags 1 to 5 (discussed in Appendix B), and Q(5) is the univariate Box-Ljung statistic for the autocorrelation in the cross-products of the Cholesky standardized residuals (derived in Appendix B) aggregated over lags 1 to 5. The time trend estimates are multiplied by 1,000.

Table 7
Logit Regression Results for Leading North American, European, and Asian Stock Markets

	Dependent Variable: Correlation Between Country (1) and Country (2)														
	US(1)/UK(1)			US(1)/GER(2)			US(1)/JPN(2)			UK(1)/JPN(2)			GER(1)/JPN(2)		
Independent variables	Coef	Std error	p-value	Coef	Std error	p-value	Coef	Std error	p-value	Coef	Std error	p-value	Coef	Std error	p-value
Panel A. Country 1 volatility alone															
Constant	0.359	0.154	0.020	0.011	0.153	0.943	0.607	0.176	0.001	0.668	0.223	0.003	0.512	0.252	0.042
Log σ_1	0.511	0.250	0.041	0.197	0.236	0.403	-0.140	0.284	0.622	-0.453	0.311	0.145	-0.322	0.271	0.235
World down trend	0.591	0.325	0.069	0.486	0.375	0.195	0.345	0.360	0.339	0.950	0.340	0.005	0.373	0.298	0.211
Time trend(x 100)	0.285	0.056	0.000	0.550	0.758	0.000	0.079	0.069	0.250	0.089	0.075	0.236	0.206	0.067	0.002
Diagnostic statistics															
QM(5)	19.61	0.238		26.79	0.044		19.05	0.266		5.12	0.995		19.22	0.258	
Q(5) z_1z_2	3.05	0.693		9.99	0.076		5.34	0.376		2.54	0.770		22.11	0.000	
Panel B. Country 2 volatility alone															
Constant	0.249	0.219	0.256	-0.466	0.209	0.026	0.401	0.534	0.453	1.117	0.447	0.012	0.333	0.423	0.431
Log σ_2	0.532	0.313	0.089	0.775	0.269	0.004	0.157	0.444	0.723	-0.573	0.406	0.158	-0.026	0.339	0.939
World down trend	0.639	0.325	0.049	0.203	0.336	0.546	0.214	0.353	0.544	0.887	0.345	0.010	0.212	0.272	0.435
Time trend(x 100)	0.318	0.059	0.000	0.495	0.728	0.000	0.064	0.065	0.320	0.018	0.066	0.781	0.161	0.068	0.017
Diagnostic statistics															
QM(5)	20.03	0.219		26.90	0.043		18.54	0.293		5.34	0.994		18.83	0.278	
Q(5) z_1z_2	5.94	0.312		7.71	0.173		5.28	0.382		2.07	0.840		21.42	0.001	
Panel C. World volatility alone															
Constant	0.047	0.205	0.817	-0.225	0.188	0.231	0.623	0.208	0.003	0.620	0.191	0.001	0.423	0.177	0.017
Log world volatility	1.121	0.324	0.001	0.769	0.365	0.035	-0.137	0.223	0.538	-0.381	0.298	0.201	-0.337	0.288	0.242
World down trend	0.130	0.338	0.701	0.105	0.395	0.790	0.349	0.279	0.212	0.938	0.380	0.014	0.418	0.296	0.158
Time trend(x 100)	0.315	0.056	0.000	0.539	0.615	0.000	0.066	0.057	0.245	0.074	0.067	0.270	0.190	0.062	0.002
Diagnostic statistics															
QM(5)	20.45	0.201		26.88	0.043		18.94	0.272		5.35	0.994		19.42	0.248	
Q(5) z_1z_2	5.86	0.320		8.71	0.121		5.82	0.324		2.53	0.772		22.88	0.000	

The sample period covers weekly observations from January 2, 1990 to January 31, 2005 (N = 790). QM(5) is a multivariate Box-Ljung statistics aggregated over lags 1 to 5 (discussed in Appendix B), and Q(5) is the univariate Box-Ljung statistic for the autocorrelation in the cross-products of the Cholesky standardized residuals (derived in Appendix B) aggregated over lags 1 to 5. The time trend estimates are multiplied by 100.