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Abstract

We examine total, market and idiosyncratic risk and correlation dynamics using daily data from 1993 to 2001 on the 6 largest euro-zone stock market indices and 42 firms from the *Dow Jones Eurostoxx50* index. We also estimate conditional correlations using the asymmetric DCC-MVGARCH model. Comparing our results with those of Campbell, Lettau, Malkiel and Xu (2001), stock correlations are higher and have declined less in the euro-zone than in the United States over the 1990s, implying a lower benefit from diversification strategies. By contrast, correlations amongst market indices have risen, with a structural break related to the process of financial integration in the euro-zone.

Key Words: Correlation dynamics, GARCH, idiosyncratic risk.
JEL Classification: C32, G12, G15.

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1. Introduction.

International fund managers usually divide their equity portfolios into a number of regions and countries, and select stocks in each country with a view to outperforming an agreed market index by some percentage. This provides asset diversity within each country together with international diversification across political frontiers. Two interrelated features of this strategy have attracted the recent attention of financial researchers and practitioners. The *first* relates to expected returns. A growing body of empirical evidence on the performance of mutual and pension fund managers has questioned the extent to which they systematically outperform their benchmarks (Blake and Timmerman, 1998, Wermers, 2000, Baks, Metrick and Wachter, 2001, and Coval and Moskowitz, 2001). To the extent that fund managers fail to add value when account is taken of their fees, the more passive strategy of buying and holding the market index for each country might yield an equally effective but more cost-efficient international diversification. The *second* relates to risk. It has been known for some time that equity return correlations do not remain constant over time, tending to decline in bull markets and to rise in bear markets (De Santis and Gerard (1997), Ang and Bekaert (1999), and Longin and Solnik (2003)). Correlations also tend to rise with the degree of international equity market integration (Erb, Harvey and Viskanta (1994) and Longin and Solnik (1995)), which has gathered pace in Europe since the mid-1990s (Hardouvelis, Malliaropulos and Priestley (2000) and Fratzschler (2002))[1]. It is of considerable interest, therefore, to investigate the relative strengths of the trends in variances and correlations at the firm level as well as at the market index level in European equity markets, because the findings have relevance for the diversification properties of passive and active international investment strategies.

[1] The latter author also notes that the euro-zone equity market has now surpassed the United States markets as the most influential determinant of euro-zone country equity returns.

In this paper, we investigate the trends in firm-level and market index correlations in European equity markets using over 2,300 daily observations from January 1993 to November 2001 on 42 stocks from the Dow Jones Eurostoxx50. We analyse the behaviour over time of market risk and aggregate idiosyncratic risk in a portfolio of these stocks. We also study the pattern of aggregate correlation between the indexes of the 5 largest euro-zone stock markets and the Eurostoxx50 index. We extend the variance decomposition methodology of Campbell, Lettau, Malkiel and Xu (2001), (henceforth CLMX (2001)) to provide a full description of the relation between changes in market risk, aggregate idiosyncratic risk and return correlations. We then apply the recently developed dynamic conditional correlation multivariate generalised autoregressive conditional heteroscedasticity (DCC-MVGARCH) model of Engle (2001) and Engle and Sheppard (2002) to capture the time series behaviour of the conditional correlations between the leading euro-zone market indexes and between the individual stocks in the Eurostoxx50 index. In doing so, we specify our model to facilitate testing for non-stationarity and asymmetries in the correlation processes.

We find that, consistently with the results reported by CLMX (2001) for the United States, average firm-level variance has trended upwards in the euro-zone area. Contrary to CLMX (2001), however, we find that market variance has also trended upwards, but by less than the rise in firm-level variance. This implies the existence of different correlation dynamics in the euro-zone area during the past 10 years to those observed in the United States, with a smaller downward trend in average correlation in our sample of euro-zone stocks. We also find significant persistence in all our conditional volatilities and correlation estimates, with the dynamics of firm-level correlations being best explained by an asymmetric component in their processes. Stock correlations tend to spike up after negative return innovations, suggesting that diversification strategies might perform poorly during prolonged bear markets. Finally, we find a significant rise in the correlations amongst euro-zone market indexes that can best be explained by a structural break reflecting the process of monetary and financial integration in Europe. It follows that portfolio managers in Europe should not over-estimate the benefits of pursuing passive international diversification strategies based on holding national stock market indexes. This conclusion is strengthened by the fact that correlations amongst the individual stocks in the euro-zone area have not been pushed upwards by the integration process, so firm level diversification strategies retain their appeal.

Our paper is structured as follows. We begin by generalising the CLMX (2001) decomposition of variance to provide a more complete description of the relation between market risk, aggregate idiosyncratic risk and correlation dynamics. In Section 3, we describe our data set, provide summary statistics, and present the salient trends in firm-level and market correlations in the euro-zone area. In Section 4, we perform a range of statistical tests to discern more formally the behaviour of market risk, firm-level risk and correlations in our dataset. We implement unit root and Wald tests, and we apply the DCC-MVGARCH model to our data. In the final Section, we summarise our main findings and draw together our conclusions.

2. Idiosyncratic Risk, Market Risk and Average Correlation.

The simplified market model can be written as an empirical version of the Sharpe (1964) and Lintner (1965) security market line.

$$r_{i,t} = \beta_i r_{m,t} + \varepsilon_{i,t} = r_{m,t} + \eta_{i,t} \tag{1}$$

Here, $r_{i,t}$ is the excess return on asset *i* at time *t*, $r_{m,t}$ is the excess return on the market portfolio, β_i is the asset's *beta* coefficient, $\varepsilon_{i,t}$ is the usual CAPM idiosyncratic residual, and $\eta_{i,t}$ is the market-adjusted excess return on asset *i* computed according to the simplified market model. Letting $w_{i,t}$ denote the weight of asset *i* in the market portfolio, we can compute the weighted average of the variance of returns on the *n* stocks in the market portfolio.

$$\sum_{i=1}^{n} w_{i,t} Var(r_{i,t}) = Var(r_{m,t}) + \sum_{i=1}^{n} w_{i,t} Var(\eta_{i,t}) + \sum_{i=1}^{n} w_{i,t} 2Cov(r_{m,t}, \eta_{i,t}) \quad (2)$$

By substituting for $\eta_{i,t}$ from (1), noting that $r_{m,t}$ and $\varepsilon_{i,t}$ are orthogonal, and recalling that the weighed average of the β_i coefficients is equal to 1, the last term on the right collapses to zero, and we are left with the CLMX (2001) variance decomposition:

$$\begin{aligned} VAR_t &= \sum_{i=1}^{n} w_{i,t} Var(r_{i,t}) \\ &= Var(r_{m,t}) + \sum_{i=1}^{n} w_{i,t} Var(\eta_{i,t}) + \sum_{i=1}^{n} w_{i,t} 2(\beta_i - 1) Var(r_{m,t}) \\ &= Var(r_{m,t}) + \sum_{i=1}^{n} w_{i,t} Var(\eta_{i,t}) \\ &= MKT_t + FIRM_t \end{aligned} \quad (3)$$

This decomposes the average excess return variance across all assets in the market portfolio (VAR_t) into two components; the variance of the excess return on the market portfolio (MKT_t) and the average firm-level variance ($FIRM_t$). It provides a CAPM-equivalent decomposition of average total risk into market risk and average idiosyncratic risk, with the considerable advantage that it bypasses the need to estimate *betas* for each firm.

CLMX (2001) note that rising average idiosyncratic risk, together with unchanged market risk, implies a decrease in the average correlation amongst the portfolio's assets, but they do not provide a theoretical specification of this relationship. Although it is intuitive that average correlation must decline if average idiosyncratic risk rises with a constant level of market risk, it is not trivial to predict what patterns in average correlation might emerge when, for example, average firm-level risk and market risk vary in the same direction but at different rates of change. To see the full set of possible configurations of market and idiosyncratic risk, we rewrite the MKT term in (3) by converting it to matrix notation.

$$MKT_t = w_t' H_t w_t \tag{4}$$

Here,

$$H_t \equiv D_t R_t D_t$$

$$[H_t]_{i,j} = h_{i,j,t}$$

$$[R_t]_{i,j} = r_{i,j,t} \in [-1, 1] \;\; \forall \;\; i \neq j, \text{ and } [R_t]_{i,j} = r_{i,j,t} = 1 \qquad \forall \;\; i = j$$

In (4), R_t is an nxn correlation matrix, D_t is an nxn diagonal matrix, with the elements on its main diagonal being the standard deviations of their excess returns, and w_t is an $nx1$ vector of weights. It follows that

$$[D_t]_{ij} = d_{i,j,t} = \sqrt{h_{i,j,t}} \quad \forall \;\; i = j, \text{ and } [D_t]_{ij} = d_{i,j,t} = 0 \;\; \forall \;\; i \neq j$$

From (4), we can write:

$$\begin{aligned} MKT_t &= w_t' D_t R_t D_t w_t \\ &= \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,t} w_{j,t} r_{i,j,t} d_{i,j,t} d_{i,j,t} \\ &= \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} r_t d_{i,i,t} d_{j,j,t} \\ &= \frac{r_t (i' D_t I D_t i)}{n} \end{aligned} \tag{5}$$

where

$$r_t = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,t} w_{j,t} r_{i,j,t}$$

In (5), I_t is a conformable (nxn) identity matrix, r_t is the weighted average correlation coefficient and i is an $nx1$ unit vector. Portfolio variance, MKT_t, rises proportionally with average correlation, r_t, if the standard deviation matrix, D_t, remains constant. Using (5), we can rewrite (3) for the variance decomposition as in (6).

$$VAR_t \;\; = \frac{r_t(\, i'D_t ID_t i\,)}{n} + FIRM_t \tag{6}$$

Solving (6) for r_t, the average correlation coefficient becomes

$$r_t = n\left(\frac{w_t' D_t D_t i}{i' D_t D_t i} - \frac{FIRM_t}{i' D_t D_t i}\right) \tag{7}$$

and for equally-weighted portfolios with $w_t = \dfrac{1}{n}\, i$, it can be rewritten as

$$r_t = n\left(\frac{1}{n}\frac{i_t' D_t D_t i}{i' D_t D_t i} - \frac{FIRM_t}{i' D_t D_t i}\right)$$

$$= 1 - \frac{FIRM_t}{(i' D_t D_t i)/n}$$

$$= 1 - \frac{FIRM_t}{VAR_t} = \frac{VAR_t - FIRM_t}{VAR_t} = \frac{MKT_t}{VAR_t} \tag{8}$$

Equation (8) provides an intuitively appealing result. Average correlation is the the ratio between market risk and average idiosyncratic risk. Moreover, we can rewrite (8) as,

$$VAR_t = r_t VAR_t + FIRM_t$$

$$= MKT_t + FIRM_t \tag{9}$$

Equation (9) tells us that, at least for an equally weighted market portfolio, we can interpret average correlation as the parameter that, for any given level of average total risk, divides the latter into market risk and idiosyncratic risk. By differentiating r_t in (8) with respect to the ratio of average idiosyncratic variance to average total variance, we obtain

$$\frac{dr_t}{d(FIRM_t / VAR_t)} = -1 \tag{10}$$

This holds exactly in the equally weighted case, but it holds approximately in general, so we write it as

$$\frac{dr_t}{d(FIRM_t / VAR_t)} \cong -1 \tag{11}$$

Equations (10) and (11) show that the variation in average correlation is inversely proportional to the variation in the ratio of average firm-level variance to market variance. The larger the number of stocks included in a portfolio, the more it resembles an equally-weighted portfolio and the better is the approximation provided by (10). Average correlation is strongly influenced by the extent to which firms diversify internally. The more the average firm diversifies (the more it resembles the market portfolio), the higher will be the average correlation for each given level of covariance risk in the economy (MKT_t). The opposite is true for average firm-level variance.

3. Data, Summary Statistics and Trends

Our dataset comes from two sources. The firm-level data is drawn from the stocks included in the *Eurostoxx50* index. This is the leading European stock market index, and the futures contract on this index is one of the most liquid in the world. It commenced on 31 December 1991 with a base value of 1000, and it comprises 50 stocks from the companies with the heaviest capitalisation in the euro-zone countries[2]. We use the Bloomberg database of daily closing prices on the constituent stocks of the index to derive daily returns for the individual stocks. Table 1 lists the stocks included in the *Eurostoxx50* index at the end of our sample period along with their weights at the date of the last reshuffle (19 September 2001). We select all 42 stocks with a continuous returns series from February 1993 to November 2001[3]. It is noteworthy that our sample of euro-zone firm-level data comprising the largest stocks in the *Eurostoxx50* index differs from that employed by CLMX (2001), which includes large, medium and small United States stocks. Table 2 provides the usual set of summary statistics for the 42 individual stock returns, and for the returns on the 6 market indices. In particular, we report the sample means, variances, skewness, kurtosis, the *Jarque-Bera* statistics and their associated significance levels. As expected, the returns exhibit significant departure from the normal distribution in most cases.

Setting $n = 42$, we define market variance (MKT_t) over a 21-day month ($T = 21$) as the sum of the squared deviations of daily market returns ($R_{m,t}$) from their sample mean[4], ($\overline{R}_m$).

$$MKT_t = \sum_{t=1}^{T} (R_{m,t} - \overline{R}_m)^2 \qquad \text{with} \quad R_{m,t} = \sum_{i=1}^{n} w_{i,t} R_{i,t} \tag{12}$$

Here, $R_{i,t}$ is the return on stock i at time t. To construct the average total variance series, VAR_t, we first compute the monthly variance for each stock in our sample, $VAR(R_{i,t})$ as the sum of the squared deviations of their daily returns from their sample mean, $\overline{R}_i$.

$$Var(R_{i,t}) = \sum_{t=1}^{T} (R_{i,t} - \overline{R}_i)^2 \tag{13}$$

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[2] Stoxx (part of the Dow Jones Telerate Group) publishes various indexes. Among these, a version of the Dow Jones Eurostoxx50 index that includes the UK stock market is also available.

[3] The excluded stocks are also listed in Table 1 and indicated by '*'s.

[4] As in CLMX (2001) we experimented also with time-varying means, but the results are almost identical.

We then average across the variances of all stocks in our sample to compute the average total variance as

$$VAR_t = \sum_{i=1}^{n} w_{i,t} Var(R_{i,t}) \tag{14}$$

Finally, using (3) we compute the average firm-level variance as the difference between VAR_t and MKT_t:

$$FIRM_t = VAR_t - MKT_t \tag{15}$$

The market variance time series (MKT_t) defined by (12), the average total variance (VAR_t) defined by (14), and the average firm-level variance ($FIRM_t$) defined by (15) each contain 103 monthly observations for the period 1993 - 2001. The stock weights are equal to $1/n$ (n = 42) in the equally-weighted case, and to the ratio of the capitalisation of each stock to the capitalisation of the market portfolio in the value-weighted case. Our resulting series are therefore equally-weighted and value-weighted averages of market, firm-level, and total risk.

In Figure 1, we plot the time series of market variance (MKT_t), average firm-level variance ($FIRM_t$), and average total variance (VAR_t) for the equally-weighted (*Panel A*) and for the value-weighted (*Panel B*) cases. It is noticeable that the equally-weighted and value-weighted series behave very similarly. Indeed, their behaviour turns out to be almost identical in all our subsequent tests, and we consequently report only the results for the equally-weighted case. Both the firm-level and the market variances start off relatively low and tend to rise towards the end of the period. This tendency is more pronounced for the firm-level variance than for the market variance. In this respect, our data appears to behave similarly to CMLX (2001) who note that average firm-level variance is usually higher then aggregate market variance. Figure 2 casts further light on this by plotting in *Panel A* the ratio of $FIRM_t$ to VAR_t .

We now define average measures of correlation amongst the stocks in our sample. To do this, we first compute the cross products of the daily return deviations from their sample means and sum them to obtain monthly correlation measures for each pair of stocks *i* and *j*,

$$r_{i,j,t} = \sum_{t=1}^{T} (R_{i,t} - \overline{R}_i)(R_{j,t} - \overline{R}_j) \qquad (16)$$

and we then average across the correlations to compute the average correlation.

$$r_t = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,t} w_{j,t} r_{i,j,t} \qquad (17)$$

The average correlation series is plotted in *Panel B* of Figure 2. It is noticeable that, consistent with (8), the average correlation mirrors the ratio of the average firm-level variance to the average total variance in *Panel A* of the Figure. This confirms our previous observation that average correlation is the mechanism that divides average total risk into aggregate firm-level variance (idiosyncratic risk) and market variance (covariance risk).

Our market index data consists of daily returns on the *Eurostoxx50* index along with the returns on the 5 national stock market indexes with the heaviest capitalisation in the euro-zone at the end of our sample period, ie, the *DAX* (Frankfurt Stock Exchange), the *CAC40* (Paris Stock Exchange), the *MIB30* (Milan Stock Exchange), the *AMX* (Amsterdam Stock Exchange) and the *IBEX* (Madrid Stock Exchange). These series start on 31 December 1991 (except for the *MIB30*, which starts a year later). As with the individual stocks, the summary statistics for the index returns in Table 2 also suggest a significant departure from the normal distribution. Noticeably, index returns always display negative skewness whereas the sign of the latter is not the same across returns on individual stocks. In Figure 3, we plot the monthly average correlation amongst the indexes. This has been computed applying (17) to our index data (with n = 6), and with all indexes being assigned equal weights. This series shows a more noticeable tendency to rise over time than does the firm-level correlations, and we now turn our attention to more formal testing of their time series behaviour.

4. Estimating the Time Series Behaviour of Idiosyncratic Risk, Market Risk and Average Correlations

We begin our formal testing of the time series behaviour of market risk, idiosyncratic risk and correlations in the euro-zone area by conducting unit root tests and Wald tests for the presence of a time-trend. We then model the time series behaviour of the correlations more directly using the DCC-MVGARCH model of Engle (2001) and Engle and Shephard (2002).

Unit Root Tests

We conduct our Dickey-Fuller (*DF*) and augmented Dickey-Fuller (*ADF*) tests allowing up to 12 lags. As pointed out by Pesaran (1997), however, there is a size-power trade-off depending on the order of augmentation, and we consequently rely on the results provided by the tests performed at the lower orders of augmentation. The null of the *DF* test is $H_0 : \rho = 1$, with the estimate of ρ being obtained from (18) and (19).

$$y_t = \alpha + \rho \; y_{t-1} + u_t \qquad\qquad u_t \sim i.i.d.N(0, \sigma^2) \tag{18}$$

$$y_t = \alpha + \rho \; y_{t-1} + \delta \; t + u_t \qquad u_t \sim i.i.d.N(0, \sigma^2) \tag{19}$$

The critical values in these tests refer to the distribution under the null of DF = $\frac{(\hat{\rho}_t - 1)}{\sigma_{\hat{\rho}_t}}$. In (18) and (19), y_t is the variable under consideration, t is a time trend, and $\sigma_{\hat{\rho}_t}$ is the variance of the ρ parameter estimate. In conducting our unit root tests, we allow the errors in (18) and (19) to be serially correlated, and we consequently estimate them with the inclusion of lagged first differences of y_t amongst the regressors. We use the estimated ρ from these augmented regression equations to compute the *ADF* test statistics.

Table 3 presents the results, reporting only the first 2 orders of augmentation for brevity. The *DF* and *ADF* tests reject the null of a unit root at the 5 percent level of significance in all our variance and correlation time series, with the exception of the average correlation amongst the *Eurostoxx50* index and the 5 EMU stock market indexes. In particular, we cannot reject the null of a unit-root in the *ADF* test with 2 orders of augmentation and no deterministic time trend. Using an *F*-test and the appropriate non-standard asymptotic distribution (Hamilton (1994)), however, we can reject at the 1 percent level the joint hypothesis that the deterministic time trend is equal to zero and the autocorrelation coefficient ρ is equal to unity. We therefore conclude that all the variance and correlation time series are stationary, including aggregate market index correlation.

Wald Tests

We first estimate the static model in (20) that includes a deterministic time-trend coefficient but no lagged value of the dependent value, and test the restriction that the former is equal to zero.

$$y_t = \alpha + \delta t + u_t \qquad u_t \sim N(0, \sigma^2) \tag{20}$$

Here, α is a constant, t denotes the deterministic time trend, and δ is its associated coefficient. Using the *DW* statistic, we test whether the residuals in (20) are auto-correlated. If they are not i.i.d., this usually arises because of auto-correlated errors or because the appropriate specification for y_t is,

$$y_t = \alpha + \beta\, y_{t-1} + \delta t + \varepsilon_t \tag{21}$$

Whenever we detect serial correlation in the residuals of the static model in (20), we estimate the dynamic model in (21) using Durbin's h[5] statistic to check that the residuals are serially independent. We conduct a Wald-type test of the restriction that the deterministic time trend coefficient is zero using Newy-West adjusted variance-covariance matrices to correct for heteroschedasticity and autocorrelation. Table 4 presents the results. We can never reject the null that the residuals from (21) are serially independent, with the exception of the average firm-level variance ($FIRM_{,t}$) and of the average correlation amongst the market indices (r_t in the bottom panel of Table 4). In the latter 2 cases, we must therefore treat the parameter estimates with caution, because inference procedures are not in general valid due to biased parameter variance estimates and inconsistent *OLS* estimates. As far as the relative sizes of the deterministic time-trend of MKT_t and $FIRM_t$ are concerned, the coefficient estimated for the latter is always greater than for the former. Moreover, the deterministic time-trend coefficient is always positive, except for the average stock returns correlation series. Not surprisingly, because of the relative size of the deterministic time trend coefficient of MKT_t and $FIRM_t$, average stock correlation is trended downwards, which is consistent with (10) and (11). One noticeable feature of average market index correlation is the large positive estimate of the deterministic time trend coefficient. This confirms that, as suggested by visual inspection of Figure 3, market correlations in the Euro-zone have greatly increased over the period 1993-2001.

Summarising our results thus far, both the variance and correlation time series, based respectively on sums of squares in (13) and sums of cross-products in (16), appear to be stationary, especially when we allow for a deterministic time trend. Both aggregate firm-level and market variance have trended upwards in the euro-zone over the period 1993-2001. Our estimated time trend coefficient for average idiosyncratic variance is smaller than the equally weighted estimate reported by

[5] In the presence of lagged values of the dependent variables the *DW* test is biased toward acceptance of the null of no error auto-correlation. We therefore test for serial correlation of the error terms using Durbin's (1970) *h*-test. We use the generalised version this test, developed by Godfrey and Breusch, based on a general Lagrange Multiplier test. Even though this procedure can detect higher order serial correlation, we only test the null of no first-order residual autocorrelation.

CLMX (2001)[6] for a large sample of United States stocks. In addition, we do not find that the average correlation amongst euro-zone stock returns has declined sharply as reported by CLMX for the United States markets[7]. This is consistent with the fact that market variance is trended upwards over our sample period, whereas it is either trended downwards or it does not display any significant trend in CLMX (2001)[8]. We do, however, find that average correlation amongst our sample of euro-zone stock returns displays a modest but statistically significant downward deterministic time trend. This difference from the results reported by CLMX (2001) could be due to the fact that the stocks in our sample are all large firms, many of which have a variety of established businesses which accord them a degree of diversification greater than would be seen in smaller firms.

DCC-MVGARCH Modelling of Correlation Dynamics

Our analysis thus far has been based upon the computation of variances and covariances, followed by the estimation of time series regression models to study their evolution over time. This strategy has yielded useful insights that can be compared directly with the United States trends studied by CLMX (2001). But it has two shortcomings. First, there is no guarantee that the sums of squares and cross-products in (12), (13) and (16) are consistent estimators of the second moments of the return distributions at each point in time. Second, the aggregation of daily data into lower frequency monthly data leads to a potential small sample problem. It is, therefore, of considerable interest to apply the

[6] CLMX (2001) decompose average total variance into market variance, average industry level variance and average firm-level variance. Therefore the time trend coefficient of aggregate idiosyncratic variance is the sum of the coefficients of average industry level variance and average firm-level variance. In the estimation that uses daily data, it is equal to 0.00103% (the sum of 0.000062% and 0.00096%, for aggregate industry and firm-level variance respectively) in the value-weighted case and to 0.012% in the equally weighted case (the sum of 0.000022% and 0.012386%, aggregate industry and firm-level variance respectively). CLMX's (2001) estimates refer to a sample of US stocks over the sample period 1963-1997.

[7] They do not estimate the trend coefficient of average stock returns correlation but report the plots of 12 (daily) and 60 months (monthly) average correlations, which shows a dramatic decrease, particularly sharp over the last 10 years (from 1992 onwards) of the sample period.

recently developed DCC-MVGARCH model of Engle (2001) and Engle and Sheppard (2002). This provides a useful way to describe the evolution over time of large systems, with the appealing feature that it preserves the simple interpretation of univariate GARCH models while providing an estimate of the full correlation matrix. In particular, the parameter estimates of the second moment matrix are the coefficients of the correlation process. In a recent application to global markets, Cappiello, Engle and Sheppard (2003) examine the correlation dynamics between the equity markets in 21 countries and the bond markets in 13 countries, using weekly data over the period from January 1987 to February 2001. They reject the null hypothesis of constant correlations in almost all cases.

To estimate the DCC-MVGARCH model on our data set, we begin by specifying the returns as follows.

$$u_t \mid \Im_{t-1} \sim N(0, H_t) \tag{22}$$

where, as in (4),

$$H_t \equiv D_t R_t D_t$$
$$[H_t]_{i,j} = h_{i,j,t}$$
$$[\mathrm{D}_t]_{i,j} = d_{i,j,t} = \sqrt{h_{ij}} \quad \forall \;\; i = j, \;\text{ and }\; [\mathrm{D}_t]_{i,j} = d_{i,j,t} = 0 \;\; \forall \;\; i \neq j$$

Here, symbols retain their prior meanings and u_t is a $nx1$ vector of zero mean return innovations conditional on the information set available at time t-1 ($\Im_{t-1}$), obtained by subtracting the means from each of the n asset returns and stacking them. The log-likelihood of the observations on u_t is given by equation (23).

[8] In particular, the deterministic time trend coefficient estimated by CLMX (2001) for MKT_t is -0.000114% in the equally-weighted case (daily data). It takes various, but small and not statistically significant values, in all other cases reported by CLMX (2001).

$$L = -0.5\sum_{t=1}^{T}(\, n\,log(\,2\pi\,) + log(|\,H_t\,|) + u_t' H_t^{-1} u_t\,)$$

$$-0.5\sum_{t=1}^{T}(\, n\,log(\,2\pi\,) + log(|\,D_t R_t D_t\,|) + u_t' D_t^{-1} R_t^{-1} D_t^{-1} u_t\,)$$

$$-0.5\sum_{t=1}^{T}(\, n\,log(\,2\pi\,) + 2\,log(|\,D_t\,|) + log(|\,R_t\,|) + \varepsilon_t' R_t^{-1} \varepsilon_t\,) \qquad (23)$$

Two components can vary in this likelihood function, L. The first part contains only terms in D_t and the second part contains only terms in R_t. Engle and Sheppard (2001) propose maximising L in two steps to overcome the well-known computational constraints of MVGARCH models. They first maximise L with respect to the parameters that govern the process of D_t. This can be done by estimating univariate models[9] of the returns on each stock nested within a univariate GARCH model of their conditional variance. One simple specification for the GARCH process followed by D_t^2 is the following.

$$D_t^2 = \overline{D}^2(1 - A - B\,) \; + \; A(u_{t-1}u_{t-1}') \; + \; BD_{t-1}{}^2 \qquad (24)$$

Here, A and B are nxn diagonal coefficient matrices that yield consistent, time-varying, estimates of D_t. Engle and Sheppard (2001) suggest maximising the second part of the likelihood function over the parameters of the process of R_t, conditional on the estimated D_t. This entails standardising u_t by the estimated D_t to obtain the $nx1$ vector ε_t[10]. The maximum likelihood estimates of the parameters of the process of R_t that maximise the second part of (23) can then be found by estimating a multivariate model of ε_t nested within a multivariate scalar GARCH model of the conditional second moments. One simple specification for the GARCH process followed by R_t is the following.

[9] The presence of an intercept term ensures that the estimated residuals are zero-mean random variables.

[10] As noted by Cappiello, Engle and Sheppard (2003), standardising return innovations largely removes their departures from normality. This justifies the assumption that the standardised

$$R_t = \overline{R}(1-\alpha-\beta) + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta R_{t-1} \tag{25}$$

In (25), α and β are scalar matrices (all the elements on the main diagonal are equal)[11] and $\overline{R}$ is a *nxn* matrix with 1s on the main diagonal. The matrix $\overline{R}$ is the long-run, baseline level to which the conditional correlations mean-revert. To hasten the estimation procedure, $\overline{R}$ can be set equal to the unconditional correlation matrix over the sample. Engle and Sheppard (2001) show that this two-stage procedure yields consistent maximum likelihood parameter estimates, and that the inefficiency in the two-stage estimation process can be overcome by modifying the asymptotic covariance of the correlation estimation parameters.

Other specifications of (25) are obviously feasible, and we will experiment with versions that allow for the inclusion of trend coefficients, asymmetric components, and constraints on the parameters. In a nested test, if we want to test the null hypothesis that the restriction is binding, the relevant statistic is -2[$ln(L_{UR})$ –$ln(L_R)$] and it asymptotically follows a c*hi*-s*quared* distribution with q degrees of freedom, denoted by $\chi^2(q)$. The expression L_{UR} is the likelihood of the unrestricted model, L_R is the likelihood of the restricted model and q corresponds to the number of restrictions[12]. This is equivalent to $T[ln|R_{UR}| - ln|R_R|] \sim \chi^2(q)$, where R_{UR} and R_R are the variance-covariance matrices of the residuals of the unrestricted and restricted model of the standardised zero-mean return innovations. The critical value of the $\chi^2(1)$ distribution at the 5 percent level is 3.841.

We use the following specification for the conditional correlation model:

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returns innovations ε_t in (23) are multivariate normal, even though the skewness, curtosis and *JB* statistics reported in Table 2 imply a non-normal distribution of row returns.

[11] Since α and β are scalar matrices, to minimise the proliferation of symbols, we will denote the elements on their main diagonal with the same symbol as the matrices themselves.

[12] The likelihood functions of both the restricted and the unrestricted model are of course evaluated at the estimated parameter values.

$$R_t = \overline{R}(1-\alpha-\beta-\theta-\delta_{Trend}) + \alpha\varepsilon_{t-1}\varepsilon'_{t-1}$$
$$+\beta R_{t-1} + \theta\ S_{t-1}\ + \delta_{Trend}\, t \tag{26}$$

In (26), the elements of the *nxn* matrix S_{t-1} are the outer-products of 2 vectors that contain only negative return innovations, θ is the coefficient of the matrix S_{t-1}, and δ_{Trend} is the deterministic time-trend coefficient. Notice that when the coefficient θ in (26) is not constrained to be zero, the correlation process can be asymmetric. Moreover, the unconditional correlation matrix to which the correlation process is forced to mean-revert, $\overline{R}$, can take values Q_1 if $t < \tau$ and Q_2 if $t > \tau$, where τ represents a selected structural break date. We estimate (26) with both firm-level and market index data. The expression τ is set equal to 15 June 1997, which splits our sample in half and allows for the possibility that the correlations amongst euro-zone stock returns might have been affected by increased integration prior to the introduction of the new currency.

Tables 5 and 6 present our DCC-MVGARCH model estimates using daily data on, respectively, the 6 market indexes and the 42 individual *Eurostoxx50* stocks. In each Table, we provide the estimates with and without trend, and with and without an asymmetric component. *Panel A* in each Table presents the coefficient estimates and *Panel B* reports selected likelihood ratio test statistics and their significance levels. Consider Table 5 firstly, which provides the results of the DCC-MVGARCH model for the 6 market indexes. We first estimate a simple symmetric specification of (26) with a deterministic time trend but no structural break. We label this specification Model 1. The estimated deterministic time trend coefficient turns out to be very small, entailing a decline in average market index conditional correlation of less than 0.5 percent over the sample period, even though it is statistically significant according to the reported *t*-statistic. Since this decline is economically negligible, however, we drop it from the model by restricting it to be zero in all subsequent specifications. We therefore estimate Model 2, which imposes on Model 1 the additional restriction that the time trend coefficient is zero.

Considering the clear rise in average market index correlation that is visible in Figure 3, together with the lack of evidence of a significant deterministic time trend, we suspect that it either contains a stochastic trend (it is not stationary) or that it undergoes a structural break in its mean. To check the stationarity of the correlation process, we test the restriction that the persistence and news parameters α and β in (26) sum to unity. The relevant LR test statistic and the associated significance level are reported at the bottom of Table 5 (Model 2 against Model 3). We reject the restriction that the parameters of the correlation process sum to unity and we conclude, therefore, that the correlation process is stationary. A structural break in the market index correlation process might, however, explain both the strong persistence of the series and its sharp increase over the sample. We therefore estimate Model 4 that allows for a structural break in June 1997, corresponding to half the sample period and roughly 18 months before the introduction of the Euro, and we test it, using the usual LR test statistic (reported at the bottom of Table 5), against the restricted model with no structural break (Model 2). We can reject this restriction at the 0.0001 significance level. Moreover, once we allow for the structural break, we cannot reject the restriction that the asymmetric component coefficient θ is equal to zero (Model 5 against Model 4). We therefore conclude that the aggregate correlation between the 5 Euro-zone stock market indices and the Eurostoxx50 index is best explained by a symmetric process with a structural break in its mean.[13] Panel A of Figure 4 plots the market index average conditional correlation estimated with the symmetric Model 5, allowing for a structural break in June 1997.

Turning to the correlation patterns amongst the 42 individual stocks in our sample, the estimation results for selected specifications of the DCC-MVGARCH model are reported in Table 6. As shown in Panel B of this Table, we can reject the restriction that both the asymmetric component coefficient θ and the deterministic time trend coefficient δ_{Trend} are equal to zero (Model 1 against Model 3), the null that the former is equal to zero (Model 1 against

[13] We also estimated each model without the *Eurostoxx50* index, and over the longer sample period 1992-2001, excluding the *MIB30* index (because its series starts a year later). We obtained very similar results in all cases, and these are not reported here for brevity.

Model 2) and the null that the latter is equal to zero (Model 1 against Model 4)[14]. Although the estimated time-trend coefficient is statistically significant, it is very small (it roughly implies a 1% change in stock correlations over a 10-year period). We therefore conclude that the salient feature of the process followed by the conditional correlations amongst the individual stocks included in the Eurostoxx50 is their asymmetric response to joint bad and good news. In particular, the estimated asymmetric component coefficient θ in Model 1 is equal to 0.051, implying a positive response to joint negative return innovations. In other words, correlations tend to rise after joint negative news more than after joint positive news. The time series of the estimated asymmetric average conditional stock return correlation is plotted in Panel B of Figure 4.

A noteworthy feature of all our estimated models, both at the market index level and at the firm-level, is the strong persistence of the conditional correlation processes, measured by the parameter β in (26). It ranges from 0.98 to 0.99 in the index models in Table 5 and it is equal to 0.90 in the model of the individual stocks in Table 6. In many cases, the sum of the persistence parameter and of the news parameter (the parameter α in (26)) is close to unity. But the similarities end there. Average index-level correlation rises, whereas average stock correlation, in the asymmetric case, actually declines towards the end of the sample period. The conditional correlation at the market index level appears to follow a symmetric process, and to be strongly characterised by a structural break that raises the correlations more than twofold, in a manner that is consistent with increased economic and financial integration within the euro-zone. This confirms the results reported by Cappiello, Engle and Sheppard (2003), and it is consistent with the rise in volatility spillovers noticed by Baele (2002). In contrast to this, the conditional correlation process at the firm level is strongly asymmetric, but there appears to be no structural break. As seen in

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[14] The standard error and associated t-ratio and p-value for Model 1 in Table 6 are not reported because, since we started the maximisation procedure with initial guesses very close to the final estimates, it was impossible to "map out" its curvature, as its gradient was already quite close to zero. Since this is a very lengthy procedure, we did not re-estimate. We therefore rely only on the *LR* test (Model 1 against Model 4 at the bottom of Table 6) in order to evaluate the significance of the deterministic time trend coefficient.

Figure 3, the estimated average correlation between the 42 individual stocks in our sample rises in connection with the 1997 stock market turmoil and with the sharp stock market decline world-wide which began in 2002. This provides the visual justification for the asymmetric component in the conditional correlation process. Because of the inclusion of this component, the aggregate conditional correlation series (in the bottom panel of Figure 4), is much smoother than its unconditional counterpart (Figure 3). Also, because of the strength and the statistical significance of the asymmetric component in the firm-level correlation process, it is natural to argue that the spikes in the unconditional correlation plot are related more to the generalised falls in stock market prices rather than to the process of integration in the euro-zone.

Finally, we use the univariate GARCH volatility estimates given by the first step of the DCC-MVGARCH estimation procedure in equation (24) to compute a GARCH version of the average total variance (VAR_t) of our portfolio of 42 stocks. We then average across the conditional correlation estimates computed in the second stage of the DCC-MVGARCH estimation procedure to obtain the conditional version of the aggregate correlation of stocks returns (r_t). We can use this to divide (according to (9)), the aggregate GARCH total variance measure into conditional market risk (the conditional version of MKT_t) and conditional idiosyncratic risk (the conditional version of $FIRM_t$). The end result is the plot of the conditional variance of the market portfolio, average firm-level variance and average total variance reported in Figure 5 for the case when both volatilities and correlations follow an asymmetric process.

5. Summary and Conclusions

Our purpose in this paper has been to examine the trends in market and firm-level volatility in European equity markets. Using over 2,300 daily observations from February 1993 to November 2001 on 6 European market indices and 42 stocks from the *Eurostoxx50* index, we analysed the time series behaviour of market risk, idiosyncratic risk, and aggregate correlations between the indices and between the individual stocks. In addition to extending the CLMX (2001) methodology to provide a full description of the relation between changes in market risk, aggregate idiosyncratic risk and return correlations, we also applied the asymmetric version of the DCC-MVGARCH model of Engle (2001) and Engle and Sheppard (2002) to capture the time series behaviour of the conditional correlations between the market indexes and between the individual stocks in the *Eurostoxx50* index.

We find that both market risk and aggregate idiosyncratic risk are trended upwards in our sample, and that the deterministic time trend at work in the latter is stronger than in the former. The rise in idiosyncratic risk implies that it takes more stocks to achieve a given level of diversification, and is consistent with the results reported by CLMX (2001) for United States markets. We also find that aggregate firm-level return correlations are trended weakly downwards in the euro-zone. Part of this finding might be explained by the fact that our sample includes large stocks that have a significant degree of diversification built into the cash flows associated with their businesses. In contrast to this, however, the average correlation amongst the 5 euro-zone stock market indices and the *Eurostoxx50* index has risen significantly over our sample period. This, we argue, is not surprising in view of the ongoing process of economic and financial integration in the euro-zone area.

In applying the DCC-MVGARCH model to further examine the behaviour of euro-zone correlations, we find that, consistent with CLMX (2001) and Capiello, Engle and Sheppard (2003), all our conditional correlation time series estimates display significant degrees of persistence. At the market index level, we can reject the restriction that the parameters of the correlation process sum to unity, but there is strong evidence of a structural break in the mean shortly before the introduction of the Euro. This explains both the strong persistence of the correlation time series and its significant rise over the sample period. We also find that the conditional correlation process is strongly asymmetrical with a negative but very small deterministic time trend. The asymmetry of the stock returns correlation process also explains why the skewness of market index returns, as reported in Table 2, is always negative whereas stock returns have either negative or positive skewness. Our finding that correlations amongst euro-zone stock returns display a much weaker tendency to decrease than reported by CLMX (2001) suggests the existence of different correlation dynamics in the euro-zone area and in the United States, at least over the portion of our sample period that overlaps (from 1993 to 1997). A number of explanations of this disparity can be tentatively advanced. Commensurate with a corporate culture in Europe that emphasis external capital markets somewhat less than in the United States, companies in Europe have probably pursued less diversification strategies than in the United States. Another possible explanation is that the tendency for companies to access the equity market at earlier stages in their life cycle is less pronounced in Europe than in the United States[15]. Moreover, the level of average correlation in our sample, especially in the case of the DCC-MVGARCH estimates, is generally higher than in the CLMX's (2001) sample[16], implying, according to (8), a higher ratio of market to total variance and a lower ratio of firm-level to total variance. This suggests that the portion of total risk represented by idiosyncratic risk in euro-zone equity markets might be smaller than in the United States, implying a lower benefit to diversification in the euro-zone area. In other words, the *opportunity-cost* of not diversifying is relatively lower. Part of this difference might be explained by the fact that our sample comprises large stocks that have a significant degree of built-in diversification. Nevertheless, our results suggest that fund managers should think through the full ramifications of seeking more cost-effective diversification by adopting the passive strategy of investing in market indexes rather than a selection of stocks from each country.

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[15] There is the possibility that this tendency might not have been detected by our estimates because we worked with a sample of stocks issued by well established firms (as it must be the case since they are included in the Eurostoxx50 Index).

[16] Our sample period and CLMX's (2001) overlap across the central portion of the 1990s (from 1993 to 1997). CLMX (2001) report that correlations based on 5 years of monthly data decline from 0.28 in the early 1960s to 0.08 in 1997 and that correlations based on 1 year of daily data (more comparable to our correlation measures) decreased from 0.12 in the early 1960s to between 0.02 and 0.04 in the 1990s.

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Table 1
Stocks Included in the Eurostoxx50 Index

	Company	Bloomberg Ticker	Market Sector	Weights (%)
1	ABN AMRO	AABA NA	BAK	1.59
2	AEGON	AGN NA	INN	1.55
3	AHOLD	AHLN NA	NCG	1.87
4	AIR LIQUIDE	AI FP	CHE	0.89
5	ALCATEL	CGE FP	THE	1.02
6	ALLIANZ	ALThe V GY	INN	2.49
7	ASSICURAZIONI GENERALI	G IM	INN	2.15
8	AVENTIS	AVE FP	HCA	3.48
9	AXA UAP	N.A.	INN	2.00
10	BASF	BAS GY	CHE	1.26
11	BAYER	BAY GY	CHE	1.40
12	BAYERISCHE HYPO & VEREINSBANK	HVM GY	BAK	0.75
13	BCO BILBAO VIZCAYA ARGENTARIA	BBVA SM	BAK	2.39
14	BCO SANTANDER CENTRAL HISP	SAN SM	BAK	2.46
15	BNP*	BNP FP	BAK	2.37
16	CARREFOUR SUPERMARCHE	CA FP	RET	1.97
17	DAIMLERCHRYSLER*	DCX GY	ATO	1.86
18	DEUTSCHE BANK R	DBK GY	BAK	2.13
19	DEUTSCHE TELEKOM*	DTE GY	TEL	2.64
20	E.ON	EOA GY	UTS	2.39
21	ENDESA	ELE SM	UTS	1.14
22	ENEL*	ENEL IM	UTS	0.83
23	ENI*	ENI IM	ENG	2.22
24	FORTIS B	FORB BB	FSV	0.98
25	FRANCE TELECOM*	FTE FP	TEL	1.06
26	GROUPE DANONE	N.A.	FOB	1.47
27	ING GROEP	INGA NA	FSV	2.95
28	L'OREAL	OR FP	NCG	1.52
29	LVMH MOET HENNESSY	N.A.	CGS	0.55
30	MUENCHENER RUECKVER R*	MUV2 GY	INN	1.70
31	NOKIA	NOK1V FH	THE	5.63
32	PHILIPS ELECTRONICS	PHIA NA	CGS	1.75
33	PINAULT PRINTEMPS REDOUTE	PP FP	RET	0.49
34	REPSOL YPF	REP SM	ENG	1.02
35	ROYAL DUTCH PETROLEUM	RDA NA	ENG	7.63
36	RWE	RWE GY	UTS	0.98
37	SAINT GOBAIN	SAN FP	CNS	0.81
38	SAN PAOLO IMI	SPI IM	BAK	0.70
39	SANOFI SYNTHELABO	N.A.	HCA	1.81
40	SIEMENS	SIE GY	THE	2.34
41	SOC GENERALE A	SGO FP	BAK	1.46
42	SUEZ	SZE FP	UTS	2.39
43	TELECOM ITALIA	TI IM	TEL	1.19
44	TELEFONICA	TEF SM	TEL	3.24
45	TIM*	TIM IM	TEL	1.22
46	TOTAL FINA ELF	FP FP	ENG	7.31
47	UNICREDITO ITALIANO	UC IM	BAK	0.84
48	UNILEVER NV	UNA NA	FOB	2.49
49	VIVENDI UNIVERSAL	N.A.	MDI	3.07
50	VOLKSWAGEN	VOW GY	ATO	0.54

Note. This table reports the stocks included in the Eurostoxx50 as of 23 November 2001 and the weights as of the date of the last reshuffle (19 September 2001) before the end of our sample period (23 November 2001). Asterisks indicate that the series has been dropped from the sample. Descriptors for the market sectors are as follows (Stoxx's Industry Codes): BAK (Banks), ATO (Auto), INN (Insurance), TEL (Telecom), NCG ((Non-Cyclical Goods and Services), UTS (Utilities), CHE (Chemical), ENG (Energy), THE (Technology), FSV (Financials), HCA (Health Care), FOB (Food & Beverages), RET (Retailer), CGS (Cyclical Goods and Services), CNS (Construction), MDI (Media).

Table 2
Summary Statistics for Stock and Market Index Returns

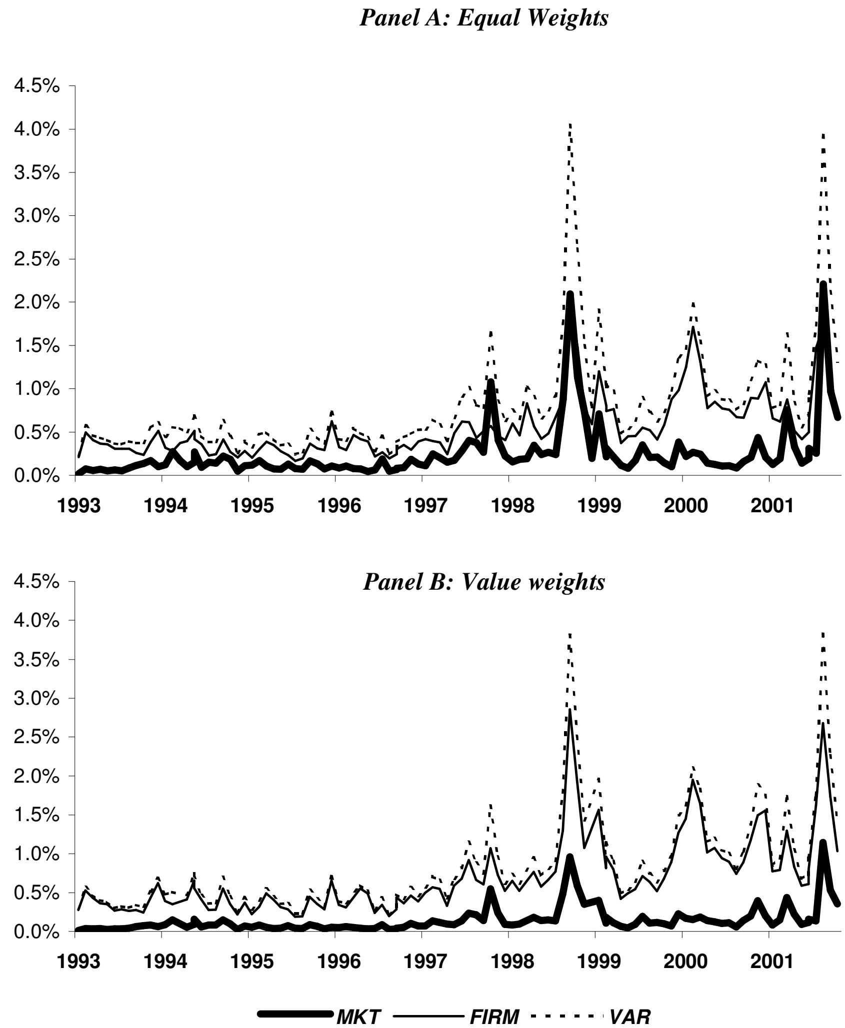
	Mean	Std. Dev.	Skew	Sig.	Kurt.	JB
Panel A: Individula Stocks						
ABN AMRO	19.10	27.57	-0.17	0.001	4.47	2104
AEGON	32.39	28.33	0.20	0.001	4.19	1848
AHOLD	22.72	25.84	0.26	0.000	2.83	865
AIR LIQUIDE	13.28	27.75	0.24	0.000	2.14	485
ALCATEL	7.68	44.33	-0.97	0.000	17.27	30517
ALLIANZ	16.46	30.45	0.13	0.009	6.76	4398
AVENTIS	21.74	32.79	0.47	0.000	4.56	1957
N.A.	19.58	31.34	-0.12	0.013	3.04	938
BCO BILBAO VIZ. ARGENTARIA	26.41	30.21	0.10	0.040	6.88	4696
BASF	17.87	27.39	0.36	0.000	4.37	1885
BAYER	15.36	26.79	-0.28	0.000	7.21	5031
BAYER. HYPO & VEREINSBANK	12.25	33.02	0.35	0.000	5.31	2755
BNP	10.83	35.28	0.33	0.000	3.21	889
BCO SANTANDER CENTRAL HISP	20.74	32.21	-0.46	0.000	7.29	5346
CARREFOUR SUPERMARCHE	20.93	29.28	0.02	0.623	2.98	896
DAIMLERCHRYSLER	-7.40	34.46	-0.01	0.868	1.74	96
N.A.	6.93	26.12	0.06	0.205	3.38	1153
DEUTSCHE BANK R	12.36	30.98	0.20	0.000	6.62	4228
DEUTSCHE TELEKOM	12.67	46.80	0.30	0.000	1.43	125
E.ON	15.66	26.46	0.22	0.000	3.28	1051
ENDESA	19.88	25.79	0.07	0.141	2.36	553
ENEL	-6.00	28.02	-0.10	0.335	2.15	101
ENI	19.59	28.55	0.13	0.039	1.33	113
FORTIS B	22.06	26.22	0.10	0.038	3.64	1343
FRANCE TELECOM	19.12	52.42	0.63	0.000	3.33	537
ASSICURAZIONI GENERALI	14.11	26.36	0.17	0.001	2.11	462
ING GROEP	27.16	28.55	-0.48	0.000	8.22	7153
L'OREAL	26.45	32.67	0.10	0.054	1.85	350
N.A.	11.31	33.50	0.40	0.000	4.11	1771
MUENCHENER RUECKVER R	29.12	40.74	-1.72	0.000	31.38	59805
NOKIA	92.62	49.62	-0.08	0.105	5.12	2624
PHILIPS ELECTRONICS	36.53	42.34	-0.18	0.000	3.92	1615
PINAULT PRINTEMPS REDOUTE	25.22	31.22	0.04	0.456	3.03	923
REPSOL YPF	16.54	24.85	0.63	0.000	6.29	4088
ROYAL DUTCH PETROLEUM	16.09	23.35	0.09	0.075	2.79	815
RWE	12.60	27.43	0.48	0.000	5.17	2659
SAINT GOBAIN	30.13	32.67	0.18	0.000	1.95	397
SAN PAOLO IMI	12.53	33.73	0.34	0.000	2.21	524
SIEMENS	16.96	32.02	0.27	0.000	6.54	4407
N.A.	16.00	32.75	0.07	0.152	3.12	983
SOC GENERALE A	13.94	30.62	0.08	0.127	2.30	539
SUEZ	12.31	26.83	0.37	0.000	2.86	855
TELECOM ITALIA	30.41	35.53	-0.26	0.000	5.23	2791
TELEFONICA	26.81	31.70	0.08	0.091	1.77	314
TIM	33.65	37.28	0.23	0.000	0.76	51
TOTAL FINA ELF	17.61	30.21	-0.03	0.527	1.59	256
UNICREDITO ITALIANO	17.85	37.28	0.76	0.000	4.33	2121
UNILEVER NV	15.45	23.98	0.31	0.000	6.45	4382
N.A.	10.23	30.21	0.18	0.000	2.74	770
VOLKSWAGEN	15.34	31.90	0.07	0.161	3.86	1532
Panel B: Market Indices						
DAX	12.33	34.10	-0.44	0.000	3.72	1,564
CAC40	10.37	19.75	-0.15	0.001	1.88	389
MIB30	13.66	23.56	-0.07	0.188	2.08	417
AEX	13.84	18.10	-0.39	0.000	4.38	2,121
IBEX	12.23	20.43	-0.28	0.000	2.82	881
EUROSTOXX50	13.23	18.03	-0.29	0.000	3.65	1,462

Notes. The table reports summary statistics for stocks included in the Eurostoxx50 on 23 November 2001. The sample period is 1993-2001. Mean and standard deviations are on a 1-year basis. *JB* denotes the *Jarque-Bera* statistics. The Kurtosis and the *JB* statistics are different from zero at the 0.1 percent level for all stocks in the sample.

Figure 1

Aggregate Market, Firm-Level and Total Variance

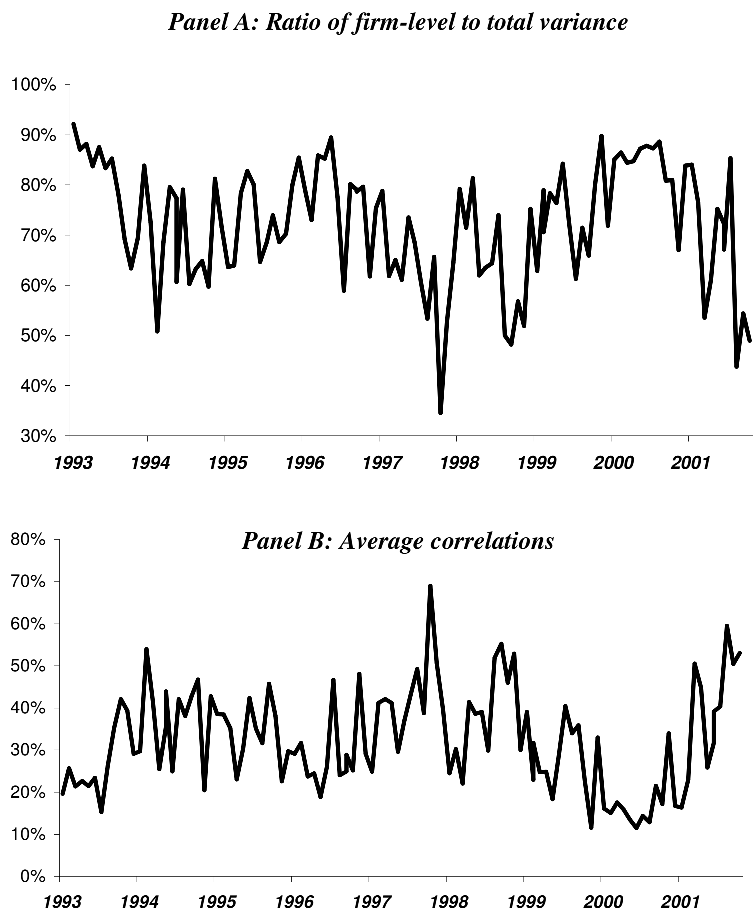
of 42 Stocks in the Eurostoxx50 Index



Note. This figure plots both the equally-weighted (*Panel A*) and the value-weighted (*Panel B*) aggregate market variance (MKT_t), average firm-level variance ($FIRM_t$) and average total variance (VAR_t) monthly time series, computed using daily closing prices of 42 stocks included in the *Eurostoxx50* index over the sample period 1993-2001.

Figure 2

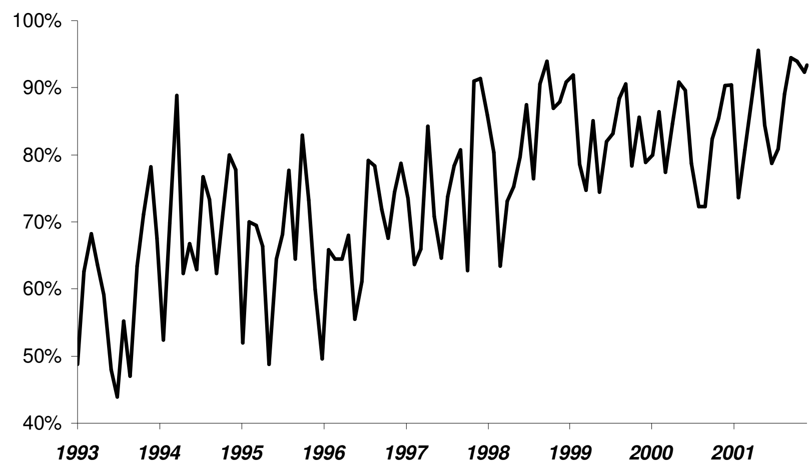
The Ratio of Firm-Level to Total Variance and Average Return Correlations amongst 42 Eurostoxx50 Stocks



Note. *Panel A* plots the ratio of the average firm-level variance ($FIRM_t$) to the average total variance (VAR_t) monthly time series. *Panel B* depicts the average correlation time series. Both series are computed using the sample of 42 stocks over the sample period 1993-2001.

Figure 3

Average Correlation amongst 5 Euro-zone Market Indexes and the Eurostoxx50 Index



Notes. This Figure plots the time series of monthly average correlation amongst 5 Euro-zone national stock market indices (ie., the DAX, CAC40, MIB30, AEX, IBEX) and the *Eurostoxx50* index.

Table 3
Unit Root Tests on Aggregate Returns, Variances and Correlations

	CV	DF	ADF1	ADF2	F-Test
		Individual Stocks			
FIRM$_t$					
Intercept, no trend	-2.89	-3.95	-4.21	-3.01	
Intercept and linear trend	-3.45	-5.23	-6.23	-4.84	
MKT$_t$	-2.89	-5.67	-4.65	-3.78	
Intercept, no trend	-3.45	-6.24	-5.26	-4.45	
Intercept and linear trend					
r_t	-2.89	-5.68	-4.07	-3.30	
Intercept, no trend	-3.45	-5.65	-4.04	-3.28	
Intercept and linear trend					
		Market Indexes			
r_t					
Intercept, no trend	-2.89	-4.95	-4.10	-2.67	620.01
Intercept and linear trend	-3.45	-7.62	-7.46	-5.57	(.000)

Notes. This Tables reports Dickey-Fuller (*DF*) tests and augmented Dickey-Fuller (*ADF1* and *ADF2*, the numbers denoting the order of augmentation) tests. *CV* denotes the critical value at the 5 percent level. All variables are defined in the text. *F-test* denotes critical value and significance level (in brackets) of the test statistic under the null that the trend coefficient is zero and the series contains a unit root.

Table 4
Specification and Wald-Type Tests

	Static Model	**Dynamic Model**				
	DW-stat.	α *(%)* (t-stat.)	δ *(%)* (t-stat.)	β (t-stat.)	*h-stat.* (sign.)	*Wald-stat.* (sign.)
			Individual Stocks			
$FIRM_t$	.86	.00	.0031	.57	8.52	10.38
		(0.01)	(3.22)	(6.94)	(.003)	(0.01)
MKT_t	1.11	-.00	.0023	.44	.009	5.44
		(0.46)	(2.33)	(5.00)	(0.92)	(0.02)
r_t	.96	16.66	-.0076	.51	2.60	.05
		(4.07)	(0.22)	(5.95)	(0.10)	(0.82)
			Market Indexes			
r_t	1.41	38.40	.1937	.29	5.08	27.40
		(7.09)	(5.24)	(3.04)	(0.02)	(0.00)

Notes. This tables reports estimates of the parameters of the model of the average firm-level variance ($FIRM_t$), market variance (MKT_t) and average correlation (r_t) series with a deterministic time trend. All variables are defined in the text. *DW* denotes the Durbin-Watson statistics of the static model from (22). All other columns report estimated coefficient and t-statistics for the dynamic model as in (23). The rightmost columns report the Durbin's *h*-statistic of the null that the dynamic model residuals are not first-order autocorrelated and the Wald statistic (in both cases with the associated significance levels) of the restriction that δ is equal to zero. All the Wald-Test statistics, standard errors and significance levels have been computed using a Newy-West adjusted variance–covariance matrix with Parzen weights to correct for heteroschedasticity and autocorrelation.

Static Model:

$$y_t = \alpha + \delta t + u_t \qquad u_t \sim i.i.d.\ N(0, \sigma^2)$$

Dynamic Model:

$$y_t = \alpha + \beta\, y_{t-1} + \delta t + u_t \qquad u_t \sim i.i.d.\ N(0, \sigma^2)$$

Table 5
DCC-MVGARCH Estimates of Market Indexes
Daily Data, 1993 - 2001

Panel A

Model	***Restriction***	***Coefficient***	***Coefficient estimate***	***T-Ratio***	***p-value***
1	$Q_1 = Q_2$	$Q_{1/2}$	.799		
	$\theta = 0$	α	.010	7.74	.000
		β	.986	410.70	.000
		δ_{Trend}	-.000	1.86	.061
2	$Q_1 = Q_2$	$Q_{1/2}$	.799		
	$\theta = 0$	α	.014	10.74	.000
	$\delta_{Trend} = 0$	β	.978	374.51	.000
3	$Q_1 = Q_2$	$Q_{1/2}$	.799		
	$\theta = 0$	α	.007	12.72	.000
	$\delta_{Trend} = 0$	β	.993	1807.09	.000
	$\alpha + \beta = 1$				
4	$\theta = 0$	Q_1	.312		
	$\delta_{Trend} = 0$	Q_2	.798		
		α	.009	17.52	.000
		β	.989	1686.47	.000
5	$\delta_{Trend} = 0$	Q_1	.312		
		Q_2	.798		
		α	.012	11.66	.000
		β	.987	986.93	.000
		θ	-.002	-3.83	.000

Panel B

Unrestricted Model	$ln(\lvert\Sigma_{UR}\rvert)$	***Restricted Model***	$ln(\lvert\Sigma_R\rvert)$	***LR Statistic***	***Significance Level***	***Restriction Rejection***
2	-5.0580	3	-5.0798	50.47	.000	*Yes*
4	-4.8310	2	-5.0580	525.50	.000	*Yes*
5	-4.8309	4	-4.8310	.23	.597	*No*

$$LR = T\ ln(\lvert\Sigma_{UR}\rvert)-ln(\lvert\Sigma_R\rvert) \sim \chi^2(q)$$

T = number of observations (2,315)

Σ_{UR} = covariance matrix of the residuals of the unrestricted model

Σ_R = covariance matrix of the residuals of the restricted model

$\chi^2(q)$ = Chi-Squared distributions with q degrees of freedom

q = number of restrictions (q = 15 for Model 4 vs. 2, q = 1 in all other tests)

Notes. *Panel A* of this Table reports coefficients, t-statistics and p-values for various specifications of the DCC-MVGARCH model of conditional correlations amongst 6 euro-zone market indexes, including the *Eurostoxx50* index, over the period 1993-2001. *Panel B* reports Likelihood Ratio (*LR*) test statistics and their significance level.

Table 6

DCC-MVGARCH Estimates of 42 Eurostoxx50 Stocks
Daily Data, 1993 - 2001

Panel A

Model	***Restriction***	***Coefficient***	***Coefficient estimate***	***T-Ratio***	***p-value***
1	$Q_1 = Q_2$	α	.056	58.00	.000
		β	.899	12011.98	.000
		θ	.051	56.42	.000
		δ_{Trend}	.000	-	
2	$Q_1 = Q_2$	α	.005	419.89	.000
	$\theta = 0$	β	.904	10793.04	.000
		δ_{Trend}	-.000	-18.68	.000
3	$Q_1 = Q_2$	α	.005	16.57	.003
	$\theta = 0$	β	.903	2784.11	.000
	$\delta_{Trend} = 0$				
4	$Q_1 = Q_2$	α	.003	15.68	.000
	$\delta_{Trend} = 0$	β	.978	627.35	.000
		θ	.000	.39	.701

Panel B

Unrestricted Model	***ln(|Σ_{UR}|)***	***Restricted Model***	***ln(|Σ_R|)***	***LR Statistic***	***Significance Level***	***Restriction Rejection***
1	-5.7840	2	-6.7771	2273.26	.000	*Yes*
1	-5.7840	3	-6.7782	2275.71	.000	*Yes*
1	-5.7840	4	-12.8915	16268.98	.000	*Yes*

$$LR = T \ln(|\Sigma_{UR}|)-\ln(|\Sigma_R|) \sim \chi^2(q)$$

T = number of observations (2,289)

Σ_{UR} = covariance matrix of the residuals of the unrestricted model

Σ_R = covariance matrix of the residuals of the restricted model

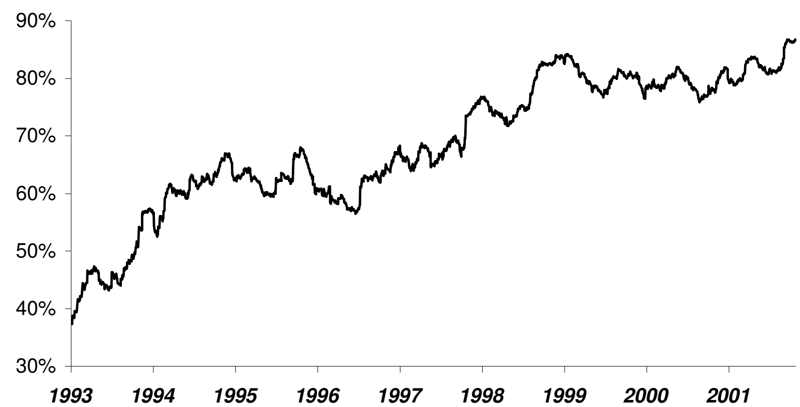
$\chi^2(q)$ = Chi-Squared distributions with q degrees of freedom

q = number of restrictions (q = 2 for Model 1 vs. 3, q = 1 in all other tests)

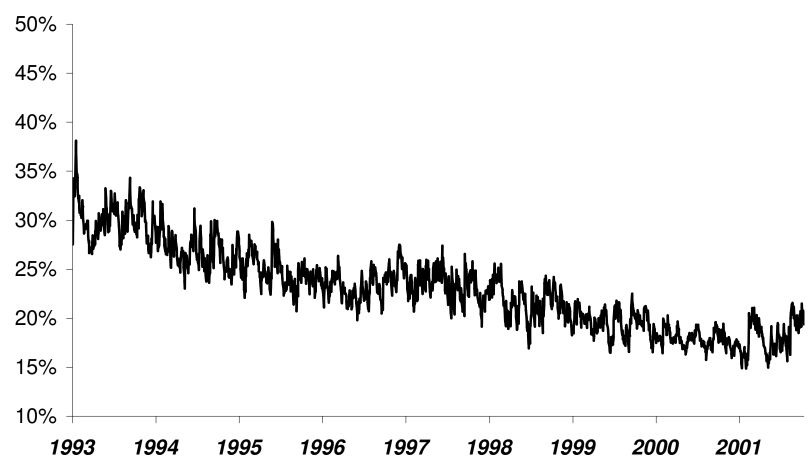
Notes. Panel A of this Table reports the coefficients, t-statistics and p-values for the DCC-MVGARCH model of conditional correlations amongst 42 stocks (k = 42) included in the *Eurostoxx50* index over the sample period 1993- 2001. Variables and their coefficients are defined in the text. Panel B reports Likelihood Ratio (*LR*) test statistics and their significance level.

Figure 4
DCC-MVGARCH Correlation Estimates
Daily Data, 1993 - 2001

Panel A: Market index correlations



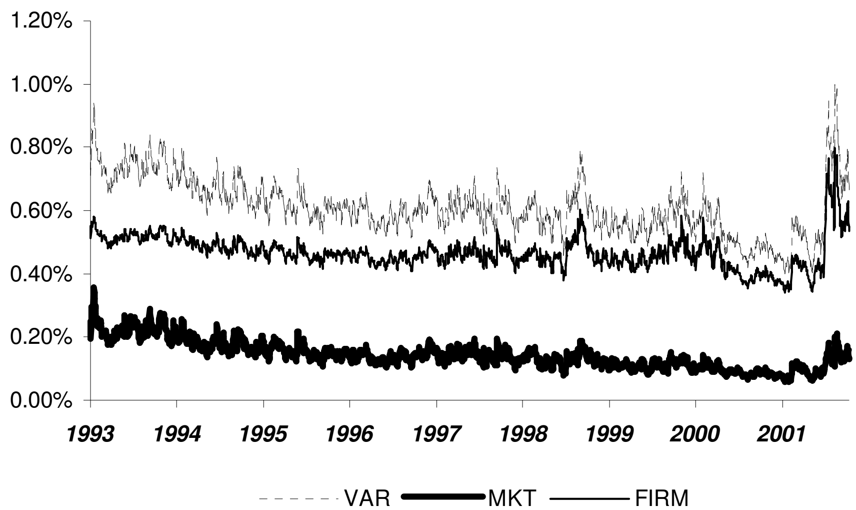
Panel B: Individual stock correlations



Notes. Panel A plots the daily average conditional correlation amongst the 5 euro-zone market indices in our sample and the Eurostoxx50 Index over the period 1993-2001, estimated with the symmetric DCC-MVGARCH(1,1) model with a structural break on the date that corresponds to half the sample period (Mid June 1997). Panel B plots the daily average conditional correlation amongst the 42 individual stocks included in the *Eurostoxx50* index over the period 1993-2001, estimated with the asymmetric DCC-MVGARCH(1,1).

Figure 5

Asymmetric DCC-MVGARCH Estimates of Total, Market and Firm-level Variances of 42 Stocks in the *Eurostoxx50* Index Daily Data, 1993 - 2001



Note. The Figure plots the average total variance (*VAR_t*), the aggregate market variance (*MKT_t*), and the average firm-level variance (*$FIRM_t$*) of a portfolio of 42 stocks from the *Eurostoxx50* Index. The series are computed using the asymmetric DCC-MVGARCH(1,1).

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