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Research in International Business and Finance 20 (2006) 305–321
RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE
www.elsevier.com/locate/ribaf

Correlation dynamics in European equity markets[☆]

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Received 26 August 2004; received in revised form 15 May 2005; accepted 25 May 2005
Available online 20 July 2005

Abstract

We examine correlation dynamics using daily data from 1993 to 2002 on the five largest Euro-zone stock market indices. We also study, for comparison, the correlations of a sample of individual stocks. We employ both unconditional and conditional estimation methodologies, including estimation of the conditional correlations using the symmetric and asymmetric DCC-MVGARCH model, extended with the inclusion of a deterministic time trend. We confirm the presence of a structural break in market index correlations reported by previous researchers and, using an innovative likelihood-based search, we find that the it occurred at the beginning the process of monetary integration in the Euro-zone. We find mixed evidence of asymmetric correlation reactions to news of the type modelled by conventional asymmetric DCC-MVGARCH specifications.

JEL classification: C32; G12; G15

Keywords: Correlation dynamics; GARCH

☆ Previous versions of this paper were presented at the European Meeting of the Financial Management Association in Dublin, June 2003 and at the Annual Meeting of the European Finance Association in Glasgow, August 2003.

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0275-5319/$ – see front matter
doi:10.1016/j.ribaf.2005.05.006

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 et al., 2001; 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; Longin and Solnik, 2001). Correlations also tend to rise with the degree of international equity market integration (Erb et al., 1994; Longin and Solnik, 1995), which has gathered pace in Europe since the mid-1990s (Hardouvelis et al., 2000; Fratzschler, 2002). It is of considerable interest, therefore, to investigate the relative strengths of the trends in correlations in European equity markets, because the findings have relevance for the diversification properties of passive and active international investment strategies.

We investigate the correlation trends and dynamics in the equity markets of the European Monetary Union (henceforth, Euro area). In particular, we study the correlation between Euro area national stock market indices over various sample periods. For comparison, we also study the correlation amongst a sample of individual Euro area stocks. We first model correlations in an unconditional setting and we test for the presence of either a stochastic or a deterministic time trend. We then model them in a conditional setting. To this end, we apply the DCC-MV GARCH model of Engle (2001, 2002) and Engle and Sheppard (2001) and we extend it with the inclusion of a deterministic time trend. In so doing, we specify the model to facilitate testing for non-stationarity, structural breaks and asymmetric dynamics in the correlation processes. To identify the date of the structural break, we employ an innovative search that maximise the likelihood of the multivariate conditional correlation model. Finally and more innovatively, to test for residual asymmetry in the distribution of asset returns not captured by our model, we employ the Engle and Ng (1993) diagnostic test in a multivariate setting.

We find significant persistence in all our conditional correlation estimates. We also provide weak evidence that index correlations tend to spike up after joint negative news, but contrary to the recent evidence of Cappiello et al. (2003) and others, this phenomenon is not well captured by a linear specification. We confirm a significant rise in the correlations amongst national stock market indexes that can best be explained by a structural break shortly before the official adoption of the Euro. It follows that portfolio managers investing in the Euro-zone should not overestimate the benefits of pursuing passive international diversification strategies based on holding national stock market indexes.

The remainder of our paper is structured as follows. In Section 2, we describe our data set and provide summary statistics. In Sections 3 and 4, we perform a range of statistical tests to discern more formally the behaviour of unconditional and conditional correlations. In the final section, we summarise our main findings and draw together our conclusions.

2. Data

Our equity return data is obtained from *Bloomberg* and consists of daily returns on the five national stock market indexes with the heaviest capitalisation in the Euro-zone at the end of our sample period, i.e., 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)[1]. These series are expressed in euro and cover the sample period 1993–2002. We also use *Datastream International Ltd.* 5-year government bond clean price indices for France, Germany, Italy, the Netherlands and Spain. Finally, we select the 42 stocks included in the *Eurostoxx50* index[2] with a continuous return history and we obtain their returns from *Bloomberg* for the same time period. The selected stocks are all traded in one of the five stock markets included in the country level sample. Table 1 lists the stocks included in the *Eurostoxx50* index after the September 2001 reshuffle[3].

Table 2 provides the usual set of summary statistics for the returns on the five market indices, the *Eurostoxx50* index and the 42 individual stocks. In particular, we report the sample means, variances, skewness, kurtosis, the *Jarque-Bera* statistics and their associated significance levels. As expected, returns exhibit significant departure from the normal distribution in most cases. Noticeably, index returns always display negative skewness whereas the sign of the latter is not the same across returns on individual stocks.

3. Unconditional correlation estimates

We first employ unconditional estimators of correlations that use the traditional, ad hoc representation of the second moments of asset returns based on sums (or averages) of return innovations squares and cross-products. Many researchers have used this approach because of its simplicity, see for example Merton (1980) and CLMX (2001). We first compute the cross products of the standardised daily log-return $R_{i,t}$ deviations from their monthly sample means and sum them to obtain monthly non-overlapping correlation estimates for each pair of indices and stocks i and j,

$$c_{i,j,t} = \frac{\sum_{k=1}^{21}(R_{i,t-k+1} - \bar{R}_{i,t})(R_{j,t-k+1} - \bar{R}_{j,t})}{\sqrt{\sum_{k=1}^{21}(R_{i,t-k+1} - \bar{R}_{i,t})^2 \sum_{k=1}^{21}(R_{j,t-k+1} - \bar{R}_{j,t})^2}} \quad (1)$$

[1] These series start on 31 December 1991 except for the MIB30, which starts a year later.

[2] The *Eurostoxx50* is the leading European stock market index. It comprises 50 stocks from the companies with the heaviest capitalisation in the Euro-zone countries.

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

Table 1
Stocks included in the Eurostoxx50 index

	Company	Bloomberg ticker	Market sector	Weights (percent)
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 19 September 2001 reshuffle. 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 and beverages), RET (retailer), CGS (cyclical goods and services), CNS (construction), MDI (media).

Table 2
Summary statistics for stock and market index returns

	Mean	S.D.	Skew	Significance	Kurtosis	JB
Panel A (Market indices)						
DAX	12.33	34.10	−0.44	0.000	3.72	1564
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	2121
IBEX	12.23	20.43	−0.28	0.000	2.82	881
EUROSTOXX50	13.23	18.03	−0.29	0.000	3.65	1462
Panel B (Individual 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

Table 2 (*Continued*)

	Mean	S.D.	Skew	Significance	Kurtosis	JB
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

Note: The table reports summary statistics for the five largest Euro area stock market indices, for the Eurostoxx50 and for the stocks included in the latter on 23 November 2001. The sample period is 1993–2002. 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.

We then average correlations across market indices and stocks to compute a synthetic equally weighted index of their average correlation.

$$\mathrm{CORR}_t = \sum_{i=1}^{n} \frac{1}{n} \sum_{j=1}^{n} \frac{1}{n} c_{i,j,t} \tag{2}$$

Here, n is either the number of national market indices or of stocks. In Fig. 1, we plot the monthly average correlation amongst the country indexes and the individual stocks. The former has been computed applying (1) and (2) to our country index data with $n = 5$. This series shows a strong tendency to rise over time. The average stock correlation series has been computed applying (1) and (2) to our stock data with $n = 42$. This series does not show

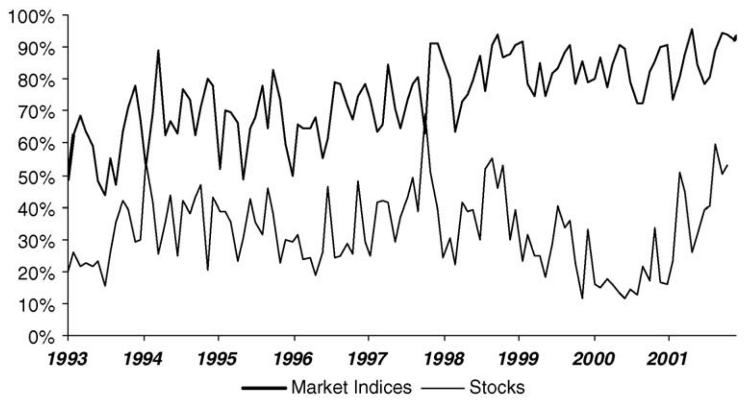

Fig. 1. Average market index and stock correlations. *Note*: This figure plots the unconditional estimates of the average correlation between the 5 largest stock market indices in the Euro area and the average correlation between 42 stocks included in the *Eurostoxx50* Index over the sample period.

Table 3
Unit root, specification and Wald-type tests

	CV	DF	ADF1	ADF2	F-Test
Panel A (unit root tests on aggregate correlations)					
Country indexes					
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	(0.000)
Individual stocks					
Intercept, no trend	−2.89	−5.68	−4.07	−3.30	
Intercept and linear trend	−3.45	−5.65	−4.04	−3.28	

Static model	Dynamic model				
DW-statistics	α (percent) (t-statistics)	δ (percent) (t-statistics)	β (t-statistics)	h-statistics (significance)	Wald-statistics (significance)
Panel B (specification and Wald-type tests)-3.28					
Country indexes					
1.41	38.40 (7.09)	0.1937 (5.24)	0.29 (3.04)	5.08 (0.02)	27.40 (0.00)
Individual stocks					
0.96	16.66 (4.07)	−0.0076 (0.22)	0.51 (5.95)	2.60 (0.10)	0.05 (0.82)

Note: Panel A of this table reports Dickey–Fuller (DF) tests and augmented Dickey–Fuller (ADF1 and ADF2, the numbers denoting the order of augmentation) tests for the presence of unit roots in the average country and stock unconditional correlations series. 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. Panel B reports estimates of the parameters of the model of the average country and stock correlations series with a deterministic time trend. DW denotes the Durbin–Watson statistics of the static model. All other columns report estimated coefficient and t-statistics for the dynamic model. 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 heteroscedasticity and autocorrelation. All variables are defined in the text.
Static model: $y_t = \alpha + \delta t + u_t,\ \ u_t \sim i.i.d.N(0, \sigma^2)$.
Dynamic model: $y_t = \alpha + \beta y_{t-1} + \delta t + u_t,\ \ u_t \sim i.i.d.\ N(0, \sigma^2)$.

any strong tendency to rise over time but rather appears very noisy and persistent. It takes a substantial amount of time to revert to a fairly stable long run mean (in the region of 20 percent) around which it oscillates.

3.1. Unit root tests

To test for the presence of a stochastic time trend, we conduct Dickey–Fuller (DF) and augmented Dickey–Fuller (ADF) tests allowing for up to 12 lags. As pointed out by Pesaran and 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. As reported in Panel A of Table 3, the *DF* and *ADF* tests reject the null of a unit root at the 5 percent level of significance for average stock correlation. For the average correlation amongst the five Euro area stock market indexes, we cannot reject the null of a unit-root in the *ADF* test with two orders of augmentation and no deterministic time trend. However, using an F-test and the appropriate non-standard asymptotic distribution (Hamilton, 1994), we can reject at the 1 percent level the joint hypothesis that the deterministic time trend is equal to zero and that there is a unit root. We therefore conclude that both correlation series are stationary and, in particular, aggregate market index correlation is trend-stationary.

3.2. Wald-type tests

To check on the possible presence of a deterministic time-trend, we regress our constructed average correlations series on the latter. However, the residuals of a static model that includes among the regressors only a constant and a deterministic time-trend are autocorrelated, as suggested by the Durbin–Watson (DW) statistic. We therefore estimate a dynamic model that also includes the first lag of the dependent variable. We then conduct Wald-type tests of the restriction that the deterministic time trend coefficient is zero using Newy–West adjusted variance–covariance matrices to correct for heteroschedasticity and autocorrelation. Panel B of Table 4 presents the results. The time trend coefficient is large and significant only for average country index correlation. It explains an increase in the latter of about 2.5 percent per year. However, the Durbin's h-statistic[4] suggests that the residuals are not serially independent. Therefore, we treat this trend coefficient estimate with caution.

4. Conditional correlations

Thus far, we have applied an unconditional estimation methodology. This strategy has yielded useful insights but it has the main shortcomings that, while the average of squares and cross-products are consistent estimators of the second moments of the return distributions, they might be biased in small samples since they are ad hoc representations of the volatility and correlation processes. Moreover, 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 recently developed DCC-MVGARCH model of Engle (2001, 2002) and Engle and Sheppard (2001). This provides a useful way to describe the evolution over time of the second moments of large systems. In particular, we use the specification of the asymmetric DCC-MVGARCH proposed by Cappiello et al., (2003) and extend it to include a deterministic time trend:

$$\begin{aligned} R_t &= \text{const} + u_t \\ u_t|\Im_{t-1} &\sim \Phi(0, H_t) \end{aligned} \tag{3}$$

[4] 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 of 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.

Table 4
ADCC-MVGARCH country correlation

Panel A

Model	Restriction	Coefficient	Coefficient estimate	T-ratio	p-Value
1	$Q_1 = Q_2$	$Q_{1/2}$	0.799		
	$\theta = 0$	α	0.010	4.50	0.000
		β	0.982	180.97	0.000
		δ_{Trend}	0.000	2.03	0.041
2	$Q_1 = Q_2$	$Q_{1/2}$	0.799		
	$\theta = 0$	α	0.010	4.55	0.000
	$\delta_{\mathrm{trend}} = 0$	β	0.985	223.82	0.000
3	$Q_1 = Q_2$	$Q_{1/2}$	0.799		
	$\theta = 0$	α	0.007	12.72	0.000
	$\delta_{\mathrm{trend}} = 0$	β	0.993	1807.09	0.000
	$\alpha + \beta = 1$				
4	$\theta = 0$	Q_1	0.611		
	$\delta_{\mathrm{trend}} = 0$	Q_2	0.908		
		α	0.002	8.30	0.000
		β	0.970	589.68	0.000
5	$\delta_{\mathrm{trend}} = 0$	Q_1	0.611		
		Q_2	0.908		
		α	0.002	3.90	0.000
		β	0.590	74.31	0.000
		θ	0.090	7.69	0.000

Panel B

Unrestricted model	$\ln(\lvert\Sigma_{\mathrm{UR}}\rvert)$	Restricted model	$\ln(\lvert\Sigma_{\mathrm{R}}\rvert)$	LR Statistic	Significance Level	Restriction Rejection
2	−5.0689	3	−5.0798	33.19	0.000	Yes
4	−5.0665	2	−5.0689	25.15	0.020	Yes
5	−5.0654	4	−5.0665	2.53	0.112	No

$\mathrm{LR} = T\,[\ln(\lvert\Sigma_{\mathrm{UR}}\rvert) - \ln(\lvert\Sigma_{\mathrm{R}}\rvert)] \sim \chi^2(1)$
T = number of observations (2297)
Σ_{UR} = covariance matrix of the residuals of the unrestricted model
Σ_{R} = covariance matrix of the residuals of the restricted model
$\chi^2(1)$ = Chi-Squared distributions with 1 degree of freedom

Note: Panel A of this table reports coefficients, t-statistics and p-values for various specifications of the ADCC-MVGARCH model of conditional correlations amongst the five largest Euro-zone market indexes. Panel B reports likelihood ratio (LR) test statistics and their significance level.

where

$$H_t \equiv D_t C_t D_t \tag{4}$$

$$D_t^2 = \bar{D}^2(1 - A - B) + A(u_{t-1}u_{t-1}') + BD_{t-1}^2 \tag{5}$$

$$C_t = \bar{C}\,(1 - \alpha - \beta) - \bar{S}\theta - \bar{t}(ii' - I)\delta_{\mathrm{trend}} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}' + \beta C_{t-1} + \theta S_{t-1} + \delta_{\mathrm{trend}}t(ii' - I) \tag{6}$$

Here, u_t is an $nx1$ vector of zero mean innovations conditional on the information set available at time $t-1$ ($\Im_{t-1}$). They follow a Φ distribution, not necessarily normal, with centred second moment matrix H_t. Also, D_t is the diagonal matrix of conditional standard deviations and C_t is the conditional correlation matrix. Both D_t and C_t and, as a consequence, H_t are assumed to be positive definite. Also, $\bar{D}$, A and B are nxn diagonal non-negative coefficient matrices, $\bar{C}$ and $\bar{S}$ are positive definite coefficient matrices, θ, α, β and δ_{trend} are scalar coefficients, i is a unit vector, I is a conformable identity matrix, t is a time trend, the elements of the nxn matrix S_{t-1} are the outer-products of two vectors that contain only negative return innovations. To complete the notation, $\bar{C}$ takes the value Q_1 if $t<\tau$ and Q_2 if $t>\tau$, where τ represents a selected structural break date. Similarly, $\bar{S}$ takes the value N_1 if $t<\tau$ and the value N_2 if $t>\tau$, $\bar{t}$ is the mid point of the sample period (the unconditional sample average of the values taken by the time trend variable).

To see why the inclusion of the deterministic time trend requires this specification, consider for simplicity but without loss of generality the univariate case of a GARCH(1, 1) with deterministic time trend, $E_{t-1}(\varepsilon_t^2) = \gamma + \alpha\varepsilon_{t-1}^2 + \beta E_{t-2}(\varepsilon_{t-1}^2) + \delta_{\text{trend}}t$. Taking unconditional expectations and using the law of iterated expectations, the unconditional variance is:

$$E(\varepsilon_t^2) = \gamma + (\alpha + \beta)E(\varepsilon_{t-1}^2) + \delta_{\text{trend}}E(t) = \gamma + (\alpha + \beta)E(\varepsilon^2) + \delta_{\text{trend}}\bar{t} \tag{7}$$

Therefore, $E(\varepsilon_t^2) = (\gamma + \delta_{\text{trend}}\bar{t})/(1 - \alpha - \beta)$ and $\gamma = E(\varepsilon_t^2)(1 - \alpha - \beta) - \delta_{\text{trend}}\bar{t}$. The specification in (6) is a generalization to the multivariate case of this result.

The elements along the main diagonal of the matrix $\bar{D}$ can be seen as the long-run, baseline levels to which conditional variances mean-revert. The matrices $\bar{C}$ and $\bar{S}$ can be seen as the long-run, baseline levels to which the conditional correlations of the return innovations and of the negative return innovations respectively mean-revert[5]. To hasten the estimation procedure, $\bar{D}$ and $\bar{C}$ can be set equal to the unconditional variance and correlation matrix over the sample, Q_1 and Q_2 can be set equal to the sample average of $\varepsilon_{t-1}\varepsilon'_{t-1}$ before and after the date τ, and N_1 and N_2 are the sample average of S_{t-1} before and after τ (in this case, the estimated conditional correlation matrix is not guaranteed to be positive-definite). When the coefficient θ is not constrained to be zero, the correlation process can be asymmetric. A symmetric DCC model gives higher tail dependence for both upper and lower tails of the multi-period joint density. An asymmetric DCC gives higher tail dependence in the lower tail of the multi-period density.

Engle (2001, 2002) and Engle and Sheppard (2001) propose maximising the log-likelihood function of (3) in two steps to overcome the well-known computational problems of MVGARCH models. They first maximise the log-likelihood with respect to the parameters that govern the process of D_t. This can be done by estimating univariate models[6] of the returns on each stock nested within a univariate GARCH model of their conditional variance. They then suggest maximising the second part of the likelihood function over the

[5] I estimate this using the sample average of the negative return innovation cross-products.

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

parameters of the process of C_t, conditional on the estimated D_t. Preliminarily, this entails standardising u_t by the estimated D_t to obtain the $nx1$ vector ε_t^7. Engle (2001, 2002) and 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 taken into account by modifying the asymptotic covariance of the correlation estimation parameters.

Table 4 presents our ADCC-MVGARCH model quasi-maximum likelihood estimates using daily data on the five market indices. We first estimate a simple restricted symmetric specification of (6) 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 statistically significant but very small. Since it is economically negligible, we drop it from all subsequent specifications. We therefore estimate Model 2, which imposes on Model 1 the restriction that the time trend coefficient is zero.

Considering the clear rise in average market index correlation visible in Fig. 1, together with the lack of evidence of a significant deterministic time trend, we then test for the presence of either a stochastic trend or a structural break. To check the stationarity of the correlation process, we test the restriction that the news and persistence parameters α and β sum to unity. The relevant LR test statistic and the associated significance level are reported at the bottom of Table 4 (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 period. In order to identify the structural break date, we seek guidance from Government bond yields[7]. The plot of the likelihood of an ADCC-GARCH model of the Government bond index returns as a function of 30 successive structural break dates, as reported in Fig. 2, peaks at the beginning of 1998. We also experimented with various possible structural break dates directly in the correlations process of the stock market indices. The model with a structural break date in January 1998 displays again the largest likelihood[8]. This hypothesis about the timing of the structural break occurrence is intuitively appealing since it is roughly 12 months before the official introduction of the Euro and thus it accounts for the likely possibility that financial markets started to discount it in the price formation mechanism somewhat in advance.

Therefore, we finally settled on the beginning of January 1998, as this date maximise the likelihood of a ADCC-GARCH model of the bond index returns, it almost exactly splits our sample in half and allows for the possibility that stock markets discount rates might have reflected the expectation of monetary policy convergence and increased financial integration prior to the introduction of the new currency. Using the usual LR test

[7] A necessary condition for the parity of expected real rates of returns is that bond yields differentials reflect inflation differentials. Under this perspective and neglecting differences in risk premia across countries, a structural break in Euro area interest rates correlations due to monetary policy convergence is a likely cause for a structural break in correlations at the stock market index level. This is also suggested, for example, by the study of Cappiello et al. (2003) and of Hardouvelis et al. (2000).

[8] Results for the other models are not reported to save space (they are a long list of structural break dates and corresponding likelihood function values) but they are available upon request.

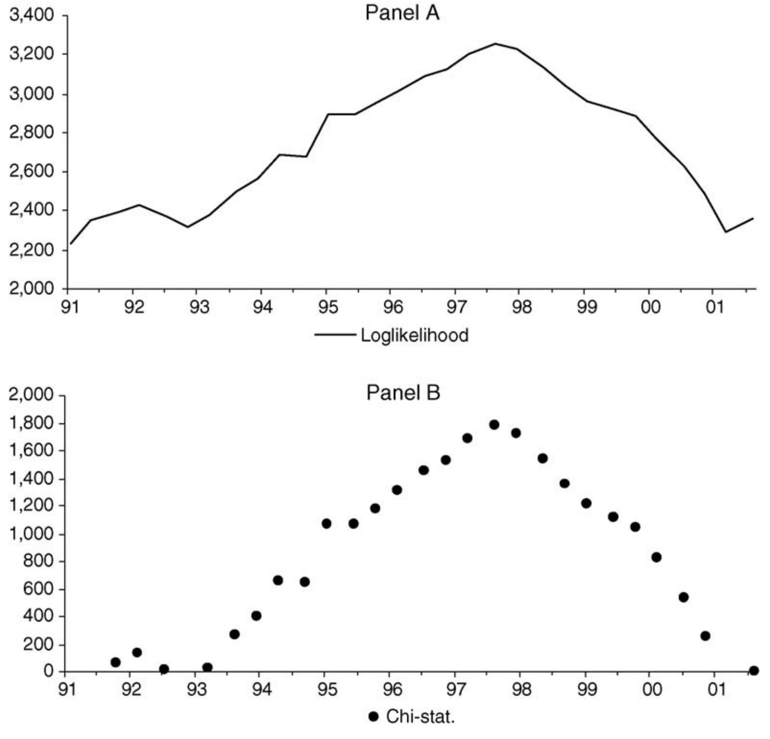

Fig. 2. Euro area government bond yields log-likelihoods and LR statistics with rolling structural break dates. *Note*: Panel A plots the likelihood of an ADCC-GARCH model of the bond index returns as a function of 30 successive structural break dates. Panel B reports the Chi-Squared statistic of the corresponding LR test. This statistic is significant at the 5 percent level for structural break dates from 1994 to 2000.The restricted model in the LR test is the model with no structural break date.

statistic, reported at the bottom of Table 5, we therefore tests Model 4 that allows for a structural break in 1998 against Model 2, the restricted model with no structural break. We can reject this restriction at the 0.020 significance level. Moreover, once we allow for the structural break, the restriction that the asymmetric component coefficient θ is equal to zero (Model 5 against Model 4) cannot be rejected at the 5 percent level. The coefficient θ is only marginally significant. Its size however is non negligible from an economic point of view. In particular, its point estimate is 45 times as large as the news reaction parameter α.

We therefore conclude that the aggregate correlation between the five Euro-zone stock market indices and the Eurostoxx50 index is best explained by a DCC-GARCH process with a structural break in its mean[9] and, perhaps, an asymmetric reaction component. Fig. 3

[9] We also estimated each model with the *Eurostoxx50* index, and over the longer sample period 1992–2002, 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.

Table 5
ADCC-MVGARCH 42 Eurostoxx50 stocks

Panel A

Model	Restriction	Coefficient	Coefficient estimate	*T*-ratio	*p*-Value
1	$Q_1 = Q_2$	α	0.002	16.51	0.000
	$\delta_{\text{trend}} = 0$	β	0.989	1222.29	0.000
	$\theta = 0$				
2	$Q_1 = Q_2$	α	0.002	15.06	0.000
	$\delta_{\text{trend}} = 0$	β	0.989	1214.20	0.000
		θ	0.001	1.55	0.121

Panel B

Unrestricted model	$\ln(\lvert\Sigma_{\text{UR}}\rvert)$	Restricted model	$\ln(\lvert\Sigma_{\text{R}}\rvert)$	LR statistic	Significance level	Restriction rejection
2	−13.6466	1	−13.6474	1.7486	0.186	No

$\text{LR} = T \ln(\lvert\Sigma_{\text{UR}}\rvert) - \ln(\lvert\Sigma_{\text{R}}\rvert) \sim \chi^2(q)$
T = number of observations (2289)
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 ($q = 1$)

Note: Panel A of this table reports the coefficients, *t*-statistics and *p*-values for the ADCC-MVGARCH model of conditional correlations amongst 42 stocks ($k = 42$) included in the *Eurostoxx50* index. The data frequency is daily. Variables and their coefficients are defined in the text. Panel B reports likelihood ratio (LR) test statistics and their significance level.

plots the market index average conditional correlation estimated with the symmetric Model 5, allowing for a structural break in 1998.

Turning to the correlation patterns at a more disaggregated level, the estimation results for the 42 individual stocks are shown in Table 5. The estimated θ is very small and the

Fig. 3. DCC-MVGARCH Country Correlation. *Notes*: This figure plots the daily average conditional correlation amongst the five Euro-zone market, estimated with the symmetric DCC-MVGARCH(1, 1) model with a structural break at the beginning of 1998.

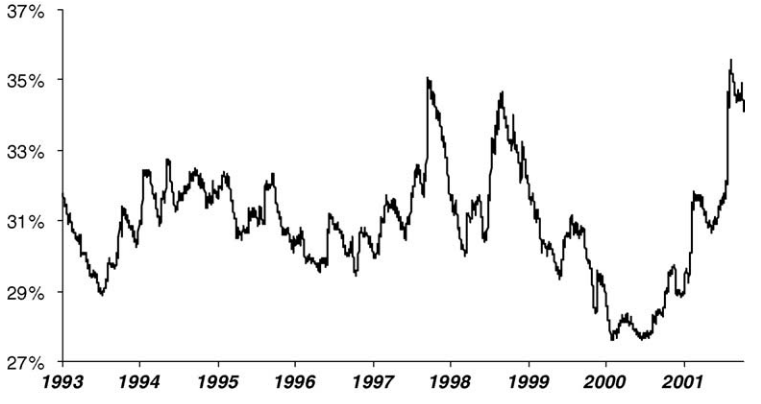

Fig. 4. DCC-MVGARCH stock correlations. *Notes*: This figure plots the daily average conditional correlation amongst 42 individual stocks included in the *Eurostoxx50* index, estimated with the symmetric DCC-MVGARCH(1, 1).

restriction that it is equal to zero[10] cannot be rejected at any conventional significance level. The time series of the estimated symmetric average conditional industry, sector and stock return correlation is plotted in Fig. 4. The plot for the asymmetric case is almost identical.

As a specification check, we apply the Engle and Ng (1993) test in a multivariate setting to our country-level MV-ADCC and MV-DCC GARCH models. Originally, this test was designed as a diagnostic check for univariate volatility models and its aim is to examine whether there is residual predictability in squared standardised conditional errors using some variables observed in the past which are not included in the volatility model. Since multivariate variance–covariance models provide estimates of all the ingredients that are needed to compute the conditional portfolio volatility if asset weights are known, we can use our first and second step MV-ADCC and MV-DCC GARCH conditional volatility and correlation estimates to compute the conditional volatility and the conditional residuals of an equally weighted portfolio. We can then apply the Engle and Ng (1993) test to returns on the latter.

In particular, we apply a test that combines the Sign Bias test (that uses as regressors dummy variables I^- that take value 1 or 0 depending on weather the lagged residual is negative or positive) and the negative and positive size bias test (that use, respectively, lagged negative and positive standardised residuals as regressors, z_{t-1}^- and z_{t-1}^+). As reported in Table 6, we can reject the null of non-predictability of the squared standardised conditional residuals. Therefore, in spite of the mixed evidence provided by the LR tests of the ADCC-MVGARCH against the DCC-MVGARCH, distributional asymmetric are important. The latter are probably of a non-linear nature[11] and we leave the difficult quest for a better specification for future research.

[10] We do not report estimates with a deterministic time trend because the estimation procedure did not converge.

[11] This, as far market indices are concerned, lies in partial contrast to those reported by Cappiello et al. (2003). However, since we were able to replicate their results with their same set of market indices, frequency and data period (these results are not reported for brevity and because they exactly match results already published by Cappiello et al. (2003) but they are available upon request), we conclude that the difference between our and

Table 6
Diagnostic tests

Model	DCC[a]
S^- [significance]	0.68 [0.394][a]
u^- [significance]	−0.123 [0.039][a]
u^+ [significance]	−0.142 [0.058][a]
Chi- squared (3) [significance]	29.64 [0.000][a]

Notes: This table reports the coefficients and *p*-values for a multivariate application of the Engle and Ng (1993) test. Variables and their coefficients are defined in the text.
[a] Country indices—daily

5. Summary and conclusions

The purpose of this paper is to contribute to the literature on the correlation dynamics in European equity markets. Our main focus has been on country-level market index correlations, but we also examined stock correlations for comparison purposes. We applied the symmetric and asymmetric version of the DCC-MVGARCH model of Engle (2001, 2002) and Engle and Sheppard (2001) to capture their behaviour over time.

We find 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. This confirms the results reported by Cappiello et al. (2003) and is consistent with the rise in volatility spillovers noticed by Baele (2002). We also find evidence that, at the level of the national stock market indices, the conditional correlation response to past positive and negative news is asymmetrical. Stock correlations instead do not appear to follow an asymmetric correlation process. These findings provide mixed support to a popular explanation see, for example, Patton (2002) for why the skewness of market index returns is often negative whereas stock returns have either negative or positive skewness (similar findings are reported in Table 2). More importantly, applying a multivariate extension of the Engle and Ng (1993) test, we find that beyond asymmetric correlation reactions to past returns innovations there must be other, perhaps more important source of asymmetry in the distribution of asset returns. This issue represents an important and fruitful topic for future research.

Overall, our results suggest that non-country factors drive the volatility of equity returns. In particular, because of the rise in correlations among the largest national stock markets indices, the stochastic components of the latter can now be expected to behave almost identically (with conditional correlations being close to 100 percent as reported in Fig. 3). This suggests that there is little expected benefit from strategies that diversify across Euro-zone

their results is due to whether non-Euro area market indices are included. Correlations amongst Euro area market indices, in particular, appear to display a substantial lower tendency to increase following joint past negative returns than those amongst markets outside the Euro area. Another likely but less important reason for why our results differ from those of Cappiello et al. (2003) with respect to the importance of asymmetric correlation reactions to past returns innovations is the different data frequency—they use only weekly data whereas we use both daily and weekly data and for the former the importance of the asymmetric correlation component is always lower. This suggests the importance of taking into account temporal aggregation issues when modelling asset returns second moments dynamics.

market indices, although diversification across stocks remains useful. This explains why, as reported by Eiling et al. (2004), the outperformance of country-based diversification strategies relative to industry-based strategies has disappeared after the introduction of the Euro. As a consequence, fund managers should think through the full ramifications of seeking cost-effective diversification in the Euro area by adopting the passive strategy of investing in market indexes rather than a selection of stocks or industries from the whole supra-national market.

More deeply, the dramatic increase in country level market index correlation rises the possibility of a 'correlation puzzle'. The relevant question from the perspective of the informational efficiency of the market pricing mechanism is whether this increase in return correlation is justified by increased correlation in fundamentals and discount rates. Adjaouté and Danthine (2001) document a significant increase in correlations between Euro area country equity indices. However, they find the same increase after they adjust for currency effects, thus suggesting that the elimination of currency risk is not the main cause. De Santis et al. (in press) show similar results. While Adjaouté and Danthine (2004) report preliminary evidence of convergence of economic fundamentals such as gross domestic product growth rates, little or no direct evidence is available on discount rates and on equity fundamentals such as dividend growth rates. Expanding this body of evidence is a fruitful area for future research.

Acknowledgement

Colm Kearney and Valerio Poti acknowledge financial support from the Irish Research Council for the Humanities and the Social Sciences.

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