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ARE THERE STILL PORTFOLIO DIVERSIFICATION BENEFITS IN EASTERN EUROPE? AGGREGATE VERSUS SECTORAL STOCK MARKET DATA*

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In this paper we measure the increase in stock integration between the three largest new European Union members (Hungary, the Czech Republic and Poland) and the Euro-zone using both country and industry level data. At the country market index level all three Eastern European markets show a considerable increase in correlations in 2006. At the industry level the dates and transition periods for the correlations differ and the correlations are lower, although also increasing. The results show that sectoral indices in Eastern European markets may provide larger diversification opportunities than the aggregate market.

1 Introduction

While there is evidence for greater integration of most European equity markets since the 1980s (see Baele, 2005), many of the founding member countries of the European Economic and Monetary Union (EMU) have shown a particular increase in integration post the introduction of the Euro; Bartram *et al*. (2007) find changes in the relationships for the larger countries in EMU, while Kim *et al*. (2005) support greater integration, and greater stability, across a wide range of EMU equity markets.[1] The evidence of

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[1]Other evidence on the increased integration of European equity markets in association with either the lead up to EMU or the introduction of the Euro can be found in Fratzscher (2002), Morana and Beltratti (2002), Guiso *et al*. (2004), Hardouvelis *et al*. (2006) and Savva *et al*. (2009).

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increased integration has led a number of authors to argue that the diversification benefits of holding European country indices are now relatively limited and that industry indices provide greater opportunities. For recent evidence see particularly Flavin (2004) and Moerman (2008).

The enlargement of the European Union (EU) from 1 May 2004 admitted new countries who are currently in transition to becoming full members of the Monetary Union. Although there is a growing literature on business cycle synchronization between new EU members and the Euro-zone less is known about the progress of these countries towards financial integration.[2] Notable exceptions are Chelley-Steeley (2005), Cappiello *et al*. (2006), Égert and Kočenda (2007) and Savva and Aslanidis (2010).

This paper computes measures of the extent of stock market integration (which we measure by correlation coefficient[3]) between the three largest new EU members (Hungary, the Czech Republic and Poland) and the Euro-zone.[4] We consider evidence as to whether the correlation across stock markets has increased following the EU accession of these countries, and whether any change has been gradual or abrupt. Sectoral data are used to disaggregate the observed shifts to industry level, addressing the question of whether specific sectors are driving the observed movements towards greater stock market integration. Additionally, the evidence from the industry-level data contributes to the debate on whether country or industrial diversification provides greater benefits.

At a theoretical level, we motivate the idea of the correlation between stock markets by adopting a simple economic model of correlations proposed by Engle (2009). The key point of this model is that correlation may mainly result either from correlation between dividend shocks or from correlation between risk premium shocks. The high correlation from news on risk premiums makes it critical to assess empirically the correlation between stock market returns. In particular, we capture time-varying correlations in the stock markets by using the recently developed smooth transition conditional correlation (STCC) and double STCC (DSTCC) models (Berben and Jansen, 2005; Silvennoinen and Teräsvirta, 2005, 2009). These models allow for the correlation of a constant conditional correlation (CCC) to change smoothly over time, which seems particularly appropriate to analyse the increasing

[2]For a comprehensive survey on economic integration see Kočenda (2001), Kutan and Yigit (2004) and Fidrmuc and Korhonen (2006).

[3]The intuition of using correlations is that the more integrated the markets are, the higher is the co-movement between their prices. Higher correlation alone is not a sufficient condition for greater market integration; however, it is a good indication. It is worth noting that there are also other types of correlations, which are based on non-parametric methods. See for instance Albuquerque (2005).

[4]Hungary, the Czech Republic and Poland joined EU in the first enlargement and have the largest GDP and equity markets of the accession countries.

integration between the Eastern European and the Euro-zone stock markets over the recent years.

Our paper is compared with the literature on Eastern European equity market integration in the following way. First, unlike other papers we put our results in a theoretical context by adopting an economic model for correlations as developed by Engle (2009). At the empirical level, in our methodology, where the unconditional correlation is allowed to change over time, we find increased financial integration with the EMU among the three countries. Chelley-Steeley (2005) also finds evidence of increasing integration for these countries using a smooth transition in correlations model with data from 1994 to 1999 prior to the EU accession. Her smooth transition model is fitted to estimated monthly correlations rather than directly to the conditional correlations as in the current paper. Cappiello *et al.* (2006) find mixed evidence for increased integration, finding none for Hungarian stocks with the Euro-area but supporting evidence for the Czech Republic and Poland based on quantile regression with an exogenously determined break point. At the other end of the spectrum, Égert and Kočenda (2007) find no evidence of a robust cointegration relationship, but only signs of short-run spillover effects for these countries and the Euro-zone. This result may be explained by the fact that they consider a very short period for estimation (June 2003–February 2005).

It also extends the work of Savva and Aslanidis (2010) in the following three ways. First, the present paper uses sectoral market indices in addition to the market aggregate. Looking into more disaggregate data gives us a good idea of why the aggregate correlation changes and we better address whether there are portfolio diversification opportunities in Eastern Europe. Second, we extend the methodology of that work since we allow for mean-spillovers (VAR), asymmetric conditional variance (GJRGARCH) and a Student's *t* distribution for the errors. Therefore, the present methodology is more general and captures more accurately the 'stylized' facts of the financial data. Finally, our sample period includes the financial crisis beginning in September 2008, which makes our analysis more interesting as well as more robust.

The empirical results show that in 2006 there is a considerable increase in correlations at the aggregate level for all three Eastern European markets, supported to a large extent by the industry data results. The increase in correlations is not only confined to few sectors but it is a more broad-based phenomenon across sectors. However, the dates of change in correlation and the length of the transition period differ across sectors. Therefore, the tendency towards greater stock market integration may not be solely driven by EU-related developments, but also by country- and industry-specific factors—similar to the findings of Berben and Jansen (2005) for developed markets. In the majority of cases, sectoral correlations are lower than those at the aggregate level. The implication is that sectors in Eastern European markets are integrating more slowly with their European equivalents than the country indices, and hence may provide larger diversification opportunities than the aggregate market.

The rest of the paper is organized as follows. Section 2 presents the economic model of correlations as well as the STCC methodology. Section 3 discusses the data and presents the results. In Section 4, we perform robustness checks to validate our results. Finally, Section 5 concludes.

2 Modelling Stock Market Correlations

2.1 A Theoretical Framework for Correlations

This subsection presents the economic model of correlations developed by Engle (2009). According to Engle unexpected stock returns have two components. The first component is the innovation to dividends while the second component is the innovation to risk premium. Mathematically, this can be expressed as

$$r_{i,t} - E_{t-1}(r_{i,t}) = \eta_t^{d_i} - \eta_t^{r_i} \qquad i = 1, 2 \tag{1}$$

where $r_{i,t}$ denotes stock returns for asset i, $\eta_t^{d_i}$ is the dividend innovation and $\eta_t^{r_i}$ is the risk premium innovation for asset i. The conditional variance of stock returns is given by

$$\mathrm{Var}_{t-1}(r_{i,t}) = \mathrm{Var}_{t-1}(\eta_t^{d_i}) + \mathrm{Var}_{t-1}(\eta_t^{r_i}) - 2\,\mathrm{cov}(\eta_t^{d_i}, \eta_t^{r_i}) \tag{2}$$

The conditional covariance between two stock returns is given by

$$\begin{aligned}\mathrm{Cov}_{t-1}(r_{1,t}, r_{2,t}) = \mathrm{Cov}_{t-1}(\eta_t^{d_1}, \eta_t^{d_2}) + \mathrm{Cov}_{t-1}(\eta_t^{r_1}, \eta_t^{r_2}) - \mathrm{cov}(\eta_t^{d_1}, \eta_t^{r_2}) \\ - \mathrm{cov}(\eta_t^{d_2}, \eta_t^{r_1})\end{aligned} \tag{3}$$

Hence, the conditional correlation is defined as the conditional covariance divided by the product of the conditional standard deviations.

$$\rho_t = \frac{\mathrm{Cov}_{t-1}(r_{1,t}, r_{2,t})}{\sqrt{\mathrm{Var}_{t-1}(r_{1,t})\mathrm{Var}_{t-1}(r_{2,t})}} \tag{4}$$

Thus, the conditional correlation may mainly result either from correlation between dividend shocks ($\mathrm{Cov}_{t-1}(\eta_t^{d_1}, \eta_t^{d_2})$) or from correlation between risk premium shocks ($\mathrm{Cov}_{t-1}(\eta_t^{r_1}, \eta_t^{r_2})$). The other two correlation components are cross terms ($\mathrm{cov}(\eta_t^{d_1}, \eta_t^{r_2})$, $\mathrm{cov}(\eta_t^{d_2}, \eta_t^{r_1})$) and indicate correlation between dividend shocks and risk premium shocks. There is evidence (e.g. Ammer and Mei, 1996) that the most important source of correlation comes from the correlation between risk premium shocks, which makes it critical to empirically assess the correlation between stock market returns (as we do in the next subsection).

2.2 Empirical Methodology

We first assume that the mean equation for the two-dimensional vector of stock returns is modelled as a VAR(p) model.

$$y_t = c_0 + \sum_{k=1}^{p} \phi_k y_{t-k} + u_t \qquad t = 1, \ldots, T \tag{5}$$

where ϕ_k ($k = 1, \ldots, p$) are 2×2 matrices of parameters capturing any possible own past effects and cross effects from one market to the other.[5] The conditional covariances of the shocks in (1) are time-varying, such that

$$u_t | \Im_{t-1} \sim t(0, H_t, v) \tag{6}$$

where t is the conditional bivariate Student's t distribution with $\boldsymbol{v}$ degrees of freedom, and $\Im_{t-1}$ is all available information at $t - 1$, thus accounting for possible excess kurtosis in the joint conditional densities of the standardized residuals. From (6), each univariate error process can be written

$$u_{i,t} = h_{ii,t}^{1/2} \varepsilon_{i,t} \qquad i = 1, 2 \tag{7}$$

where $h_{ii,t} = E\left(u_{i,t}^2 / \Im_{t-1}\right)$ and $\varepsilon_{i,t}$ is a sequence of independent random variables with mean zero and variance one. Each conditional variance is assumed to follow a univariate GJRGARCH(1,1) process

$$h_{ii,t} = \omega_i + \alpha_i u_{i,t-1}^2 (1 - I[u_{i,t-1} < 0]) + \gamma_i u_{i,t-1}^2 I[u_{i,t-1} < 0] + \beta_i h_{ii,t-1} \tag{8}$$

with non-negativity and stationarity restrictions imposed. The choice of an asymmetric model for volatilities is motivated by the fact that negative shocks may have stronger effects on volatilities than positive shocks of the same magnitude.

Next, we allow the conditional correlations between the standardized errors from the above system to be time-varying by considering the STCC specification proposed in Silvennoinen and Teräsvirta (2005) and Berben and Jansen (2005).[6] This model assumes two states (regimes) with state-specific constant correlations, and allows for a smooth change over time between correlation regimes (ρ_1, ρ_2). More specifically, the correlation ρ_t follows

$$\rho_t = \rho_1 (1 - G_t(s_t; \gamma, c)) + \rho_2 G_t(s_t; \gamma, c) \tag{9}$$

The function $G_t(s_t; \gamma, c) = \{1 + \exp[-\gamma(s_t - c)]\}^{-1}$ is the transition logistic function and s_t is the transition variable. As our focus is on dominant, long-run trends in correlations, there is one change in correlation regime and the transition variable is specified as a linear function of time, $s_t = t/T$. The

[5]To determine the appropriate order, p, of equation (5) we use the Schwartz Information Criterion for the maximum of 12 lags. In practice, in most of the cases, we find the Schwartz Information Criterion chooses the first lag.

[6]The model of Berben and Jansen (2005) is bivariate with a time trend as the transition variable, while the framework of Silvennoinen and Teräsvirta (2005) is multivariate and their transition variable can be deterministic or stochastic.

parameter c is the threshold, while the slope parameter γ determines the smoothness of the change in the transition and gives versatility to the model. For instance, when γ is large the transition between the two extreme correlation states becomes abrupt, and the model with time transition approaches a structural break model in conditional correlations.

Before considering the STCC model it is important to determine whether the change in correlation is statistically significant. To that purpose, we perform the Lagrange Multiplier test (LM_{CCC}) of Silvennoinen and Teräsvirta (2005). Under the null hypothesis the model is a CCC model (Bollerslev, 1990), whereas the alternative model is an STCC. Only in case we reject the hypothesis of constant correlation, we proceed with the estimation of the STCC model.

The STCC model allows for a monotonic change in correlations. In practice, this might be restrictive and therefore it would be of interest to extend the model to allow for non-monotonic correlation patterns. This possibility is investigated by using the Lagrange Multiplier test (LM_{STCC}) of Silvennoinen and Teräsvirta (2009). Under the null hypothesis a single STCC (one change in correlations) is adequate whereas the alternative supports a DSTCC (two changes in correlations). If evidence of a second change in correlations is found, then we estimate the DSTCC given by the following equation

$$\begin{aligned}\rho_t = {}&\rho_1(1-G_{1t}(s_t;\gamma_1,c_1))+\rho_2 G_{1t}(s_t;\gamma_1,c_1)(1-G_{2t}(s_t;\gamma_2,c_2))\\ &+\rho_3 G_{1t}(s_t;\gamma_1,c_1)G_{2t}(s_t;\gamma_2,c_2)\end{aligned} \tag{10}$$

The second transition variable is also a function of time ($s_t = t/T$), and hence (10) allows the possibility of a non-monotonic change in correlation over the sample. This is a special case of Silvennoinen and Teräsvirta (2009) as the transition variables are the same. The transition functions $G_{1t}(s_t; \gamma_1, c_1)$ and $G_{2t}(s_t; \gamma_2, c_2)$ are logistic functions as defined before.

To account for possible leptokurtosis in the data we estimate the (D)STCC model by maximum likelihood using the bivariate Student's t distribution. In particular, the likelihood function at time t is given by

$$\begin{aligned}l_t(\theta) = {}&\ln\Gamma\left(\frac{2+v}{2}\right)-\ln\Gamma\left(\frac{v}{2}\right)-\ln[\pi(v-2)]-\ln|D_t|-0.5\ln|R_t|\\ &-\frac{2+v}{2}\ln\left[1+\frac{1}{v-2}(\varepsilon_t' R_t^{-1}\varepsilon_t)\right]\end{aligned} \tag{11}$$

where v is the number of degrees of freedom, $\Gamma(\cdot)$ is the gamma function, $D_t = \mathrm{diag}(h_{11,t}^{1/2}, h_{22,t}^{1/2})$ is a 2×2 diagonal matrix of time-varying standard deviations from univariate GJRGARCH(1,1) and R_t is the conditional correlation matrix. The log-likelihood for the whole sample, $L(\theta)$, is maximized with respect to all parameters of the VAR-GJRGARCH-(D)STCC model simultaneously, using numerical derivatives of the log-likelihood.[7]

[7]All computations are carried out using GAUSS 6.0.

3 Empirical Results

The data set consists of daily returns on stock indices for Hungary, the Czech Republic, Poland and the Euro-area (using the Euro STOXX 600 index[8]) from 1 January 1999 to 19 March 2010, a total of 2925 observations. All prices are denominated in Euros.[9] The sample contains the aggregate market indices and where available eight industry stock indices: Industrials, basic materials, financials, basic resources, utilities, consumer services, consumer goods and technology. All data are obtained from DataStream.[10] Descriptive statistics for the returns are presented in Table 1, which shows that the Polish, Czech and Hungarian markets provide higher returns, but also have higher standard deviations, than the Euro-area. Although data were examined for Hungarian industrials and technology sectors these were discarded due to the excessive amount of zero price movement and discontinuities in the series, most likely indicative of low activity and low liquidity in these indices.

In most cases, the results for the VAR and volatility models are very close to those found elsewhere and are hence omitted for brevity. For example, in the GJRGARCH equations the betas are usually between 0.85 and 0.95, although in a few cases they range between 0.60 and 0.80. Figure 1 plots the effects of negative and positive shocks on volatilities in the estimated GJRGARCH models, confirming that negative shocks appear to have stronger effects on volatilities than positive shocks of the same magnitude.

Table 2 shows the CCC estimates for the aggregate and sector indices.[11] As seen, correlations at the aggregate level are higher than those at the sectoral level. Typically, aggregate correlations are above 0.48, whereas sectoral correlations, with the exception of the Polish sectors, are below 0.25. This suggests that stock returns in Eastern European markets (and particularly in Hungary and the Czech Republic) may contain a significant European component shared by all sectors and that the variance of the specific component unique to a sector–country combination may be relatively large. This has obvious implications for portfolio diversification suggesting that sectors may provide larger diversification opportunities than the aggregate market. This finding supports that reported by Berben and Jansen (2005) for an earlier period. The authors examine the correlation structure among the stock markets of Germany, Japan, the UK and the USA using aggregate as

[8]Results with respect to the German Stock Index (DAX) were qualitatively similar to those presented here.

[9]Estimates using data denominated in local currencies have also been performed with the results remaining qualitatively the same.

[10]The codes for these series are: BMATRXX, INDUSXX, FINANXX, BRESRXX, CNSMSXX, UTILSXX, CNSMGXX, TECNOXX, BUDINDX(PI), CZPXIDX(PI) and POLWG20(PI), where XX = CZ, HN and PO.

[11]Consistent with Susmel and Engle (1994) greater efficiency is observed with *t*-distributed errors than normal distributed errors. This is also confirmed by a log-likelihood ratio test where the increase in maximal value of the likelihood function from Normal to *t* distribution is statistically significant. Results are available upon request.

Table 1
Summary Statistics of the Stock Returns 1999–2010

	Minimum	*Maximum*	*Mean*	*St.dev.*	*Skewness*	*Kurtosis*
Hungary						
Market index	–18.579	15.402	0.044	1.910	–0.246	8.464
Basic materials	–20.302	12.260	0.000	2.087	–0.602	10.139
Financials	–21.420	22.277	0.059	2.623	–0.109	7.921
Utilities	–9.237	10.763	0.011	1.678	–0.003	4.101
Consumer services	–36.367	31.121	0.007	2.200	–0.655	40.641
Consumer goods	–27.444	27.763	0.006	2.486	–0.038	15.419
Czech Republic						
Market index	–16.580	14.469	0.050	1.637	–0.371	11.836
Industrials	–12.835	18.758	0.050	1.008	5.767	120.29
Basic materials	–41.203	12.075	0.069	1.706	–5.184	124.17
Financials	–19.246	14.389	0.092	2.148	–0.380	9.201
Basic resources	–14.272	12.968	0.014	2.335	–0.089	8.332
Utilities	–16.047	20.952	0.089	1.788	–0.174	15.433
Consumer services	–33.918	29.952	–0.040	3.090	–0.797	20.017
Consumer goods	–21.314	37.445	0.040	1.670	3.330	104.49
Technology	–13.835	20.801	–0.024	1.461	0.786	36.193
Poland						
Market index	–12.533	11.172	0.025	2.006	–0.210	3.104
Industrials	–11.896	9.015	0.019	1.814	–0.195	2.690
Basic materials	–16.812	13.222	0.055	2.044	–0.357	4.448
Financials	–13.446	11.666	0.040	1.902	–0.232	4.934
Basic resources	–19.601	14.665	0.084	2.345	–0.305	4.376
Utilities	–13.914	19.897	0.023	2.532	0.370	6.064
Consumer services	–12.116	10.138	0.014	1.947	–0.149	2.728
Consumer goods	–12.440	10.266	0.044	1.640	0.044	4.947
EURO						
Market index	–8.250	9.962	–0.003	1.408	–0.091	4.664
Industrials	–10.470	11.052	0.013	1.474	–0.112	7.079
Basic materials	–8.647	11.376	0.022	1.557	–0.027	6.329
Financials	–9.985	13.373	–0.014	1.724	0.041	7.025
Basic resources	–13.889	15.967	0.023	2.011	–0.149	7.719
Utilities	–9.004	15.673	0.004	1.351	0.238	12.506
Consumer services	–7.838	8.592	–0.023	1.366	–0.157	4.215
Consumer goods	–15.377	22.425	0.001	1.430	1.167	30.592
Technology	–14.023	11.223	–0.013	2.286	–0.025	2.691

Note: Data source is DataStream.

well as sectoral data during the 1980s and 1990s. Across sectors, financials appear to be the most correlated sector. This is not surprising given the financial innovation and integration in the global markets experienced by Eastern European countries.

The finding that sectoral as well as aggregate correlations in Poland are typically higher than in the Czech Republic and Hungary may relate to different approaches taken to financial innovation and development. In particular, Poland started innovation with legal reform and afterwards listing of stocks while, for example, the Czech Republic initiated large-scale

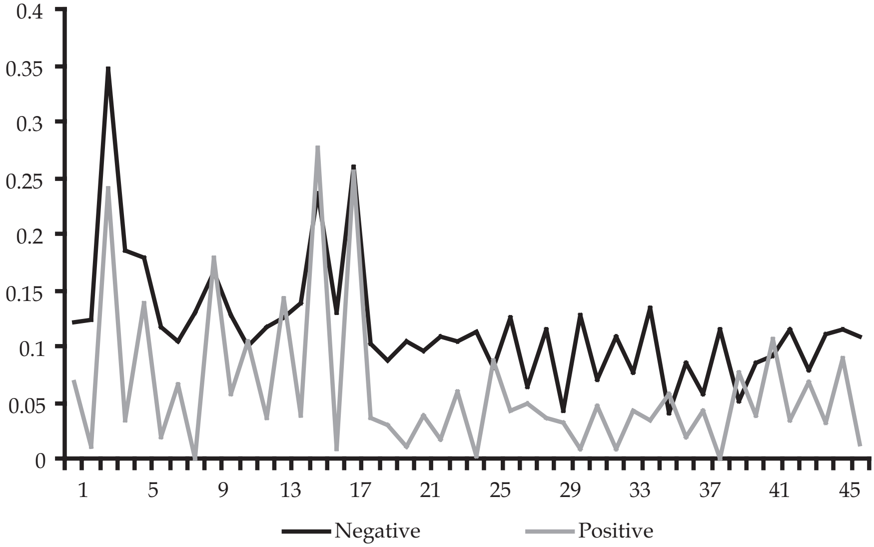


FIG. 1. Asymmetry in Volatility—Effects of Negative and Positive Shocks

privatizations in the early 1990s which led to many listings, and subsequent de-listings. Moreover, Poland may be expected to have a higher correlation with the Euro-area markets also because of its larger size compared with the other two markets.

As these three countries joined the EU in the first enlargement on 1 May 2004 we wish to establish whether the correlations between them and the Euro-area have changed over the sample period, consistent with increased financial integration with the EU. The results of the constancy test of Silvennoinen and Teräsvirta (2005) against the alternative hypothesis of an STCC model are shown in Table 3. For the aggregate indices the null hypothesis of constant correlation is strongly rejected for all three markets. For the sectors, the test rejects in three out of five cases in Hungary, six out of eight cases in the Czech Republic, and in all sectors in Poland.

The constancy results at the sectoral level also demonstrate that financials, basic materials and consumer services are the sectors that have changed its correlation in all three markets. In the case of utilities, consumer goods and industrials the correlation changed in two out of three markets. The results for utilities contrast with Berben and Jansen (2005) for developed markets where they argue that the lack of evidence for increased integration in utilities is due to the 'sheltered nature' of this sector. The geographic barriers in the EU to utilities integration is significantly lower than across Japan, the USA, the UK and Germany and this may be a contributing factor.

Table 2
CCC-GJRGARCH-t Models

	ρ	v	*Log-like*
Hungary–EURO			
Market index	0.497	9.347	–9619
	(0.015)	(1.012)	
Basic materials	0.244	6.380	–10,384
	(0.019)	(0.526)	
Financials	0.406	8.872	–10,887
	(0.017)	(0.934)	
Utilities	0.130	5.691	–9558
	(0.020)	(0.444)	
Consumer services	0.248	9.049	–10,285
	(0.019)	(0.963)	
Consumer goods	0.162	5.246	–10,715
	(0.020)	(0.435)	
Czech Republic–EURO			
Market index	0.487	10.150	–9032
	(0.015)	(1.160)	
Industrials	0.104	4.614	–6588
	(0.020)	(0.295)	
Basic materials	0.210	5.787	–9379
	(0.020)	(0.433)	
Financials	0.320	8.124	–10,295
	(0.018)	(0.808)	
Basic resources	0.075	3.346	–9848
	(0.021)	(0.184)	
Utilities	0.281	8.806	–9296
	(0.018)	(0.947)	
Consumer services	0.251	5.422	–10,137
	(0.019)	(0.379)	
Consumer goods	0.170	5.626	–7273
	(0.020)	(0.414)	
Technology	0.138	4.537	–7931
	(0.020)	(0.278)	
Poland–EURO			
Market index	0.547	9.678	–9844
	(0.014)	(1.102)	
Industrials	0.336	7.445	–10,107
	(0.018)	(0.678)	
Basic materials	0.393	7.693	–10,379
	(0.017)	(0.718)	
Financials	0.437	8.374	–9982
	(0.016)	(0.838)	
Basic resources	0.369	7.542	–11,530
	(0.018)	(0.707)	
Utilities	0.205	5.588	–8798
	(0.022)	(0.466)	
Consumer services	0.371	9.835	–10,042
	(0.017)	(1.109)	
Consumer goods	0.297	9.274	–9491
	(0.018)	(1.009)	

Notes: The table presents maximum likelihood estimates for the parameters of CCC-GJRGARCH-t models; remaining parameter estimates are available upon request; values in parentheses are standard errors; *Log-like* is the obtained log-likelihood value.

Table 3
Tests of CCC against STCC

	LM_{CCC}	*p value*
Hungary–EURO		
Market index	27.251	0.000**
Basic materials	43.673	0.000**
Financials	46.583	0.000**
Utilities	0.217	0.641
Consumer services	79.202	0.000**
Consumer goods	0.002	0.961
Czech Republic–EURO		
Market index	45.128	0.000**
Industrials	15.060	0.000**
Basic materials	11.423	0.000**
Financials	18.093	0.000**
Basic resources	0.425	0.514
Utilities	18.423	0.000**
Consumer services	7.289	0.007**
Consumer goods	10.071	0.002**
Technology	2.764	0.096
Poland–EURO		
Market index	27.192	0.000**
Industrials	63.753	0.000**
Basic materials	108.130	0.000**
Financials	54.562	0.000**
Basic resources	90.109	0.000**
Utilities	16.682	0.000**
Consumer services	22.952	0.000**
Consumer goods	17.023	0.000**

Notes: LM_{CCC} is the Lagrange Multiplier statistic for constant correlations.
* and ** denote significance at the 5 per cent and 1 per cent level, respectively.

Table 4 reports the estimated STCC for the models that rejected the CCC model in favour of the STCC specification at the 5 per cent significance level. In a number of cases the parameter γ becomes large and imprecisely estimated, signifying an abrupt change in the conditional correlations. In this case we report the value of γ as 500 as indicative; other authors adopt a similar convention.[12] The parameter c defines the middle of the transition period and is expressed as a fraction of the sample size. The heading 'Date' reports the day corresponding to c.

At the aggregate level, in all three Eastern European markets the estimates point to a considerable increase in correlation in the second part of the sample. This can be seen clearly in Fig. 2(a), which plots the correlations implied by the models. Until early 2006, the correlations for Hungary and the Czech Republic were about 0.4, while by mid-2006 correlations increased to 0.65. For Poland the correlation increased from 0.48 to 0.68 in the fall of that

[12]Berben and Jansen (2005) use 400, Silvennoinen and Teräsvirta (2005) use 100.

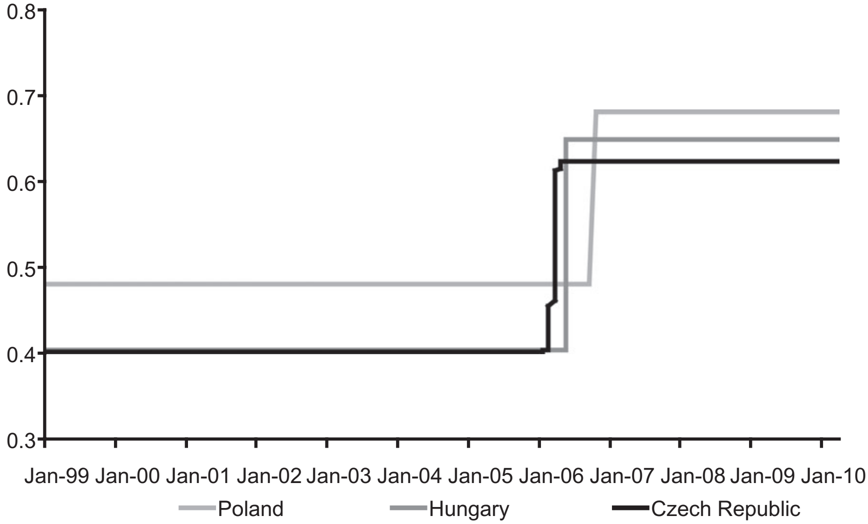
Table 4
STCC-GJRGARCH-*t* Models

	ρ_1	ρ_2	γ	c	v	*Date*	*Log-like*
Hungary–EURO							
Market index	0.404	0.650	500	0.654	9.492	02 May 06	−9579
	(0.021)	(0.018)	(·)	(0.005)	(1.038)		
Basic materials	0.151	0.516	3.318	0.771	6.588	23 Aug 07	−10,362
	(0.028)	(0.115)	(1.769)	(0.090)	(0.557)		
Financials	0.295	0.691	19.165	0.691	9.025	29 Sep 06	−10,842
	(0.023)	(0.016)	(12.457)	(0.016)	(0.967)		
Consumer services	0.126	0.512	19.164	0.682	9.497	24 Aug 06	−10,234
	(0.024)	(0.027)	(9.889)	(0.016)	(1.048)		
Czech Republic–EURO							
Market index	0.403	0.623	154.34	0.641	10.616	09 Mar 06	−9001
	(0.021)	(0.019)	(202.29)	(0.009)	(1.267)		
Industrials	0.055	0.429	428.12	0.892	4.691	31 Dec 08	−6567
	(0.022)	(0.046)	(733.69)	(0.003)	(0.303)		
Basic materials	0.113	0.384	195.36	0.654	5.831	02 May 06	−9356
	(0.025)	(0.029)	(423.34)	(0.008)	(0.439)		
Financials	0.277	0.403	15.538	0.705	8.127	27 Nov 06	−10,289
	(0.023)	(0.033)	(33.973)	(0.059)	(0.809)		
Utilities	0.205	0.399	500	0.646	8.853	30 Mar 06	−9281
	(0.024)	(0.026)	(·)	(0.007)	(0.952)		
Consumer services	0.211	0.304	500	0.546	5.458	15 Feb 05	−10,134
	(0.026)	(0.028)	(·)	(0.004)	(0.384)		
Consumer goods	0.088	0.293	3.300	0.657	5.638	15 May 06	−7264
	(0.033)	(0.073)	(2.840)	(0.136)	(0.416)		
Poland–EURO							
Market index	0.482	0.680	500	0.691	9.546	29 Sep 06	−9814
	(0.018)	(0.017)	(·)	(0.013)	(1.074)		
Industrials	0.239	0.452	500	0.558	7.643	05 Apr 05	−10,087
	(0.027)	(0.024)	(·)	(0.009)	(0.730)		
Basic materials	0.184	0.481	68.51	0.308	7.937	17 Jun 02	−10,346
	(0.035)	(0.018)	(61.250)	(0.011)	(0.764)		
Financials	0.350	0.589	17.61	0.681	8.395	21 Aug 06	−9953
	(0.023)	(0.023)	(19.08)	(0.023)	(0.843)		
Basic resources	0.081	0.461	5.823	0.250	7.846	22 Oct 01	−11,497
	(0.077)	(0.021)	(3.659)	(0.042)	(0.816)		
Utilities	0.178	0.278	500	0.279	5.571	18 Feb 02	−8796
	(0.028)	(0.042)	(·)	(0.019)	(0.508)		
Consumer services	0.255	0.661	15.06	0.973	10.100	25 Nov 09	−10,032
	(0.019)	(0.197)	(22.92)	(0.044)	(1.164)		
Consumer goods	0.272	0.354	500	0.727	9.279	26 Feb 07	−9488
	(0.022)	(0.031)	(·)	(0.006)	(1.010)		

Notes: The table presents maximum likelihood estimates for the parameters of STCC-GJRGARCH-*t* models; remaining parameter estimates are available upon request; *Date* is the day that corresponds to c (threshold); values in parentheses below estimates are standard errors; *Log-like* is the obtained log-likelihood value; in a number of cases the parameter γ becomes large and imprecisely estimated, signifying an abrupt change in the conditional correlations. In this case we report the value of γ as 500 as indicative.

year. Thus, for all three countries the increase in correlation was effected very quickly around similar dates. These findings are comparable to those by Savva and Aslanidis (2010) and Chelley-Steeley (2005). Savva and Aslanidis (2010) find that the Czech and Polish markets have increased their correlation

(a)



(b)

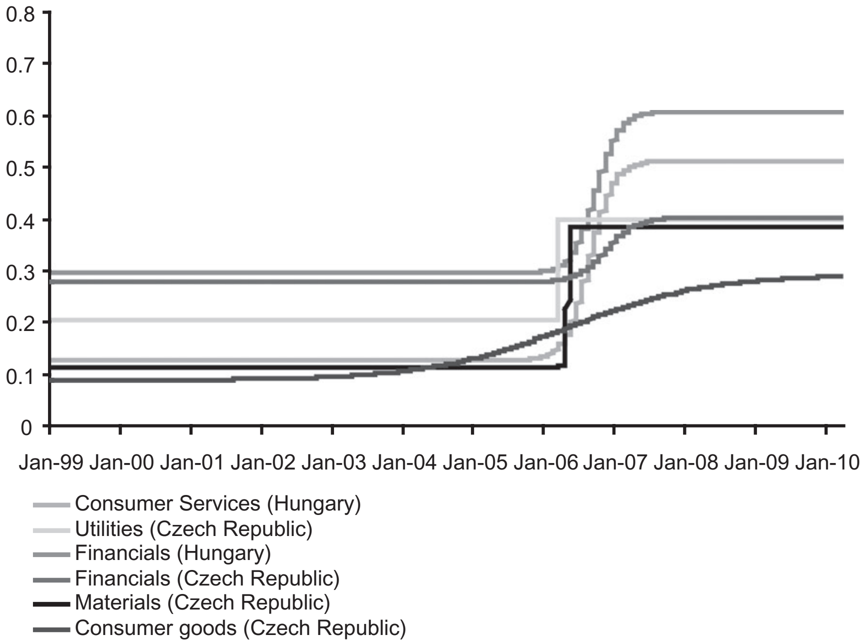


FIG. 2. *Continued on next page*

(c)

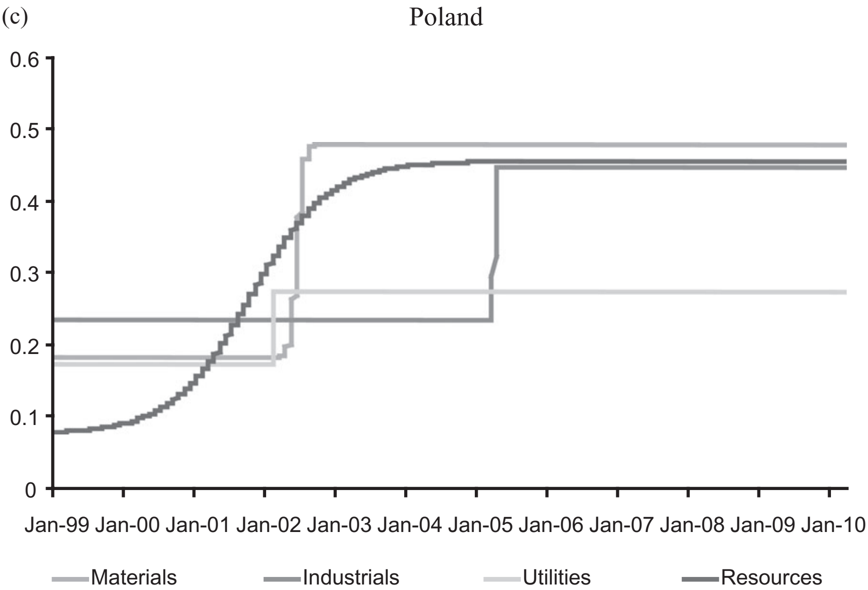


FIG. 2. Time-varying STCC for Various Indices with Euro STOXX Index

to the Euro-zone in recent years. Chelley-Steeley (2005) investigates the correlation of the stock markets of Hungary, the Czech Republic, Poland and Russia with developed markets but for the period 1994–99. She found that Hungary and Poland became more integrated, with the Czech Republic showing slow progress.

This reduction in market segmentation and therefore increase in stock market integration took place after the accession to the EU in May 2004. This result is consistent with Kim *et al*. (2005), Bartram *et al*. (2007) and Christiansen and Ranaldo (2009). The authors argue that a monetary union led to stock market integration in the old EU member states.[13] Moreover, in a way this result relates to the finding in Frankel and Rose (1998) that countries that enter a monetary union are likely to experience more correlated business cycles than before. In our context, this may also imply that countries that are about to enter a monetary union are likely to have more correlated stock markets than before.[14]

The increase in stock market correlation is also supported to a large extent by the analysis at the industry level. From 20 sectoral correlations, 16 increased while four remained the same. In some cases, increases in correla-

[13]Other authors have argued that actually it is the anticipation rather than the existence of a monetary union that increases the level of the European stock market integration (e.g. Bley, 2009).

[14]All new EU members are expected to join the Euro at some point in the near future.

Table 5
Direct Investment Flows 1994–2005

	Hungary	*Czech Republic*	*Poland*
1994	n/a	n/a	693
1995	n/a	n/a	2496
1996	n/a	n/a	3509
1997	n/a	n/a	3726
1998	n/a	2742.5	5028
1999	1937.2	5286.4	6521.2
2000	n/a	3961.1	8827.8
2001	2810.9	4923	5267.3
2002	1866.4	7531.4	3887.7
2003	2995.6	840.7	3534.3
2004	2551.9	3675.8	10,915.1
2005	6390.1	9559.7	7857.3

Notes: The table presents figures for direct investment flows from the EU-15 to Hungary, the Czech Republic and Poland (in millions of US dollars). An n/a means no figures were recorded. Source is International Monetary Fund International Financial Statistics.

tions are substantial. For instance, basic materials and consumer services in the Hungary–EURO model, industrials, basic materials and consumer goods in the Czech–EURO and basic resources in the Poland–EURO model are estimated to have more than tripled their correlations compared with the beginning of the sample.

The tendency towards greater equity market integration is not only confined to few sectors but it is a more broad-based phenomenon across sectors. This is supported by Table 5, which reports information on the value of EU-15 direct investment flows to the three Eastern European countries during 1994–2005. As these figures indicate there has been an upward movement in EU-15 direct investment for all three countries, which may explain the higher correlations in the sectors that receive a good part of the foreign direct investment (FDI) flows (e.g. industrials, basic materials).

The dates of change and the length of the transition period differ across sector–country combinations. For example, financials and consumer services in the Hungarian market, and basic materials, financials, utilities and consumer goods in the Czech market show an increase in correlation in 2006 (as the aggregate indices), although at differing speeds (see Fig. 2(b)). On the other hand, for most sectors in the Polish market the switch was accomplished in the first part of the sample (see Fig. 2(c)). These findings suggest that stock market integration in Eastern European countries with the Euro-area is not solely driven by EU-related developments, and that sector–country-specific factors play a significant role. From a methodological point of view, this illustrates the advantages of a model with endogenously determined change points in correlations.

Table 6
Tests of STCC against DSTCC

	LM_{STCC}	*p value*
Hungary–EURO		
Market index	22.134	0.000**
Basic materials	4.890	0.027*
Financials	14.240	0.000**
Consumer services	2.414	0.120
Czech Republic–EURO		
Market index	0.249	0.618
Industrials	0.6911	0.406
Basic materials	47.489	0.000**
Financials	24.009	0.000**
Utilities	2.050	0.152
Consumer services	104.37	0.000**
Consumer goods	2.181	0.141
Poland–EURO		
Market index	17.072	0.000**
Industrials	19.242	0.000**
Basic materials	33.929	0.000**
Financials	48.071	0.000**
Basic resources	23.674	0.000**
Utilities	1.113	0.291
Consumer services	1.992	0.183
Consumer goods	6.567	0.010*

Notes: LM_{STCC} is the Lagrange Multiplier statistic for an additional transition in STCC-GJRGARCH.
* and ** denote significance at the 5 per cent and 1 per cent level, respectively.

Despite the increase in correlations, in the majority of cases sectoral correlations remain lower than those at the aggregate level, retaining the implication that sectors in Eastern Europe may provide greater portfolio diversification opportunities than the aggregate market.

To investigate whether the STCC is sufficiently flexible to capture the process of integration we test whether a second transition process is warranted using the LM test developed by Silvennoinen and Teräsvirta (2009), reported in Table 6. The results support a second change for the market index in Hungary and Poland, for financials in all markets and for quite a few Polish sectors. These indices are subsequently modelled by a DSTCC model and the results are reported in Table 7.

A distinctive feature of our results in Table 7 is the generation of some non-monotonic correlation patterns due to the existence of two changes and therefore three distinct correlations for the specified models. At an aggregate level, the Polish market experienced a U-curved pattern with an initial slight decline and a subsequent large increase in correlations. On the other hand, the Hungarian market showed an inverted-U correlation pattern. Nevertheless, the final time-pattern of increase in correlation is similar to that implied

TABLE 7
DSTCC-GJRGARCH-*t* MODELS

	ρ_1	ρ_2	ρ_3	γ_1	γ_2	c_1	c_2	v	*Date 1*	*Date 2*	*Log-like*
Hungary–EURO											
Market index	0.410	0.737	0.617	12.003	500	0.692	0.827	9.329	18 Oct 06	09 Apr 08	–9579
	(0.021)	(0.044)	(0.026)	(6.211)	(·)	(0.021)	(0.004)	(1.011)			
Basic materials	0.151	0.386	0.511	5.694	14.853	0.685	0.913	6.584	06 Sep 06	27 Mar 09	–10,362
	(0.031)	(0.140)	(0.102)	(8.442)	(51.949)	(0.097)	(0.068)	(0.589)			
Financials	0.294	0.564	0.702	21.722	399.42	0.684	0.920	9.210	01 Sep 06	24 Apr 09	–10,837
	(0.023)	(0.027)	(0.030)	(17.029)	(1000.4)	(0.019)	(0.006)	(1.005)			
Czech Republic–EURO											
Basic materials	0.117	0.102	0.385	500	500	0.519	0.657	5.835	27 Oct 04	15 May 06	–9356
	(0.030)	(0.066)	(0.031)	(·)	(·)	(0.089)	(0.003)	(0.419)			
Financials	0.234	0.301	0.403	500	16.307	0.242	0.715	8.114	19 Sep 01	08 Jan 07	–10,288
	(0.039)	(0.028)	(0.039)	(·)	(54.989)	(0.001)	(0.106)	(0.807)			
Consumer services	0.339	–0.359	0.395	7.150	1.582	0.335	0.428	5.469	04 Oct 02	20 Oct 03	–10,123
	(0.040)	(0.027)	(0.030)	(2.914)	(1.911)	(0.067)	(0.512)	(0.386)			
Poland–EURO											
Market index	0.496	0.364	0.680	500	21.435	0.571	0.674	9.469	27 May 05	24 Jul 06	–9813
	(0.019)	(0.074)	(0.018)	(·)	(16.165)	(0.001)	(0.016)	(1.057)			
Industrials	0.236	0.525	0.992	500	29.166	0.723	0.989	7.662	08 Feb 07	02 Jan 10	–10,062
	(0.024)	(0.029)	(0.516)	(·)	(39.722)	(0.012)	(0.002)	(0.728)			
Basic materials	0.154	0.360	0.788	66.393	1.839	0.228	0.889	7.964	24 Jul 01	18 Dec 08	–10,335
	(0.041)	(0.056)	(0.430)	(125.9)	(1.634)	(0.013)	(0.317)	(0.765)			
Financials	0.234	0.414	0.587	3.048	33.027	0.223	0.695	8.455	03 Jul 01	17 Oct 06	–9951
	(0.131)	(0.055)	(0.023)	(5.770)	(38.215)	(0.154)	(0.024)	(0.858)			
Basic resources	0.084	0.362	0.556	9.777	52.990	0.210	0.715	7.768	10 May 01	08 Jan 07	–11,484
	(0.059)	(0.029)	(0.024)	(7.372)	(78.057)	(0.036)	(0.021)	(0.745)			
Consumer goods	0.502	0.252	0.567	500	2.794	0.075	0.972	9.558	04 Nov 99	24 Nov 09	–9482
	(0.052)	(0.030)	(0.206)	(·)	(7.836)	(0.321)	(0.233)	(1.125)			

Notes: The table presents maximum likelihood estimates for the parameters of DSTCC-GJRGARCH-*t* models; remaining parameter estimates are available upon request; *Date 1* is the day that corresponds to *c1* (threshold 1) and *Date 2* is the day that corresponds to *c2* (threshold 2); values in parentheses are standard errors; *Log-like* is the log-likelihood value obtained; in a number of cases the parameter γ becomes large and imprecisely estimated, signifying an abrupt change in the conditional correlations. In this case we report the value of γ as 500 as indicative.

by the single transition STCC model in Table 4. These correlations are shown in Fig. 3(a) and (b).

At the industry level, the DSTCC estimates for the financials in the Czech and Polish markets (Fig. 3(c) and (d)) and Polish basic resources (Fig. 3(f)) point to a twice increasing correlation pattern, comparable to the more gradual rise in correlation implied by the STCC specification. On the other hand, the estimates for Polish industrials imply a further increase in correlation in early 2010, shown in Fig. 3(e).

4 Sensitivity Analysis

Four robustness checks are undertaken in this section. These are: first, a comparison of the results with a dynamic conditional correlation (DCC) specification; second, sensitivity to an alternative transition variable; third, exploring whether the increase in correlations is due to global conditions, and finally an analysis of the importance of volatility spillovers in the data.

The DCC model of Engle (2002) allows correlations to vary over time with the dynamics driven by past correlations,

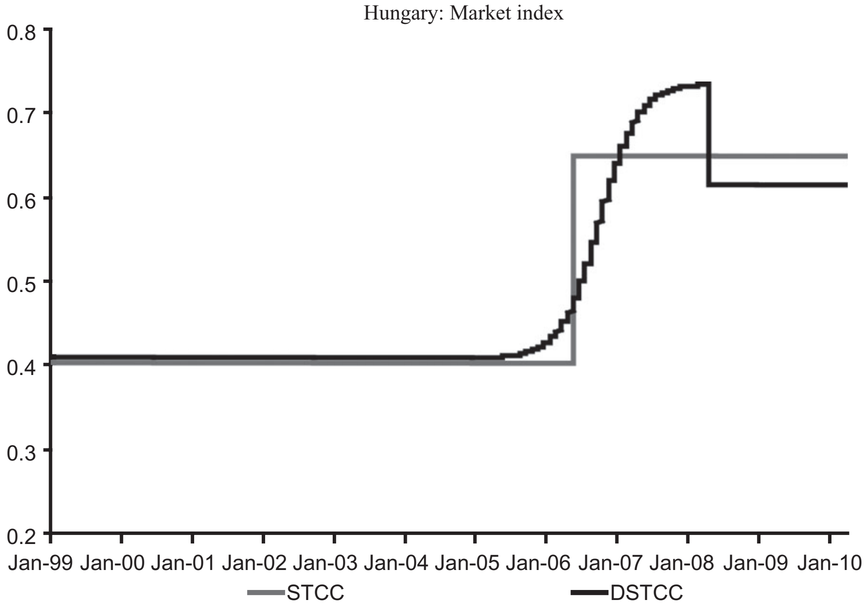
$$q_{ij,t} = \bar{\rho}_{ij}(1-\alpha-\beta)+\alpha\,\varepsilon_{i,t-1}\varepsilon_{j,t-1}+\beta\,q_{ij,t-1} \qquad i,\, j=1,2 \tag{12}$$

where $\bar{\rho}_{ij}$ is the (assumed constant) unconditional correlation between $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ (standardized residuals), α is the news coefficient and β is the decay coefficient. For comparison with the VAR-GJRGARCH-(D)STCC model the DCC specification models the conditional returns as a VAR(1), the conditional volatilities as GJRGARCH(1,1) with t-distributed residuals so that the main difference between the (D)STCC and DCC models is in the definition of the correlations. The focus of reporting results will be on conditional correlations implied by selected models.[15]

The correlations implied by various (D)STCC and DCC models are presented in Figs 4 and 5. The general upward tendency in correlations shown in the (D)STCC models is also present in the DCC models, although the DCC model implies correlations that fluctuate frequently (see also the figures in Kim *et al*., 2005). For a number of indices the DCC and (D)STCC correlations track quite well; for example, the Polish aggregate index (Fig. 4(c)), the Czech basic materials and utilities (Fig. 5(b) and (c)) and the Polish financials and basic resources (Fig. 5(d) and (f)). In each of these cases the DCC process is highly persistent as measured by $\alpha+\beta$ (typically above 0.991), which may indicate structural shifts in the DCC model. Table 8 reports estimates of the persistence of correlations in the DCC model, and in the DCC model with structural breaks in the unconditional correlations

[15]For conciseness, we do not present parameter estimates of the models.

(a)



(b)

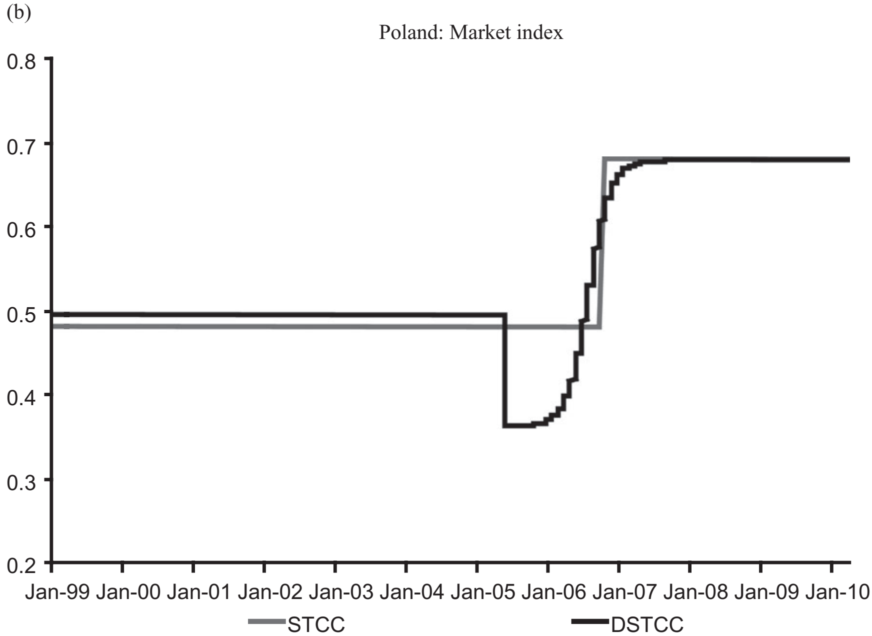
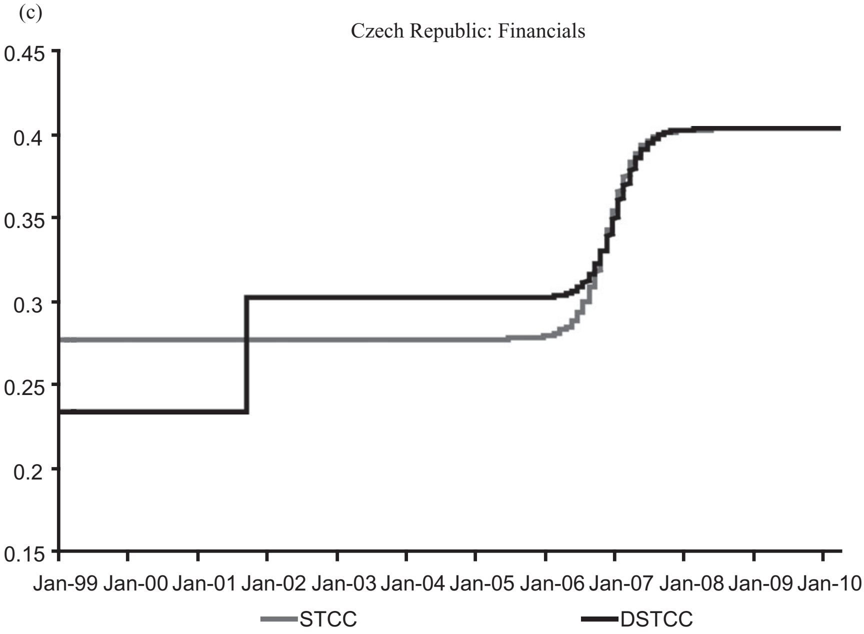


FIG. 3. *Continued on next page*

(c)



(d)

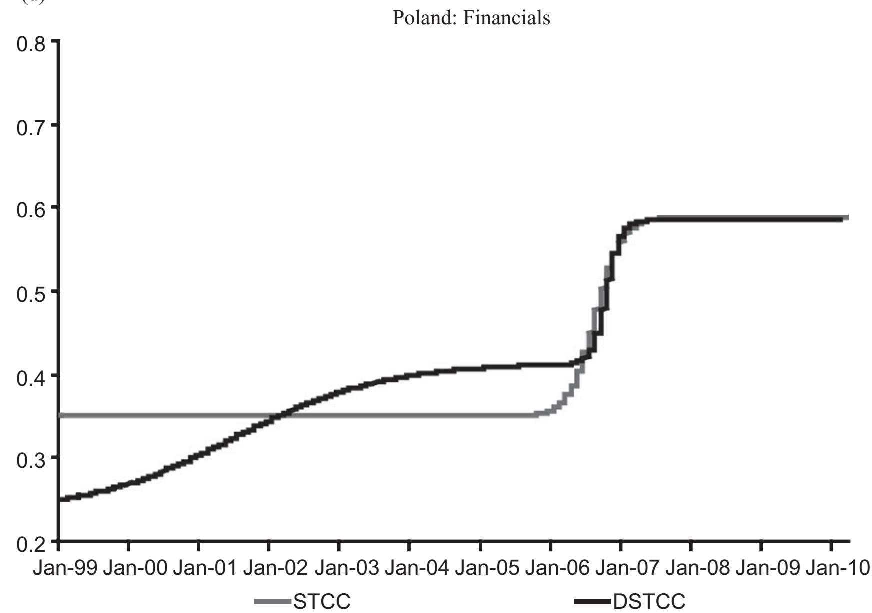
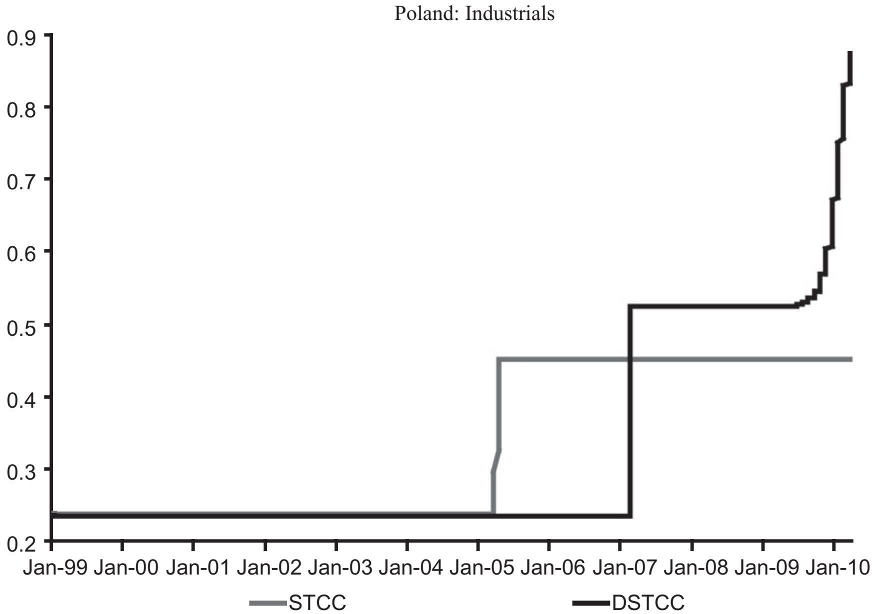


FIG. 3. *Continued on next page*

(e)



(f)

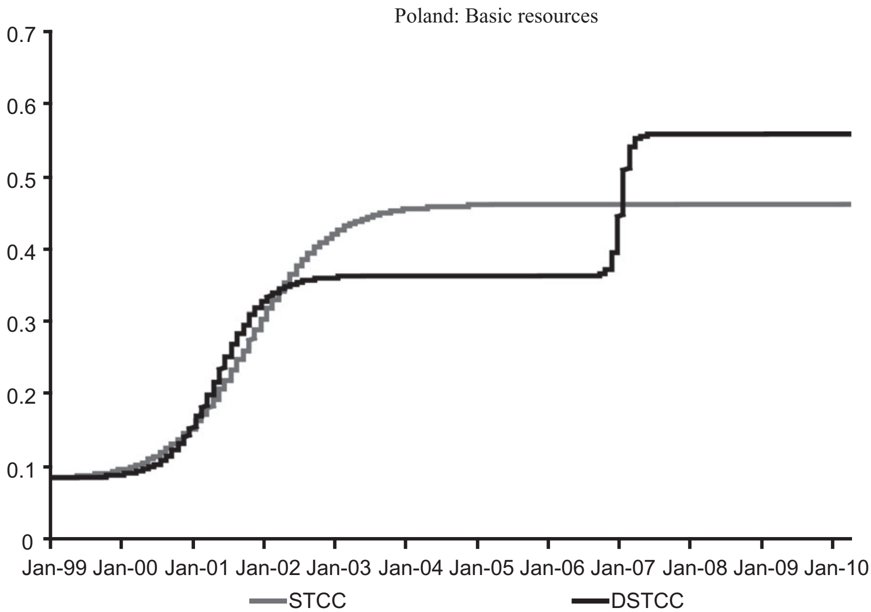
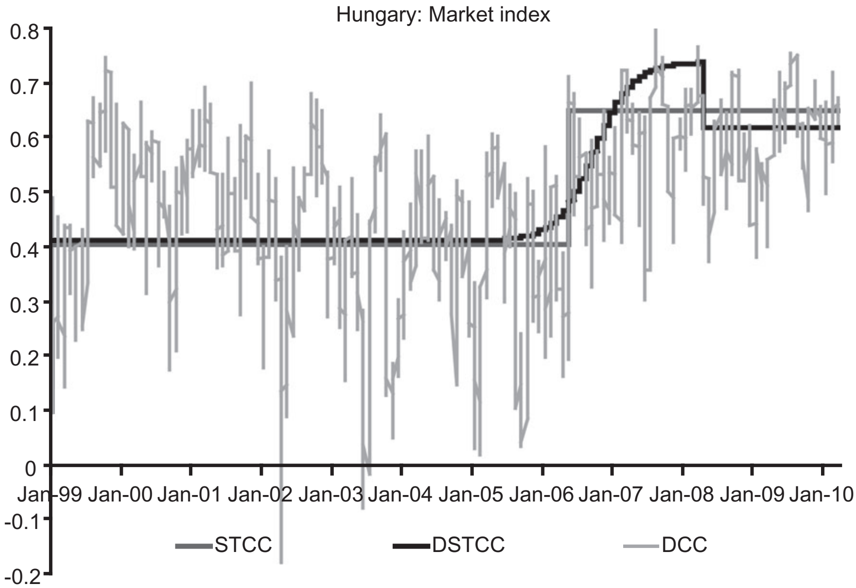


Fig. 3. DSTCC and STCC for Various Indices with Euro STOXX Index

(a)



(b)

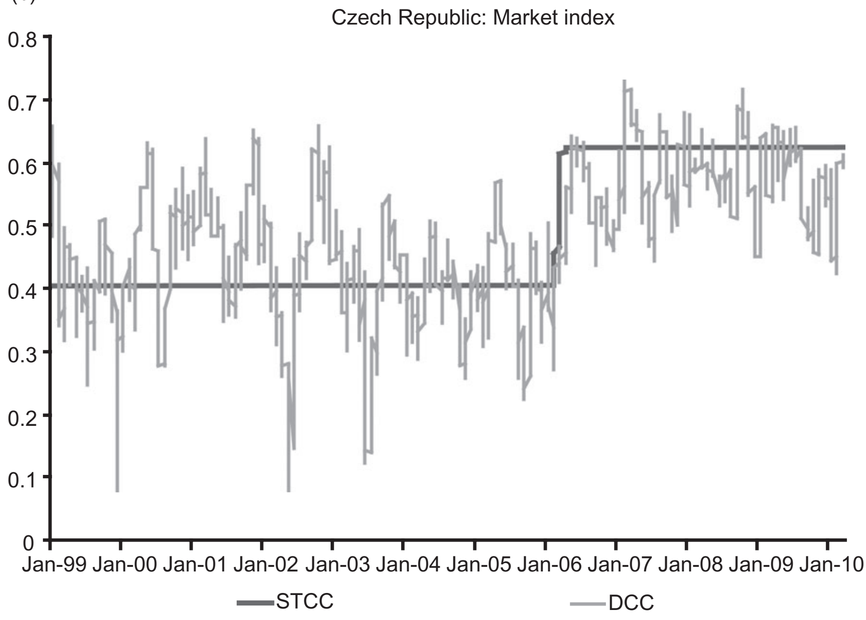


FIG. 4. *Continued on next page*

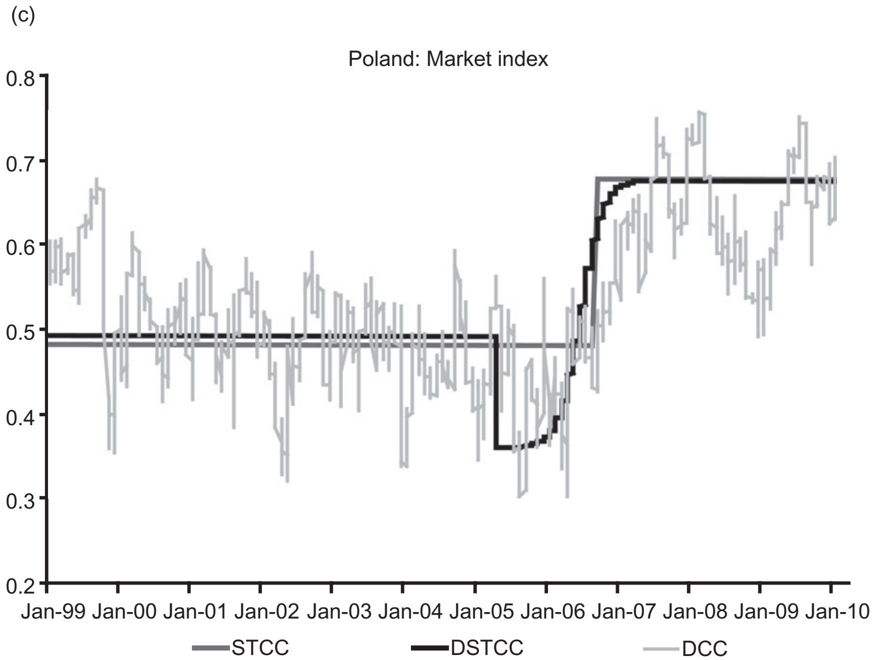


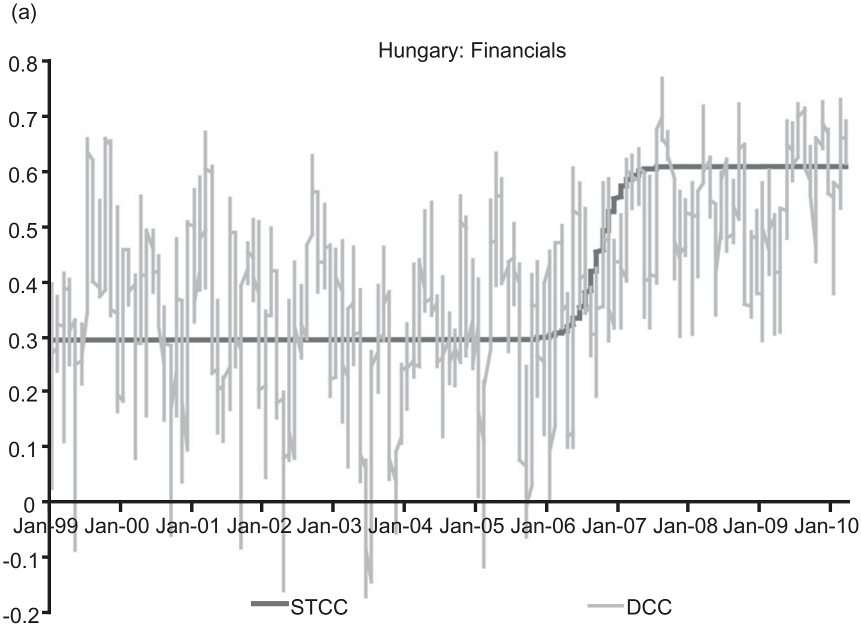
FIG. 4. Time-varying Correlations with Euro STOXX Index for Market Indices

occurring at the dates (thresholds) implied by the (D)STCC estimates.[16] The results show that allowing for structural breaks in correlations decreases the persistence of conditional correlations, which is in line with van Dijk *et al.* (2005).

The second sensitivity test is based on previous findings that co-movements are stronger in volatile times than in more tranquil periods (King and Wadhwani, 1990; Longin and Solnik, 1995, 2001; Ramchand and Susmel, 1998; Ang and Bekaert, 2002; Ang and Chen, 2002; Forbes and Rigobon, 2002; Patton, 2004). To control for this we test the constancy of correlations against a model with the Dow Jones Euro STOXX volatility index (VSTOXX) as the transition variable. As before, we perform the constancy test of Silvennoinen and Teräsvirta (2005).[17] The results show that the

[16]It might be argued that a gradual change in unconditional correlations, giving rise to a smooth transition DCC, may be more realistic than the DCC with discrete changes that we use. However, an unfortunate feature of allowing for gradual changes is that correlation targeting cannot be used to reduce the number of parameters. For our purposes here, we focus on a DCC model with discrete changes. For more details on this issue, see van Dijk *et al.* (2005).

[17]An alternative way to considering a correlation model governed by volatility could be to use a FACTOR DCC model (as in Engle, 2009) that blends factor models with the DCC to produce a model with features of both approaches.



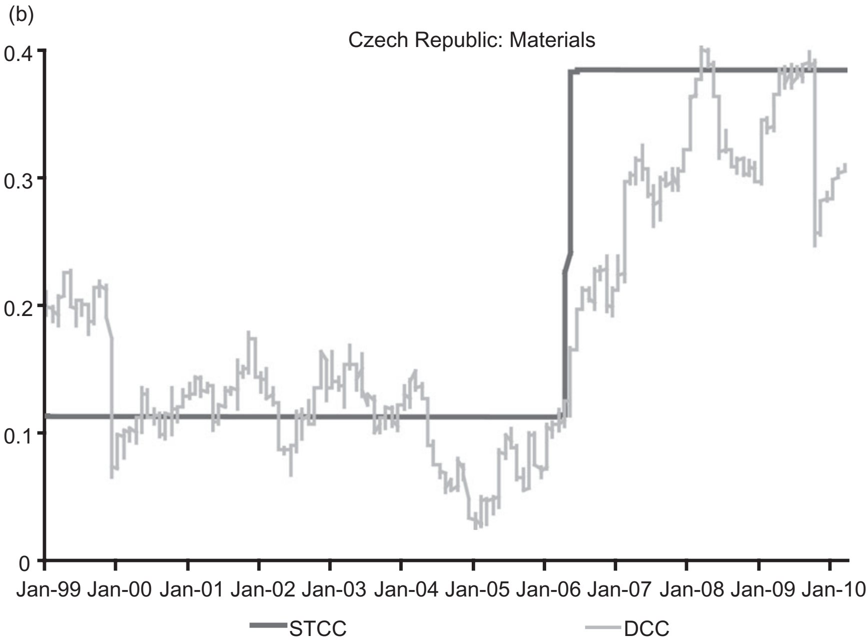


FIG. 5. *Continued on next page*

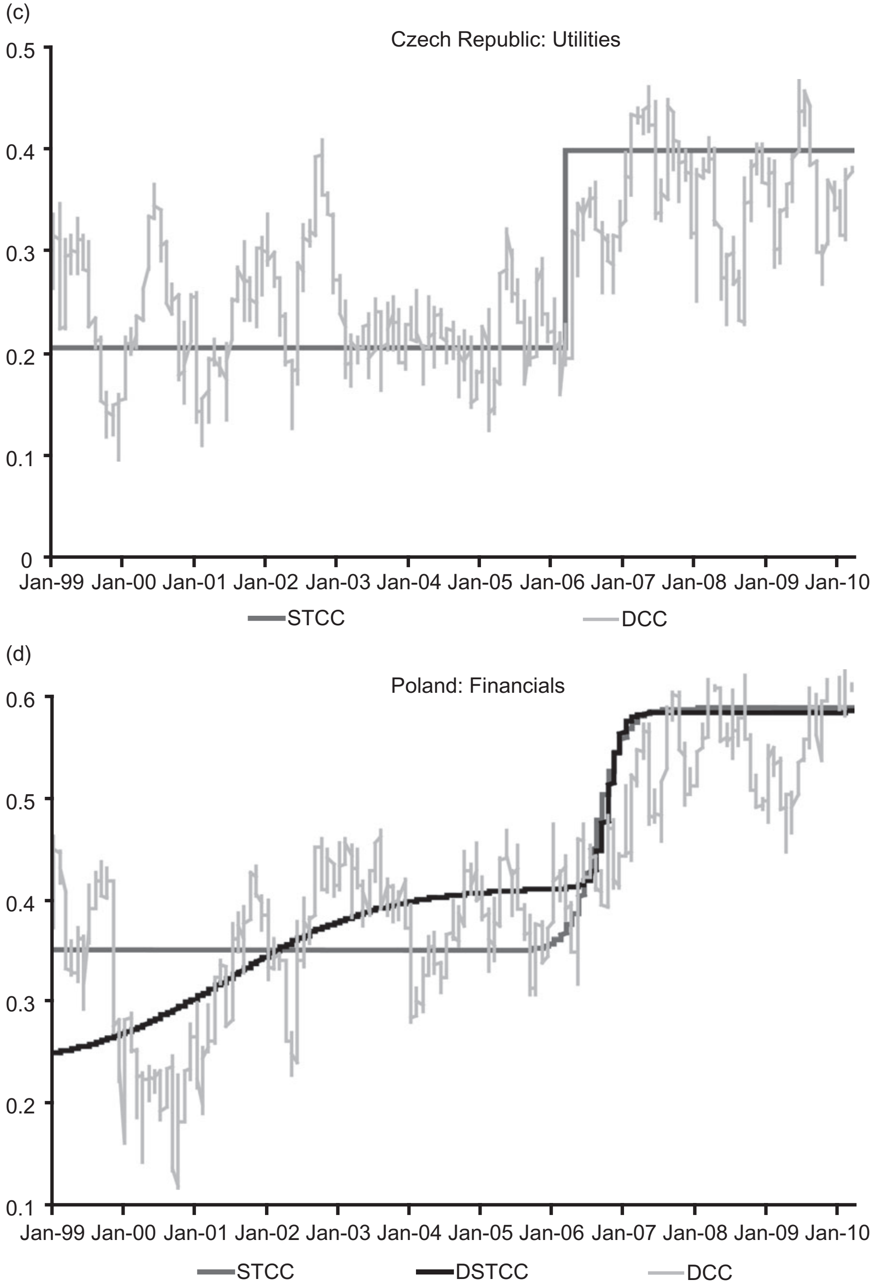


FIG. 5. *Continued on next page*

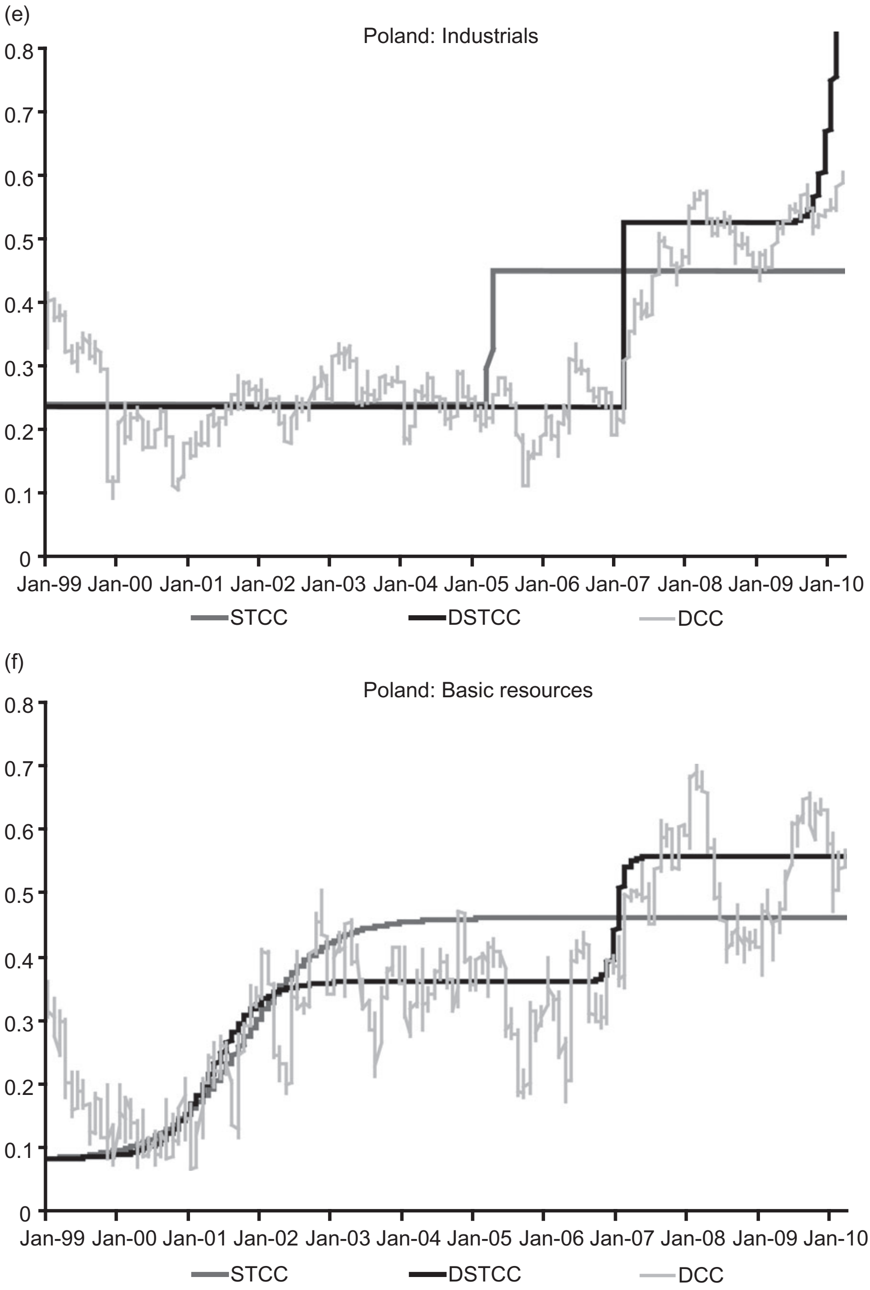


FIG. 5. Time-varying Correlations with Euro STOXX Index for Industry Indices

TABLE 8
PERSISTENCE OF DCC-t CORRELATIONS

	DCC-t	*SB-DCC-t*
Hungary–EURO		
Market index	0.976	0.954
Basic materials	0.997	0.967
Financials	0.973	0.903
Consumer services	0.999	0.984
Czech Republic–EURO		
Market index	0.985	0.604
Industrials	0.994	0.938
Basic materials	0.998	0.860
Financials	0.696	0.606
Utilities	0.993	0.971
Consumer services	0.993	0.982
Consumer goods	0.997	0.974
Poland–EURO		
Market index	0.995	0.840
Industrials	0.999	0.881
Basic materials	0.995	0.973
Financials	0.997	0.818
Basic resources	0.998	0.981
Utilities	0.959	0.924
Consumer goods	0.996	0.614

Notes: The table reports estimates of the persistence of conditional correlations in the DCC-t model as measured by $\alpha + \beta$; point estimates of the parameters α and β are available upon request; *DCC-t* denotes the model with no structural breaks; *SB-DCC-t* denotes the model with structural breaks in the unconditional correlations occurring at the dates (thresholds) implied by the (D)STCC-t estimates.

null hypothesis of constant correlations is rejected only in two cases. In particular, the rejections are for consumer services and consumer goods in the Hungarian market (p values are 0.025 and 0.030, respectively). In sum, it seems that, although considering a correlation model governed by volatility may be worthwhile, the time transition (D)STCC model is sufficient flexible to capture the dominant trends in correlations.

Next, we explored whether the increase in correlations found in the Czech Republic–, Hungary– and Poland–EURO models for the aggregate market indices is due to global conditions or even emerging market conditions. For this, we estimated STCC correlations for these markets versus the USA and Russia for same sample period. The results rejected (not reported) the hypothesis of increased correlation versus the USA. On the other hand, against Russia there is an increase in correlation in all three markets. This increase is however in a lesser degree compared with Euro-area supporting the Euro-area driven nature of the increasing integration of the Eastern European data. A similar result has also been found in Cappiello *et al*. (2006) and Savva and Aslanidis (2010). Moreover, the results in Hanousek *et al.* (2008) may also be consistent with ours as they document that the three largest Central Eastern European (CEE) markets (Hungary, the Czech Republic and Poland) react to macroeconomic shocks, especially those originating from the EU.

Finally, we examine possible volatility linkages (spillovers in volatilities). A simple criterion to analyse these linkages is the correlation between the estimated variances of two assets

$$\rho_{h_{ii,t}h_{jj,t}} = \frac{\sum_{t=1}^{T}\left(h_{ii,t}-\bar{h}_{ii}\right)\left(h_{jj,t}-\bar{h}_{jj}\right)}{\sqrt{\sum_{t=1}^{T}\left(h_{ii,t}-\bar{h}_{ii}\right)^{2}\sum_{t=1}^{T}\left(h_{jj,t}-\bar{h}_{jj}\right)^{2}}}$$

The conditional variances are found to be moderately correlated with an average correlation of 0.22. Not surprisingly, the correlation among the variances of the aggregate markets is higher than that of the industry-level data. At the aggregate level the average correlation is 0.34, while the corresponding figure at the industry level is 0.18. Hence, we conclude that at the aggregate level there is some scope for generalizing the GJRGARCH(1,1) processes to allow for spillovers in volatilities, but in most cases this model captures the dynamics in volatilities quite adequately.

5 Conclusions

The advent of the EMU is associated with an increase in equity market integration among member countries. This paper addressed the extent to which the three largest new EU members (Hungary, the Czech Republic and Poland) have experienced increased integration with the Euro-zone since their accession.

The methodological approach was to incorporate the potential for smoothly time-varying transitions between correlation regimes in the equity markets, implemented by an STCC model, and additionally allowing for more than one shift using a DSTCC model. The well-known autoregressive, volatility clustering, asymmetric volatility and fat tails effects in this data were accommodated by embedding the STCC models into a VAR-GJRGARCH framework. The combination of these modelling elements is appropriate for the problem under consideration.

The results of the application showed that at an aggregate level each equity market has shown a significant increase in correlation with the Euro-zone, particularly from 2006. Further detail from industry-level indices supported the broad basis for the increase in correlation with the EU. The results supported that greater diversification opportunities remained within the sectoral indices of these new EU members than demonstrated at the aggregate index level.

References

Albuquerque, P. H. (2005). 'Optimal Time Interval Selection in Long-run Correlation Estimation', Mimeo, University of Minnesota Duluth.

Ammer, J. and Mei, J. (1996). 'Measuring International Economic Linkages with Stock Market Data', *Journal of Finance*, Vol. 51, pp. 1743–1763.

Ang, A. and Bekaert, G. (2002). 'International Asset Allocation with Regime Shifts', *Review of Financial Studies*, Vol. 15, pp. 1137–1187.

Ang, A. and Chen, J. (2002). 'Asymmetric Correlations of Equity Portfolios', *Journal of Financial Economics*, Vol. 63, pp. 443–494.

Baele, L. (2005). 'Volatility Spillover Effects in European Equity Markets', *Journal of Financial and Quantitative Analysis*, Vol. 40, pp. 373–401.

Bartram, S., Taylor, S. and Wang, Y. (2007). 'The Euro and European Financial Market Dependence', *Journal of Banking and Finance*, Vol. 31, pp. 1461–1481.

Berben, R. P. and Jansen, W. J. (2005). 'Comovement in International Equity Markets: a Sectoral View', *Journal of International Money and Finance*, Vol. 24, pp. 832–857.

Bley, J. (2009). 'European Stock Market Integration: Fact or Fiction?', *Journal of International Financial Markets, Institutions, and Money*, Vol. 19, pp. 759–776.

Bollerslev, T. (1990). 'Modeling the Coherence in Short-run Nominal Exchange Rates: a Multivariate Generalized ARCH model', *Review of Economics and Statistics*, Vol. 72, pp. 498–505.

Cappiello, L., Gérard, B., Kadareja, A. and Manganelli, S. (2006). 'Financial Integration of New EU Member States', *Working Paper Series 683*, ECB.

Chelley-Steeley, P. L. (2005). 'Modelling Equity Market Integration Using Smooth Transition Analysis: a Study of Eastern European Stock Markets', *Journal of International Money and Finance*, Vol. 24, pp. 818–831.

Christiansen, C. and Ranaldo, A. (2009). 'Extreme Coexceedances in New EU Member Stakes' Stock Markets', *Journal of Banking and Finance*, Vol. 33, pp. 1048–1057.

van Dijk, D., Munandar, H. and Hafner, C. (2005). 'The Euro Introduction and Non-Euro Currencies', Mimeo, Erasmus University Rotterdam.

Égert, B. and Kočenda, E. (2007). 'Interdependence between Eastern and Western European Stock Markets: Evidence from Intraday Data', *Economic Systems*, Vol. 31, pp. 184–203.

Engle, R. (2002). 'Dynamic Conditional Correlation: a Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models', *Journal of Business and Economic Statistics*, Vol. 20, pp. 339–350.

Engle, R. (2009). *Anticipating Correlations: a New Paradigm for Risk Management*, Princeton, NJ, Princeton University Press.

Fidrmuc, J. and Korhonen, I. (2006). 'A Meta-analysis of the Business Cycle Correlation between the Euro-area and CEECs: What do we Know and Who Cares?', *Journal of Comparative Economics*, Vol. 34, pp. 518–537.

Flavin, T. (2004). 'The Effect of the Euro on Country versus Industry Portfolio Diversification', *Journal of International Money and Finance*, Vol. 23, pp. 1137–1158.

Forbes, K. and Rigobon, R. (2002). 'No Contagion, Only Interdependence: Measuring Stock Market Co-movements', *Journal of Finance*, Vol. 57, pp. 2223–2261.

Frankel, J. A. and Rose, A. K. (1998). 'The Endogeneity of the Optimum Currency Area Criteria', *Economic Journal*, Vol. 108, pp. 1009–1025.

Fratzscher, M. (2002). 'Financial Market Integration in Europe: on the Effects of EMU on Stock Markets', *International Journal of Finance and Economics*, Vol. 7, pp. 165–193.

Guiso, L., Jappelli, T., Padula, M. and Pagano, M. (2004). 'Financial Market Integration and Economic Growth in the EU', *Economic Policy*, Vol. 19, pp. 523–577.

Hanousek, J., Kočenda, E. and Kutan, A. M. (2008). 'The Reaction of Asset Prices to Macroeconomic Announcements in New EU Markets: Evidence from Intraday Data', *Working Papers Series 349*, CERGE-EI, Charles University, Prague.

Hardouvelis, A., Malliaropulos, D. and Priestley, R. (2006). 'EMU and European Stock Market Integration', *Journal of Business*, Vol. 79, pp. 365–392.

Kim, S. J., Moshirian, F. and Wu, E. (2005). 'Dynamic Stock Market Integration Driven by the European Monetary Union: an Empirical Analysis', *Journal of Banking and Finance*, Vol. 29, pp. 2475–2502.

King, M. and Wadhwani, S. (1990). 'Transmission of Volatility between Stock Markets', *Review of Financial Studies*, Vol. 3, pp. 5–33.

Kočenda, E. (2001). 'Macroeconomic Convergence in Transition Economies', *Journal of Comparative Economics*, Vol. 29, pp. 1–3.

Kutan, A. M. and Yigit, T. M. (2004). 'Nominal and Real Stochastic Convergence of Transition Economies', *Journal of Comparative Economics*, Vol. 32, pp. 23–36.

Longin, F. and Solnik, B. (1995). 'Is the Correlation in International Equity Returns Constant: 1960–1990?', *Journal of International Money and Finance*, Vol. 14, pp. 3–26.

Longin, F. and Solnik, B. (2001). 'Extreme Correlation and International Equity Markets', *Journal of Finance*, Vol. 56, pp. 649–676.

Moerman, G. A. (2008). 'Diversification in Euro Area Stock Markets: Country vs. Industry', *Journal of International Money and Finance*, Vol. 27, pp. 1122–1134.

Morana, C. and Beltratti, A. (2002). 'The Effects of the Introduction of the Euro on the Volatility of European Stock Markets', *Journal of Banking and Finance*, Vol. 26, pp. 2047–2064.

Patton, A. (2004). 'On the Out-of-sample Importance of Skewness and Asymmetric Dependence for Asset Allocation', *Journal of Financial Econometrics*, Vol. 2, pp. 130–168.

Ramchand, L. and Susmel, R. (1998). 'Volatility and Cross Correlation across Major Stock Markets', *Journal of Empirical Finance*, Vol. 5, pp. 397–416.

Savva, C. S., Osborn, D. R. and Gill, L. (2009). 'Spillovers and Correlations between U.S. and Major European Stock Markets: the Role of the Euro', *Applied Financial Economics*, Vol. 19, pp. 1595–1604.

Savva, C. S. and Aslanidis, N. (2010). 'Stock Market Integration between New EU Member States and the Euro-zone', *Empirical Economics*, Vol. 39, pp. 337–351.

Silvennoinen, A. and Teräsvirta, T. (2005). 'Multivariate Autoregressive Conditional Heteroskedasticity with Smooth Transitions in Conditional Correlations', *Working Paper Series in Economics and Finance 577*, SSE/EFI.

Silvennoinen, A. and Teräsvirta, T. (2009). 'Modelling Multivariate Conditional Heteroskedasticity with the Double Smooth Transition Conditional Correlation GARCH Model', *Journal of Financial Econometrics*, Vol. 7, pp. 373–411.

Susmel, R. and Engle, R. F. (1994). 'Hourly Volatility Spillovers between International Equity Markets', *Journal of International Money and Finance*, Vol. 13, pp. 3–25.