Modelling change in financial market integration: Eastern Europe

Nektarios Aslanidis*, Mardi Dungey+ and Christos S. Savva%

* Department of Economics, University Rovira Virgili, Spain

\+ University of Tasmania; CFAP, University of Cambridge; and CAMA, Australian National University

% Economics Research Centre, University of Cyprus
and
Department of Commerce, Finance and Shipping, Cyprus University of Technology

January 2009

Abstract

This paper measures the increase in stock market integration between the three largest new EU members (Hungary, the Czech Republic and Poland who joined in May 2004) and the Euro-zone. A potentially gradual transition in correlations is accommodated in a single VAR model by embedding smooth transition conditional correlation (STCC) models with fat tails, spillovers, volatility clustering, and asymmetric volatility effects (GJRGARCH). This VAR-GJRGARCH-STCC-*t* specification is subject to a number of sensitivity tests, including alternative transition variables and variance spillovers, as well as a direct comparison with the dynamic conditional correlation (DCC) model of Engle (2002). We find evidence of progress towards financial integration with the EMU in each of the three countries. In 2006 there is a considerable increase in correlations at the aggregate level for all three Eastern European markets. We test for a common transition structure of the Hungarian, Polish and Czech markets with the EMU. The results reject the common transition structure, and we determine that this is due to the differing behaviour of the Czech Republic data.

JEL classifications: C32; C51; F36; G15

Keywords: Multivariate GARCH; Smooth Transition Conditional Correlation; Stock Return Comovement; Sectoral correlations; New EU Members

Comments on an earlier version of the paper from conference participants at International Workshop on Computational and Financial Econometrics (Neuchâtel, 2008) and seminar participants at the University of Vigo are greatly appreciated. We would also like to thank Tom Flavin, Denise Osborn and Lenno Uusküla for helpful comments. Author contacts are: Aslanidis, nektarios.aslanidis@urv.es; Dungey, mardi.dungey@utas.edu.au; Savva, christos.savva@ucy.ac.cy.

1. Introduction

Modeling changing correlation structures in financial market data presents a number of challenges. These include the need to simultaneously consider multiple asset returns with data which are known to display non-normal characteristics with fat tails and volatility clustering. Additionally, changes in correlation may occur relatively slowly or abruptly. The practical importance of changing correlations is illustrated by their use in assessing bull and bear markets (Butler and Joaquin, 2002), for defining financial crises (Forbes and Rigobon, 2002) and examining changes in financial market integration, for example the case of Mexico in Rigobon (2002). This paper examines the use of changing correlation structures in measuring the financial market integration of Eastern European stock markets with the Euro zone for the period since the introduction of the Euro. However, the techniques developed in the paper are general, and could be applied to many other situations.

To capture the characteristics of changing correlations in financial market data the paper adopts a smooth transition conditional correlation (STCC) model which allows for both gradual and abrupt correlation transitions; see Berben and Jansen (2005), Silvennoinen and Teräsvirta, (2005) and recently Silvennoinen and Teräsvirta (2007). To capture market interrelationships, the STCC model is embedded in a vector autoregression of returns, whose conditionally *t*-distributed residuals follow a GJRGARCH model to account for fat tails in returns, clustering and asymmetry in volatility. This VAR-GJRGARCH-STCC model (VGS henceforth) generalises those proposed by Silvennoinen and Teräsvirta (2005, 2007) and Berben and Jansen (2005) by removing their assumptions of constant mean, symmetric GARCH variances and normal errors, and extends the approach of Kim, Moshirian and Wu (2005) who incorporate spillovers between returns, by encompassing the possibility of endogenous changes in the correlation process. Additionally, we model multiple assets by allowing for correlation-specific transition mechanisms, which adds flexibility to the Silvennoinen-Teräsvirta (2005, 2007) models.

The model is applied to the integration of three Eastern European stock markets, Hungary, Poland and the Czech Republic, with those of the Euro zone using daily data over the period from 1 January 1999 to 1 November 2007. Existing evidence supports a particular increase in integration between many of the European Economic and Monetary Union (EMU) countries since the introduction of the Euro in January 1999; Kim, Moshirian and Wu (2005).[1] The enlargement of the European Union from May 1, 2004 admitted new countries, which are in transition to full membership of the EMU. Of these, Hungary, Poland and the Czech Republic have the largest GDP and equity markets. While there is evidence that the business cycles of these countries has synchronized with the Euro-area, the evidence on financial integration is mixed[2]; Baltzer, Cappiello, De Santis and Manganelli (2008) and Égert and Kočenda (2007) argue for relatively low integration in equity markets, while Cappiello, Gérard, Kadareja and Manganelli (2006) and Chelley-Steeley (2005) document increasingly strong comovements.

The proposed model improves on the existing methodologies applied to this problem by integrating the smooth transition model within a VAR, accounting for the non-normality of the data and endogenising the choice of transition date. This generalizes the analysis beyond the DCC models of Égert and Kočenda (2007) and extends the smooth transition model of Chelley-Steely (2005) which is applied to

---

[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 Baele (2005), Fratzscher (2002), Morana and Beltratti (2002), Guiso, Jappelli, Padula and Pagano (2004), Hardouvelis, Malliaropulos and Priestley (2006) and Savva, Osborn and Gill (2008).

[2] For a comprehensive survey on business cycle integration see Fidrmuc and Korhonen (2006).

estimated monthly correlations rather than directly to conditional correlations. It also endogenises the transition period, unlike the Gaussian copula applied in conjunction with GJR-GARCH by Bartram, Taylor and Wang (2007) and the quantile regressions of Cappiello, Gérard, Kadareja and Manganelli (2006).

Results from the VGS model find evidence of progress towards financial integration with the EMU in each of the three countries. In 2006 there is a considerable increase in correlations at the aggregate level for all three Eastern European markets. An advantage of the VGS model is that it can be applied to multiple assets simultaneously. We use this feature to test for a common transition structure of the Hungarian, Polish and Czech markets with the Euro zone. The results reject the common transition structure, and we determine that this is due to the differing behaviour of the Czech Republic data. The Czech Republic took a fast-track approach to financial market liberalization, in direct contrast to the more conservative liberalization in Poland and Hungary. Poland and Hungary exhibit a common transition structure in their integration with the Euro-zone.

The VGS specification is subject to a number of sensitivity tests, including alternative transition variables and the inclusion of spillovers, as well as a direct comparison with the DCC model. The preferred VGS model has the advantage of embedding the transition measures in a full specification of the dynamics of the market returns with endogeneous change points for the correlations, and captures the main features of the data. While the Gaussian copula approach of Bartram, Taylor and Wang (2007) produced similar results to a DCC (see their Figure 5) in the current paper the VGS model is shown to better explain the long run dynamics than a DCC specification.

The VGS model is applied both to market level indices for the three countries, but also to a number of industry level indices. Recent literature has argued that with increasing integration, industry indices may provide greater diversification opportunities; see Flavin (2004) and Moerman (2008). Bivariate VGS sectoral results for integration of industry indices largely confirm the aggregate index results, although the dates of change in correlation and length of transition period differ across sectors.

The rest of the paper is organised as follows. Section 2 presents the proposed VGS model in bivariate and multivariate form as well as the discussion of the testing procedures and sensitivity tests. Section 3 discusses the data and presents the results for both market level and industry level indices, in bivariate and multivariate specifications. In Section 4, we perform robustness checks to validate our results. Section 5 discusses implications for policy diversification. Finally, Section 6 concludes.

2. Econometric methodology

As many existing studies of equity market integration are conducted between pairs of assets, the bivariate case is presented first. Common interdependencies between a vector (y_t) of 2 stock returns are modelled as a VAR (p)

$$\phi(L)y_t = c_0 + u_t \tag{1}$$

where $\phi(L) = I - \phi L - \phi L^2 - ... - \phi L^p$ with time varying conditional covariances of the residuals distributed

$$u_t | \Im_{t-1} \sim t(0, H_t, v) \tag{2}$$

where t is the conditional bivariate student´s t distribution with ν degrees of freedom, and $\Im_{t-1}$ is the information set at t-1. Each univariate error process can be written as

$$u_{i,t} = h_{ii,t}^{1/2}\, \varepsilon_{i,t}\,,\; i = 1, 2 \tag{3}$$

where $h_{ii,t} = E(u_{i,t}^2 / \Im_{t-1})$ and $\varepsilon_{i,t} = \dfrac{u_{i,t}}{h_{ii}^{1/2}}$. The conditional variances are assumed to follow a univariate *GJR*-*GARCH* (1,1) process

$$h_{ii,t} = \omega_i + \alpha_i u_{i,t-1}^2 + \vartheta_i u_{i,t-1}^2 I[u_{i,t-1} < 0] + \beta_i h_{ii,t-1} \tag{4}$$

with the standard non-negativity and stationarity restrictions imposed. As the focus of investigations is on the conditional correlations it is helpful to define

$$\rho_t = h_{12,t}(h_{11,t} h_{22,t})^{-1/2} \tag{5}$$

where $h_{12,t}$ is the conditional covariance between stock returns. The proposed model has two state-specific constant correlations, with a potentially smooth transition between them, such as in the smooth transition conditional correlation (STCC) specification of Silvennoinen and Teräsvirta (2005) and Berben and Jansen (2005). Silvennoinen and Teräsvirta (2005) suggest an LM test for this form against the null of constant conditional correlation (LM_{CCC}). When the STCC model applies, the correlation ρ_t follows

$$\rho_t = \rho_1(1 - G_t(s_t;\gamma,c)) + \rho_2 G_t(s_t;\gamma,c) \tag{6}$$

where, the function $G_t(s_t;\gamma,c)$ is the transition function, assumed continuous and bounded by zero and unity, with parameters γ and c, and where s_t is the transition variable. An advantage of the current application is that the transition variable is clearly defined as a function of time. Here the transition variable is specified as a linear function of time, $s_t = t/T$.[3]

A plausible and widely used specification for the transition function is the logistic function

$$G_t(s_t;\gamma,c) = \frac{1}{1+\exp[-\gamma(s_t - c)]}, \quad \gamma > 0 \tag{7}$$

where c is the threshold parameter and when $\gamma \to \infty$, $G_t(s_t;\gamma,c)$ becomes a step function ($G_t(s_t;\gamma,c) = 0$ if $s_t < c$ and $G_t(s_t;\gamma,c) = 1$ if $s_t > c$), representing an abrupt transition.[4]

The model of equations (1) to (7) incorporates the potential for a single change in correlation between the assets. However, a single change in correlation may not be a sufficient description of the data. Using the Lagrange Multiplier test (LM_{STCC}) of Silvennoinen and Teräsvirta (2007) the null hypothesis of a single STCC (one change in correlations) can be tested against the alternative of a double STCC (two changes in correlations). If evidence of a second change in correlations is found, the double smooth transition conditional correlation (DSTCC) can be implemented by replacing equation (6) with

$$\rho_t = \rho_1(1 - G_{1t}(s_t;\gamma_1,c_1)) + \rho_2 G_{1t}(s_t;\gamma_1,c_1)(1 - G_{2t}(s_t;\gamma_2,c_2)) + \rho_3 G_{1t}(s_t;\gamma_1,c_1) G_{2t}(s_t;\gamma_2,c_2) \tag{8}$$

The second transition variable here is also a function of time ($s_t = t/T$), and hence (8) allows the possibility of a non-monotonic change in correlation over the sample. This is a special case of Silvennoinen and Teräsvirta (2007) as both 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

[3] 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.

logistic functions as defined in (7). The parameters γ_i and c_i (i=1,2) are interpreted in the same manner as for the STCC model, but to ensure identification we require $c_1 < c_2$ and hence that the two correlation transitions occur at different points of time.

2.1 Higher-dimension models

The model of the previous section can be extended to an N dimensional vector of assets by replacing the bivariate model of Eq. (6) with the multivariate STCC model given by

$$P_t = [\rho_{ij,t}]_{i,j=1,\dots,N}$$

$$\rho_{ij,t} = \rho_{ij1}(1 - G_{ij,t}(s_t;\gamma_{ij},c_{ij})) + \rho_{ij2}G_{ij,t}(s_t;\gamma_{ij},c_{ij}), \qquad i,j = 1,\dots,N \tag{9}$$

where P_t with the (i,j)-th element denoted as $\rho_{ij,t}$, is the possibly time-varying correlation matrix with correlation-specific transition functions. The transition functions are the logistic functions

$$G_{ij,t}\left(s_t;\gamma_{ij},c_{ij}\right) = \frac{1}{1+\exp[-\gamma_{ij}\left(s_t - c_{ij}\right)]}, \quad \gamma_{ij} > 0, \qquad i,j = 1,\dots,N \tag{10}$$

As before, the transition variable is a function of time ($s_t = t/T$), although an extension to multiple transition variables is conceivable. The positive definiteness of P_t at each point in time is guaranteed by constrained maximum likelihood (CML) estimation. If the transition function is common across correlations, then $G_{ij,t}\left(s_t;\gamma_{ij},c_{ij}\right) = G_t\left(s_t;\gamma,c\right)$ and (9) is equivalent to the multivariate STCC with common transition function proposed by Silvennoinen and Teräsvirta (2005). In this case, the correlation matrix is given by

$$P_t = [\rho_{ij,t}]_{i,j=1,\dots,N}$$

[4] In practice, we scale ($t/T - c$) by $\sigma_{t/T}$, the standard deviation of the transition variable t/T, to make

$$\rho_{ij,t}=\rho_{ij1}(1-G_t(s_t;\gamma,c))+\rho_{ij2}G_t(s_t;\gamma,c)\,,\qquad i,j=1,...,N \tag{11}$$

Tests for common transition paths can be implemented as Wald tests. For example, a test for common breaks in the logistic functions of (10) involves a Wald test for the null hypothesis of $H_0{:}c_{ij}=c$ in (9) and (10).

In summary the VGS specification provides an extension of the models proposed by Silvennoinen and Teräsvirta (2005, 2007) and Berben and Jansen (2005) who assume constant mean, GARCH(1,1) variances and normal distribution for the conditional errors. Neglected mean and variance effects may affect the specification for the correlation equation. Allowing for correlation-specific transition functions adds flexibility to the Silvennoinen-Teräsvirta model.

2.2 Estimation

The likelihood function at time t is given by

$$I_t(\theta)=\ln\left[\frac{\Gamma((N+v)/2)}{\Gamma(v/2)(\pi(v-2))^{N/2}}\,|H_t|^{-1/2}\,(1+\frac{1}{v-2}(u'_tH_t^{-1}u_t))^{-(N+v)/2}\right]$$

…

$$=\ln\Gamma(\frac{N+v}{2})-\ln\Gamma(\frac{v}{2})-\frac{N}{2}\ln(\pi(v-2))-\ln|D_t|-0.5\ln|P_t|$$

$$-\frac{N+v}{2}\ln(1+\frac{1}{v-2}(\varepsilon'_tP_t^{-1}\varepsilon_t)) \tag{12}$$

where $\Gamma(.)$ is the gamma function, $D_t=diag(h_{11,t}^{1/2},h_{22,t}^{1/2},...,h_{NN,t}^{1/2})$ is a NxN diagonal matrix of time varying standard deviations from univariate *GJR-GARCH* (1,1) and N is the number of stock returns.

estimates of γ comparable across different sample sizes.

The log-likelihood for the whole sample, $L(\theta)$, is maximized with respect to all parameters of the *VGS* model simultaneously, employing numerical derivatives of the log-likelihood. All computations are carried out in Gauss 6.0.

2.3 Sensitivity

The specification so far makes three important empirical assumptions. The first is that the data are better characterized by a number of constant correlation regimes linked with transition functions than by either a constant conditional correlation (CCC) or a DCC model (Engle, 2002). The constant correlation coefficient is tested against the STCC alternative for each series using the LM_{CCC} test of Silvennoinen and Teräsvirta (2005). The DCC model of Engle (2002) allows correlations to vary over time with the dynamics driven by past correlations

$$q_{ij,t} = \overline{\rho}_{ij}(1-\alpha-\beta) + \alpha\,\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta\, q_{ij,t-1}, \quad i, j = 1,\ldots,N \tag{13}$$

where $\overline{\rho}_{ij}$ is the (assumed constant) unconditional correlation between the standardized residuals $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$, α is the news coefficient and β is the decay coefficient. For comparison with the VGS model the DCC specification is estimated modelling the conditional returns as a VAR(p), the conditional volatilities as GJR-GARCH (1,1) and 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 the implied conditional correlations from each model.

The second assumption concerns the choice of transition variable and a number of alternatives can be considered such as stock market volatility. The final assumption concerns the role of volatility spillovers, which are not included in the simple GJR-GARCH(1,1) framework of the proposed model. A simple criterion to analyze these linkages is the correlation between the estimated variances of two assets

$$\rho_{h_{ii,t}h_{jj,t}} = \frac{\sum_{t=1}^{T}(h_{ii,t}-\overline{h}_{ii})(h_{jj,t}-\overline{h}_{jj})}{\sqrt{\sum_{t=1}^{T}(h_{ii,t}-\overline{h}_{ii})^2 \sum_{t=1}^{T}(h_{jj,t}-\overline{h}_{jj})^2}}, \qquad i,j=1,\ldots,N$$

To the extent that these are non-zero provides evidence of some gain to be obtained from incorporating volatility spillovers into the specification.

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 index) from January 1, 1999 to November 1, 2007, a total of 2305 observations. All prices are denominated in Euros to avoid exchange rate fluctuations; results in local currency denominated indices were similar.[5] The sample contains aggregate market indices and where available 8 industry stock indices: Industrials, basic materials, financials, basic resources, utilities, consumer services, consumer goods and technology. All data are obtained from DataStream.[6]

Descriptive statistics for the returns are presented in Table 1, which shows that the Polish 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 prevalence of zero price movement and discontinuities in the series, most likely indicative of low activity and low liquidity in these indices.

The parameter estimates for the VAR and volatility models in the VGS are very close to those found elsewhere and are omitted in the reported results for brevity. For example, in the GJR-GARCH equations the betas are usually between 0.85 and 0.95,

[5] Bartram, Taylor and Wang (2007) also report non-sensitivity to numeraire currency.

[6] 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.

although in a few cases they range between 0.60-0.80. The estimates also support asymmetry, with negative shocks having stronger effects on volatilities than positive shocks of the same magnitude.

Table 2 shows the bivariate constant conditional correlation (CCC) estimates for the aggregate and sector indices using t-distributed errors. The figures in parentheses in the final column show the increase in log likelihood from t-distributed errors compared with Gaussian errors. This observed improvement in efficiency is consistent with Susmel and Engle (1994). Correlations at the aggregate level are typically higher (above 0.43) than those at the sectoral level (below 0.25). Berben and Jansen (2005) report a similar finding for the developed markets of Germany, Japan, the UK and the US. The implication is that aggregate indices provide fewer diversification opportunities than the sectoral indices. Across sectors, financials appear to be the most correlated sector.

As the three Eastern European countries joined the EU in the first enlargement on May 1, 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 constant conditional correlation 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 rejected for all three markets, with the Czech and Polish cases implying strong rejections. For the sectors, the test rejects in 2 out of 5 cases in Hungary, 4 out of 8 cases in the Czech Republic, and 6 out of 7 sectors in Poland. The LM statistics for the Polish sectors are very high implying strong rejection of the constancy hypothesis.

The constancy results at the sectoral level also demonstrate that it is very difficult to identify a sector or a group of sectors to which the observed correlation change at the aggregate level can be attributed. Financials is the only sector that has changed its correlation in all three markets. In the case of utilities, consumer services and basic materials correlation changed in two out of three markets. The results for utilities contrast with Berben and Jansen (2005) for Japan, the US, the UK and Germany. However, the geographic barriers between these countries are significantly higher than those in the European Union where cross country suppliers exist.

3.1 Market index results

Bivariate models

As many studies of financial market integration in the EU consider bivariate analysis we begin with the equivalent VGS models. Table 4 reports the estimated STCC coefficients from bivariate VGS models where the data rejected the constant conditional correlation model in favour of the STCC specification at the 5% 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.[7] 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 towards the end of the sample. This can be seen clearly in Figure 1(a), which plots the correlations implied by the models. Until early 2006, correlations were all about 0.4, while by early 2007 for the Czech Republic correlations increased to about 0.64 and for Hungary and Poland to 0.72. In general the increase took place within a time span of about one year. Furthermore, for the Czech market the increase was almost instantaneous, while for the other two markets it was more gradual. The stark difference between these patterns seems to relate to the different approaches taken to development – Poland and Hungary initiated change with legal reform and subsequent listing of stocks while the Czech Republic initiated large scale privatization in 1992 which led to many listings, and subsequent delistings; Caviglia, Krause, Thimann (2002), Baltzer, Cappiello, De Santis and Manganelli (2008).[8] In the scheme of things, however, the transition period is rather rapid, the same degree of change from less than 0.4 to around 0.6 stock market correlation occurred for the UK-Germany and US-Germany over a period of some 10 years in Berben and Jansen (2005). Within 3 years of attaining EU membership the correlation of these markets with Europe has reached the same degree as the major international markets. This result is consistent with Kim, Moshirian and Wu (2005) and Batram, Taylor and Wang (2007) who argue that monetary union, or the anticipation thereof, led to stock market integration in the old EU member states.

To explore whether the relatively common pattern in the bivariate results for these markets with the Euro zone is due to global conditions, or even emerging market conditions the bivariate model was also applied to equity market indices for Russia, China and India for the same sample period.[9] Table 5 reports that in the case of India the constant correlation coefficient model is rejected in favour of the STCC

---

[7] Berben and Jansen (2005) use 400, Silvennoinen and Teräsvirta (2005) use 100. Note that when conducting tests on the model, however, we do not impose this value on the function.

[8] A comparison of the early development of these markets may be found in Zsámboki (2002), Ihnat and Prochazka (2002) and Bednarski and Osiński (2002).

[9] The codes for these series are: RSAKMCO(PI) for Russia, CHSCOMP(PI) for China and IBOMBSE(PI) for India.

model, which supports a single transition occuring in early April 2001, much earlier in the sample than the Eastern European data; see Table 6. In the cases of Russia and China the correlation of the market indices with the Euro area stocks is estimated as unchanged over the sample period. This additional evidence supports the Euro area driven nature of the increasing integration of the Eastern European data.

Multivariate model

Table 7 reports a selection of parameter estimates from the VGS model of equations (9) and (10) for the four equity market indices simultaneously. The correlations between the Eastern European and the Euro-zone markets behave similarly to their counterparts in the bivariate models and the estimated transition function parameters coincide with the corresponding estimates from the two bivariate models.

The transition paths of the correlation estimates for the Hungary-Euro, Czech Republic-Euro and Poland-Euro stock pairs are shown in Figure 1(b). Two of the paths look quite similar, while the third, that between the Czech Republic and the EU differs in form with an extended rather than abrupt transition.

A Wald test as to whether the evidence supports that the threshold points of Hungary, the Czech Republic and Poland path towards higher correlation with the Euro-zone are statistically alike is carried out on the appropriate threshold parameters, that is H_0: $c_{\text{Hungary-Euro}} = c_{\text{Czech-Euro}} = c_{\text{Poland\_Euro}}$ for the case of equality in all three threshold parameters involving the Euro. The lower panel of Table 7 reports the resulting test statistics and *p*-values which show that the test of equality in the threshold parameter is rejected for all cases involving the Czech Republic, but that the correlations between Hungary-Euro and Poland-Euro have statistically similar thresholds.

3.2 Industry index results

Bivariate models

The increase in stock market correlation is also supported to a large extent by the analysis at the industry level. From 20 sectoral correlations, 11 increased, 8 remained the same, and 1 decreased. In some cases, increases in correlations are very large. For instance, consumer services in the Hungary-EURO model, and financials and basic resources in the Poland-EURO model are estimated to have tripled their correlations compared with the beginning of the sample. Only consumer services in the Czech-EURO model do not take part in the trend towards greater equity market integration. In fact, the correlation decreases in November 2001.

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, basic materials and utilities in the Czech market show an increase in correlation towards the end of the sample, although at differing speeds; see Figure 2(a). On the other hand, for most sectors in the Polish market the switch was accomplished in the first part of the sample and in some cases it was very rapid (e.g., industrials, utilities, consumer goods); see Figure 2(b). 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.

Multivariate model

The financial sector indices in the Hungarian and Polish models are estimated to have similar transition function parameters. In order to examine whether the threshold estimates in these indices are statistically similar we estimate a four variable VGS model with correlation-specific transition functions for the Hungarian, Czech, Polish and Euro-area financial indices. The estimates are presented in Table 8. As in the bivariate results, there is evidence of increased correlation among the Eastern European financials.

The lower panel of Table 8 reports Wald test statistics and *p*-values for the test of equality in the which show that the test of equality in the threshold parameter in the model. The null of equality is rejected for all cases involving the Czech Republic; however, correlations between Hungary-Euro and Poland-Euro have statistically similar thresholds.

3.3 Non-monotonic correlation patterns

The possibility that the bivariate correlations may include a second transition process is tested using the LM_{STCC} test of Silvennoinen and Teräsvirta (2007). The results reported in Table 9, support a second change in correlation for financials in the Czech market, and for industrials, financials and the market index in the Polish market. For Hungary a second correlation change in the market index is supported at the 10% level (*p*-value is 0.053). These indices are subsequently modelled using a bivariate DSTCC model and the results are reported in Table 10.[10]

A distinctive feature of our results in Table 10 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 Hungarian market experienced a U-curved pattern with an initial slight decline and a subsequent large increase in correlations. Nevertheless, the final time-pattern of

[10] In each case the DSTCC model is also preferred to the CCC model directly.

increase in correlation is similar to that implied by the single transition STCC model in Table 4. On the other hand, the Polish market demonstrated a twice increasing correlation pattern generating a stepwise process. These correlations are shown in Figures 3(a) and (b).

At the industry level, the DSTCC estimates for the Czech and Polish financials sector point to a twice increasing correlation pattern; see Figures 3(c) and (d). The estimates for Polish industrials and basic resources imply a further (abrupt) increase in correlation in February 2007, shown in Figures 3(e) and (f).

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.

4. Sensitivity analysis

Three robustness checks are undertaken in this section. These are: first, a comparison of the bivariate VGS model results with a DCC specification; second, sensitivity to an alternative transition variable; and finally an analysis of the importance of volatility spillovers in the data.

The general upward tendency in correlations shown in the VGS models with STCC or DSTCC specifications is also present in the DCC models, although the DCC model implies correlations that fluctuate frequently as shown in Figures 4 and 5 (see also the figures in Kim, Moshirian and Wu, 2005). [11] For a number of indices the DCC and (D)STCC correlations track quite well; for example the Polish aggregate index (Figure 4(c)), the Czech basic materials and utilities (Figure 5(b) and (c)) and

[11] Full parameter estimates are available from the first author.

the Polish financials and basic resources (Figure 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 11 reports estimates of the persistence of correlations in the DCC model, and in the DCC model with structural breaks in the unconditional correlations occurring at the dates (thresholds) implied by the (D)STCC estimates.[12] The results show that allowing for structural breaks in correlations decreases the persistence of conditional correlations, which is in line with van Dijk, Munandar and Hafner (2005).

The second sensitivity test concerns the choice of transition variable. Previous research has suggested co-movements are stronger during more volatile periods than during periods of tranquility (King and Wadhwini, 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 50 volatility index (VSTOXX) as the transition variable. The VSTOXX represents the Euro market expectations of near-term volatility and is based on DJ EURO STOXX 50 option prices sourced from DataStream. As before, we perform the constancy test of Silvennoinen and Teräsvirta (2005). The results show that the 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 0.031 and 0.040, respectively). In sum, it seems that although considering a correlation model governed by volatility may be worthwhile, the time transition (D)STCC model is sufficiently flexible to capture the dominant trends in correlations.

---

[12] 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

Finally, we examine possible volatility linkages (spillovers in volatilities). The conditional variances are found to be moderately correlated with an average correlation of 0.210. 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 0.364, while the corresponding figure at the industry level is 0.187. Hence, we conclude that while at the aggregate level there is some scope for generalizing the GJR-GARCH(1,1) processes to allow for spillovers in volatilities, in most cases this model captures the dynamics in volatilities quite adequately.

In summary, the results of the empirical analysis strongly support that the market equity indices of Hungary, Poland and the Czech Republic have become more correlated with a European equity index since the enlargement of the EU. Further, the transition to higher correlation happened relatively quickly, not immediately after the Accession of these countries to the EU but before full membership of the EMU. As in Bartram, Taylor and Wang (2007) this infers a level of credibility to the claims of these countries to successful EMU membership.

At an industry level, the equity market indices are far less correlated, with the possible exception of the financials index, suggesting that new member country equity indices will provide fewer portfolio diversification benefits than industry level indices following EU accession. The finding reinforces those of Flavin (2004) using firm level data and Moerman (2008) using European data.

6. Conclusions

Modelling change in financial markets requires a model which accounts for both changing correlation structures and the characteristics of the data in a multivariate

---

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, Munandar and Hafner (2005).

framework. The framework developed in this paper nests a smooth transition conditional correlation model, capable of accommodating both rapid and gradual change, within a VAR. It includes GJR-GARCH(1,1) effects and t-distributed errors to account for fat tails and asymmetric volatility clustering. The model generalizes a number of existing approaches by incorporating asymmetric GARCH effects, non-normal error distributions, multiple assets in a simultaneous framework, and endogenizing the change in correlation structure.

The framework is used to assess evidence for increasing financial integration between the Eastern European equity markets of the Czech Republic, Hungary and Poland with the EU, in the period following the introduction of the Euro in January 1999 through to November 2007. These countries joined the EU in May 2004 and are the largest by GDP and equity market of the Accession countries. Using equity market indices the results demonstrate that each Eastern European equity market index increased its correlation with the Euro area in 2006. However, while the transition paths of Hungary and Poland are more gradual and statistically similar, the Czech Republic has an abrupt transition. This is consistent with the rate of change in the microstructure of these markets, where the Hungarian and Polish reforms began with a legal basis and progressed more slowly compared with the Czech market which provided a fast, and not always successful, route via mass privatisation.

References

Ang A. and G. Bekaert (2002), International asset allocation with regime shifts, *Review of Financial Studies* **15,** 1137-1187.

Ang A. and J. Chen (2002), Asymmetric correlations of equity portfolios, *Journal of Financial Economics* **63,** 443-494.

Baele L. (2005), Volatility spillover effects in European equity markets, *Journal of Financial and Quantitative Analysis* **40**, 373-401.

Baltzer M., L. Cappiello, R.A. De Santis and S. Manganelli (2008), Measuring financial integration in new EU member states, Occasional Paper Series No. 81, ECB.

Bartram S., S. Taylor and Y. Wang (2007), The Euro and European financial market dependence, *Journal of Banking and Finance* **31,** 1461-1481.

Bednarski P. and J. Osiński (2002), Financial sector in Poland, in C.Thimman (ed), Financial Sectors in EU Accession Countries, July 2002, ECB, pp.171-188.

Berben R.P. and W.J. Jansen (2005), Comovement in international equity markets: A sectoral view, *Journal of International Money and Finance* **24**, 832-857.

Butler K.C. and D.C. Joaquin (2002), Are the gains from international portfolio diversification exaggerated? The influence of downside risk in bear markets, *Journal of International Money and Finance* **21,** 981-1011.

Cappiello L., B. Gérard, A. Kadareja and S. Manganelli (2006), Financial integration of new EU member states. Working Paper Series No. 683, ECB.

Caviglia G., G. Krause and C. Thimann (2002), Key features of the financial sectors in EU accession countries, in C.Thimman (ed), Financial Sectors in EU Accession Countries, July 2002, 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* **24**, 818-831.

Égert B. and E. Kočenda (2007), Time-varying comovements in developed and emerging European stock markets: Evidence from intraday data. William Davidson Institute Working Paper Series No. 861, University of Michigan.

Engle R. (2002), Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, *Journal of Business and Economic Statistics* **20,** 339-350.

Fidrmuc J. and I. Korhonen (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* **34,** 518-537.

Flavin T. (2004), The effect of the Euro on country versus industry portfolio diversification, *Journal of International Money and Finance* **23,** 1137-1158.

Forbes K. and R. Rigobon (2002), No contagion, only interdependence: Measuring stock market co-movements, *Journal of Finance* **57,** 2223-2261.

Fratzscher M. (2002), Financial market integration in Europe: On the effects of EMU on stock markets, *International Journal of Finance and Economics* **7,** 165-193.

Guiso L., T. Jappelli, M. Padula and M. Pagano (2004), Financial market integration and economic growth in the EU, *Economic Policy* **19,** 523-577.

Hardouvelis A., D. Malliaropulos and R. Priestley (2006), EMU and european stock market integration, *Journal of Business* **79,** 365-392.

Ihnat P. and P. Prochazka (2002), The financial sector in Czech Republic: An assessment of its current state of development and functioning, in C.Thimman (ed), Financial Sectors in EU Accession Countries, July 2002, ECB, pp. 67-84.

Kim S.J., F. Moshirian and E. Wu (2005), Dynamic stock market integration driven by the European Monetary Union: An empirical analysis, *Journal of Banking and Finance* **29,** 2475-2502.

King M. and Wadhwani S. (1990), Transmission of volatility between stock markets, *Review of Financial Studies* **3,** 5-33.

Longin F. and B. Solnik (1995), Is the correlation in international equity returns constant:1960-1990?, *Journal of International Money and Finance* **14,** 3-26.

Longin F. and B. Solnik (2001), Extreme correlation and international equity markets, *Journal of Finance* **56**, 649-676.

Moerman G.A. (2009), Diversification in euro area stock markets: Country vs. industry, *Journal of International Money and Finance*, forthcoming.

Morana C. and A. Beltratti (2002), The effects of the introduction of the Euro on the volatility of European stock markets, *Journal of Banking and Finance* **26,** 2047-2064.

Patton A. (2004), On the out-of-sample importance of skewness and asymmetric dependence for asset allocation', *Journal of Financial Econometrics* **2,** 130-168.

Ramchand L. and R. Susmel (1998), Volatility and cross correlation across major stock markets, *Journal of Empirical Finance* **5**, 397-416.

Rigobon R. (2002), The curse of non-investment grade countries, *Journal of Development Economics* **69,** 423-449.

Savva C.S., D.R. Osborn L. Gill (2009), Spillovers and correlations between U.S. and major European stock markets: The role of the Euro, *Applied Financial Economics*, forthcoming.

Silvennoinen, A. and T. Teräsvirta (2005), Multivariate autoregressive conditional heteroskedasticity with smooth transitions in conditional correlations. Working Paper Series in Economics and Finance No. 577, SSE/EFI.

Silvennoinen A. and T. Teräsvirta (2007) Modelling multivariate conditional heteroskedasticity with the double smooth transition conditional correlation GARCH model. Working Paper Series in Economics and Finance No. 652, SSE/EFI.

Susmel R. and R.F. Engle (1994), Hourly volatility spillovers between international equity markets, *Journal of International Money and Finance* **13,** 3-25.

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

Zsámboki B. (2002), The financial sector in Hungary, in C.Thimman (ed), Financial Sectors in EU Accession Countries, July 2002, ECB.

Table 1: Summary statistics of the stock returns 1999-2007

	min	max	mean	st.dev	skewness	kurtosis
Hungary						
Market Index	-7.528	7.161	0.058	1.528	-0.180	4.584
Basic Materials	-7.588	8.104	0.043	1.727	0.200	5.513
Financials	-11.35	10.62	0.089	2.024	0.005	4.718
Utilities	-7.796	7.290	0.007	1.523	-0.040	5.628
Consumer Services	-9.333	8.515	0.052	1.927	-0.052	4.687
Consumer Goods	-27.44	27.76	0.021	2.519	-0.033	21.06
Czech Republic						
Market Index	-6.558	7.154	0.080	1.287	-0.262	5.254
Industrials	-2.481	2.153	0.008	0.557	-0.235	7.801
Basic Materials	-7.621	6.730	0.111	1.487	-0.308	7.118
Financials	-7.991	7.598	0.111	1.604	-0.148	5.393
Basic Resources	-5.105	4.463	0.037	1.246	-0.037	5.740
Utilities	-7.163	6.586	0.127	1.383	-0.161	5.342
Consumer Services	-8.648	7.070	0.025	1.890	-0.053	5.388
Consumer Goods	-5.588	4.932	-0.006	0.741	-0.884	20.17
Technology	-9.687	6.139	-0.067	0.874	-3.126	35.86
Poland						
Market Index	-7.156	8.114	0.077	1.533	-0.161	4.898
Industrials	-8.784	7.434	0.067	1.668	-0.207	5.106
Basic Materials	-8.815	7.213	0.089	1.736	-0.403	5.000
Financials	-8.093	8.221	0.074	1.526	-0.109	4.955
Basic Resources	-10.20	9.273	0.129	2.052	-0.178	4.936
Utilities	-8.463	10.13	0.040	1.886	0.034	5.031
Consumer Services	-7.302	7.766	0.054	1.527	-0.121	5.470
Consumer Goods	-11.41	10.34	0.015	2.329	0.027	5.664
EURO						
Market Index	-5.751	6.152	0.017	1.241	-0.082	5.587
Industrials	-5.654	5.368	0.034	1.149	-0.161	4.953
Basic Materials	-6.229	6.666	0.030	1.267	-0.047	5.742
Financials	-6.340	5.686	-0.004	1.312	-0.365	6.222
Basic Resources	-6.380	7.949	0.050	1.477	0.077	5.220
Utilities	-5.137	5.422	0.025	1.102	-0.048	5.418
Consumer Services	-5.400	6.134	-0.008	1.258	-0.131	5.808
Consumer Goods	-5.449	6.007	0.013	1.165	-0.141	5.033
Technology	-9.162	11.22	0.012	2.290	0.079	5.252

Notes: Source is DataStream.

Table 2: Bivariate CCC-GJRGARCH-*t* models

	ρ	v	*Log-Like*
Hungary-EURO			
Market Index	0.437	9.053	-7239.9 (65.8)
	(0.018)	(1.050)	
Basic Materials	0.179	6.336	-7807.1 (114.6)
	(0.022)	(0.581)	
Financials	0.324	8.574	-8072.5 (69.8)
	(0.020)	(0.972)	
Utilities	0.110	5.871	-7213.7 (116.2)
	(0.022)	(0.547)	
Consumer Services	0.169	8.487	-7975.8 (73.3)
	(0.021)	(0.957)	
Consumer Goods	0.143	4.537	-8243 (204.1)
	(0.022)	(0.405)	
Czech Republic-EURO			
Market Index	0.437	9.476	-6766.5 (61.4)
	(0.018)	(1.131)	
Industrials	0.043	4.344	-4676.8 (256.2)
	(0.023)	(0.297)	
Basic Materials	0.152	5.728	-7347.9 (153)
	(0.022)	(0.480)	
Financials	0.270	7.592	-7533 (85.2)
	(0.022)	(0.819)	
Basic Resources	0.052	3.560	-7364.4 (233.7)
	(0.023)	(0.232)	
Utilities	0.240	8.362	-6965.8 (64.3)
	(0.021)	(0.956)	
Consumer Services	0.217	5.427	-7424.7 (216.9)
	(0.021)	(0.421)	
Consumer Goods	0.115	5.413	-4899.9 (274)
	(0.022)	(0.437)	
Technology	0.105	4.080	-6047.9 (514.9)
	(0.023)	(0.262)	
Poland-EURO			
Market Index	0.461	9.717	-7162.3 (54.8)
	(0.017)	(1.209)	
Industrials	0.258	7.213	-7584.1 (96.1)
	(0.021)	(0.713)	
Basic Materials	0.326	7.363	-7786.2 (95.4)
	(0.020)	(0.735)	
Financials	0.377	7.790	-7346.9 (84)
	(0.019)	(0.816)	
Basic Resources	0.300	7.245	-8636 (87.2)
	(0.020)	(0.729)	
Utilities	0.245	10.14	-7695.1 (49)
	(0.020)	(1.293)	
Consumer Services	0.259	8.711	-7237.2 (62.8)
	(0.021)	(0.996)	
Consumer Goods	0.363	10.33	-8080.3 (41.7)
	(0.019)	(1.398)	

Notes: The table presents maximum likelihood estimates of part of the parameters of bivariate CCC-GJRGARCH-*t* models; remaining parameter estimates are available upon request; values in parentheses are standard errors; *Log-Like* is the obtained log-likelihood and value in parenthesis is the increase in the log-likelihood compared to the Gaussian bivariate CCC-GJRGARCH model.

Table 3: Tests of CCC- against STCC

	LM_{CCC}	p-value
Hungary-EURO		
Market Index	4.836	0.027*
Basic Materials	1.817	0.177
Financials	13.97	0.000**
Utilities	0.451	0.501
Consumer Services	12.63	0.000**
Consumer Goods	0.118	0.730
Czech Republic-EURO		
Market Index	21.34	0.000**
Industrials	0.406	0.523
Basic Materials	4.564	0.032*
Financials	10.22	0.001**
Basic Resources	0.503	0.477
Utilities	7.726	0.005**
Consumer Services	4.059	0.043*
Consumer Goods	0.547	0.459
Technology	0.136	0.711
Poland-EURO		
Market Index	30.72	0.000**
Industrials	16.29	0.000**
Basic Materials	47.58	0.000**
Financials	37.17	0.000**
Basic Resources	51.16	0.000**
Utilities	5.602	0.017*
Consumer Services	0.335	0.562
Consumer Goods	14.02	0.000**

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

Table 4: Bivariate VGS model for Eastern European stocks:
based on a STCC-GJRGARCH(1,1) model with t-distributed errors

	ρ_1	ρ_2	γ	c	v	Date	*Log-Like*
Hungary-EURO							
Market Index	0.400	0.712	12.29	0.877	9.147	02 Oct 06	-7221.6 (64.9)
	(0.020)	(0.054)	(6.816)	[0.828, 0.926]	(1.063)		
Financials	0.281	0.676	11.96	0.893	8.882	22 Nov 06	-8052.9 (64.4)
	(0.023)	(0.066)	(7.643)	[0.855, 0.930]	(1.035)		
Consumer Services	0.118	0.890	5.892	0.931	8.830	26 Mar 07	-7950.7 (66)
	(0.024)	(0.402)	(3.426)	[0.807, 1.054]	(1.029)		
Czech Republic-EURO							
Market Index	0.394	0.640	120.7	0.814	9.996	13 Mar 06	-6748.2 (54)
	(0.020)	(0.028)	(244.1)	[0.786, 0.841]	(1.253)		
Basic Materials	0.112	0.326	39.55	0.813	5.740	09 Mar 06	-7340.9 (149.3)
	(0.026)	(0.050)	(52.50)	[0.736, 0.889]	(0.483)		
Financials	0.239	0.298	264.6	0.450	7.633	24 Dec 02	-7531.9 (81.9)
	(0.032)	(0.031)	(5656)	[0.375, 0.524]	(0.835)		
Utilities	0.203	0.427	12.36	0.847	8.552	27 Jun 06	-6958.8 (60.8)
	(0.024)	(0.077)	(12.60)	[0.737, 0.956]	(0.996)		
Consumer Services	0.350	0.140	500	0.324	5.427	13 Nov 01	-7413.3 (219.2)
	(0.032)	(0.028)		[0.310, 0.337]	(0.420)		
Poland-EURO							
Market Index	0.428	0.737	14.48	0.891	9.893	15 Nov 06	-7143.3 (52)
	(0.019)	(0.046)	(9.224)	[0.855, 0.926]	(1.257)		
Industrials	0.231	0.539	500	0.917	7.306	07 Feb 07	-7573.6 (100.4)
	(0.023)	(0.053)		[0.897, 0.936]	(0.758)		
Basic Materials	0.148	0.408	37.49	0.293	7.590	06 Aug 01	-7768.5 (88.5)
	(0.041)	(0.023)	(61.90)	[0.261, 0.324]	(0.778)		
Financials	0.344	0.597	18.21	0.876	7.859	28 Sep 06	-7336.2 (76.5)
	(0.022)	(0.046)	(22.09)	[0.827, 0.925]	(0.829)		
Basic Resources	0.074	0.394	5.804	0.282	7.525	29 Jun 01	-8616.9 (80.2)
	(0.061)	(0.026)	(4.073)	[0.195, 0.368]	(0.783)		
Utilities	0.188	0.287	500	0.381	10.40	15 May 02	-7692.2 (46.4)
	(0.032)	(0.026)		[0.357, 0.404]	(1.363)		
Consumer Goods	0.216	0.406	500	0.208	10.89	03 Nov 00	-8071.8 (36.2)
	(0.043)	(0.021)		[0.194, 0.221]	(1.559)		

Notes: The table presents maximum likelihood estimates of part of the parameters of bivariate 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 and value in parenthesis is the increase in the log-likelihood compared to the Gaussian bivariate STCC-GJRGARCH model; values in square brackets below the threshold form its 95% confidence interval; 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.

Table 5: CCC models for Indian, Russian and Chinese equity indices

	CCC-GJRGARCH-t models			Test of CCC against STCC
	ρ	V	*Log Like*	LM_{CCC}
India-EURO				
Market Index	0.294 (0.021)	9.827 (1.221)	-7456.7	25.549 (0.000)**
Russia-EURO				
Market Index	0.352 (0.020)	7.477 (0.809)	-7919.1	1.623 (0.203)
China-EURO				
Market Index	0.051 (0.022)	8.659 (1.037)	7400.1	1.061 (0.303)

Notes: Numbers below parameter estimates in parentheses are standard errors. LM_{CCC} is the Lagrange Multiplier statistic for constant correlations, numbers in parentheses below the estimated test-statistics in the final column are p-values; ** denote significance at the 1% level.

Table 6: Bivariate VGS model for Indian market index based on a STCC-GJRGARCH(1,1) model with t-distributed errors

	ρ_1	ρ_2	γ	c	v	Date
India-EURO						
Market Index	0.068	0.394	2.351	0.256	10.178	06 Apr 01
	(0.228)	(0.056)	(3.375)	[-0.104, 0.616]	(1.303)	

Notes: See notes to Table 4.

Table 7: Four variable VGS model for market indices of the Czech Republic, Hungary, Poland and the Euro Area:

based on STCC with correlation-specific transition functions given in equations (9) and (10) estimated with an GJRGARCH(1,1) and t-distributed errors.

	ρ_{ij1}	ρ_{ij2}	γ_{ij}	c_{ij}	Date
Hungary-Cz. Rep.	0.383	0.621	500	0.695	22 Feb 05
	(0.022)	(0.022)		[0.691, 0.698]	
Hungary-Poland	0.422	0.686	27.77	0.664	12 Nov 04
	(0.023)	(0.019)	(31.52)	[0.638, 0.689]	
Hungary-Euro	0.397	0.720	10.39	0.873	19 Sep 06
	(0.021)	(0.050)	(6.349)	[0.835, 0.910]	
Cz Rep-Poland	0.341	0.619	500	0.700	09 Mar 05
	(0.023)	(0.022)		[0.692, 0.707]	
Cz Rep- Euro	0.392	0.635	215.9	0.811	02 Mar 06
	(0.020)	(0.028)	(698.2)	[0.803, 0.818]	
Poland – Euro	0.435	0.741	11.97	0.889	09 Nov 06
	(0.020)	(0.052)	(8.596)	[0.853, 0.924]	
v	10.14				
	(0.877)				
Log Like	-13996				

Wald tests for equal threshold parameters:

	Wald statistic	*p*-value
Correlations of:		
Hungary-Euro, Czech-Euro and Poland-Euro	21.22	0.000**
Hungary-Euro and Czech-Euro	9.418	0.002**
Hungary-Euro and Poland-Euro	0.418	0.517
Czech-Euro and Poland-Euro	16.51	0.000**

Notes: See notes to Table 4.

Table 8: Four variable VGS model for financial market indices of the Czech Republic, Hungary, Poland and the Euro Area:

based on STCC with correlation-specific transition functions given in equations (9) and (10) estimated with an GJRGARCH(1,1) and t-distributed errors.

	ρ_{ij1}	ρ_{ij2}	γ_{ij}	c_{ij}	Date
Hungary-Cz. Rep.	0.274	0.396	500	0.676	22 Dec 04
	(0.025)	(0.030)		[0.668, 0.683]	
Hungary-Poland	0.337	0.535	500	0.695	22 Feb 05
	(0.023)	(0.027)		[0.691, 0.698]	
Hungary-Euro	0.281	0.653	40.97	0.896	01 Dec 06
	(0.022)	(0.064)	(18.69)	[0.856, 0.935]	
Cz Rep-Poland	0.219	0.399	500	0.551	14 Nov 03
	(0.027)	(0.027)		[0.547, 0.554]	
Cz Rep- Euro	0.255	0.324	500	0.671	06 Dec 04
	(0.023)	(0.031)		[0.667, 0.674]	
Poland - Euro	0.346	0.563	421.89	0.871	12 Sep 06
	(0.021)	(0.038)	(418.60)	[0.851, 0.890]	
v	8.066				
	(0.588)				
Log Like	-15824				

Wald tests for equal threshold parameters:

	Wald statistic	*p*-value
Correlations of:		
Hungary-Euro, Czech-Euro and Poland-Euro	435.29	0.000**
Hungary-Euro and Czech-Euro	120.01	0.000**
Hungary-Euro and Poland-Euro	1.355	0.244
Czech-Euro and Poland-Euro	374.11	0.000**

Notes: See notes to Table 4.

Table 9: Tests of STCC- against DSTCC

	LM_{STCC}	p-value
Hungary-EURO		
Market Index	3.719	0.053
Financials	0.071	0.789
Consumer Services	1.515	0.218
Czech Republic-EURO		
Market Index	0.040	0.840
Basic Materials	1.546	0.213
Financials	24.12	0.000**
Utilities	0.265	0.606
Poland-EURO		
Market Index	7.068	0.007**
Industrials	4.505	0.033*
Basic Materials	2.639	0.104
Financials	28.67	0.000**
Basic Resources	3.513	0.060
Utilities	0.643	0.422
Consumer Goods	0.003	0.952

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

Table 10: Bivariate VGS models based on a DSTCC-GJRGARCH(1,1) model with t-distributed errors.

	ρ_1	ρ_2	ρ_3	γ_1	γ_2	c_1	c_2	v	Date1	Date2	*Log-Like*
Hungary-EURO											
Market Index	0.482	0.069	0.773	1.444	9.964	0.722	0.838	9.067	19 May 05	29 May 06	-7216.4 (66.3)
	(0.105)	(1.535)	(0.620)	(3.595)	(6.435)	[-0.022, 1.466]	[0.738, 0.937]	(1.036)			
Cz. Rep-EURO											
Financials	0.200	0.290	0.366	500	500	0.307	0.881	7.654	19 Sep 01	13 Oct 06	-7529.6 (82.9)
	(0.037)	(0.027)	(0.055)			[0.303, 0.310]	[0.879, 0.882]	(0.790)			
Poland-EURO											
Market Index	0.343	0.454	0.736	500	16.17	0.169	0.895	10.03	30 Jun 00	29 Nov 06	-7140.4 (51.3)
	(0.042)	(0.021)	(0.044)		(10.80)	[0.157, 0.180]	[0.859, 0.930]	(1.288)			
Industrials	0.184	0.249	0.539	500	500	0.214	0.917	7.355	23 Nov 00	07 Feb 07	-7572.7 (90.9)
	(0.043)	(0.026)	(0.050)			[0.210, 0.217]	[0.915, 0.918]	(0.739)			
Financials	0.252	0.399	0.605	4.857	386.1	0.303	0.900	7.910	06 Sep 01	14 Dec 06	-7331.8 (76.3)
	(0.053)	(0.034)	(0.041)	(5.144)	(747.4)	[0.050, 0.555]	[0.880, 0.919]	(0.846)			
Basic Resources	0.103	0.360	0.569	7.567	500	0.279	0.917	7.544	20 Jun 01	07 Feb 07	-8630.8 (59.1)
	(0.055)	(0.027)	(0.046)	(6.378)		[0.186, 0.371]	[0.915, 0.918]	(0.784)			

Notes: The table presents maximum likelihood estimates of part of the parameters of bivariate DSTCC-GJRGARCH-*t* models; remaining parameter estimates are available upon request; 'Date1' is the day that corresponds to c_1 (threshold 1) and 'Date2' is the day that corresponds to c_2 (threshold 2); values in parentheses are standard errors; *Log-Like* is the obtained log-likelihood and value in parenthesis is the increase in the log-likelihood compared to the Gaussian bivariate DSTCC-GJRGARCH model; values in brackets below the threshold form its 95% confidence interval; 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.

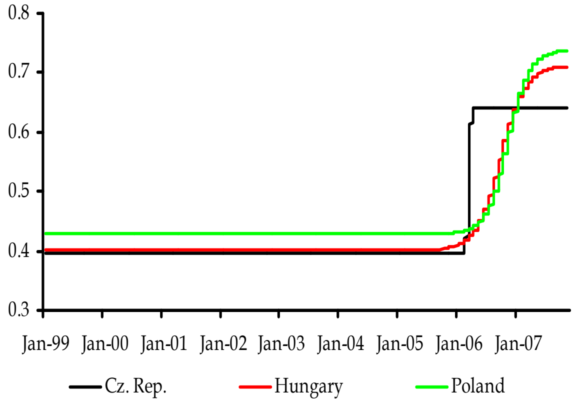
Table 11: Persistence of DCC-*t* correlations

	DCC-t	*SB-DCC-t*
Hungary-EURO		
Market Index	0.963	0.951
Financials	0.947	0.904
Consumer Services	1.000	0.972
Czech Republic-EURO		
Market Index	0.977	0.772
Basic Materials	0.995	0.623
Financials	0.549	0.035
Utilities	0.990	0.980
Consumer Services	0.990	0.970
Poland-EURO		
Market Index	0.995	0.912
Industrials	0.916	0.658
Basic Materials	0.986	0.954
Financials	0.996	0.819
Basic Resources	0.999	0.972
Utilities	0.992	0.850
Consumer Goods	0.994	0.990

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.

Figure 1: Time-varying (STCC) correlations for market indices for the Czech Republic, Hungary and Poland with Euro STOXX index estimated from VGS models

(a) Bivariate Estimates



(b) Multivariate Estimates

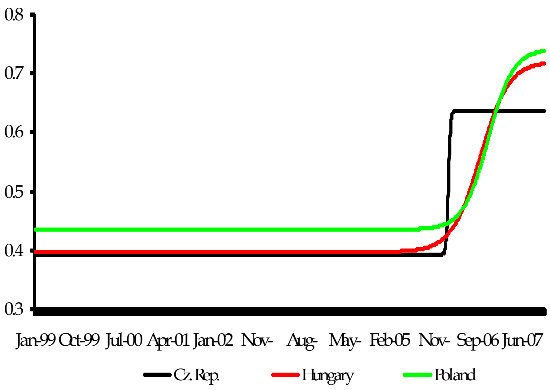
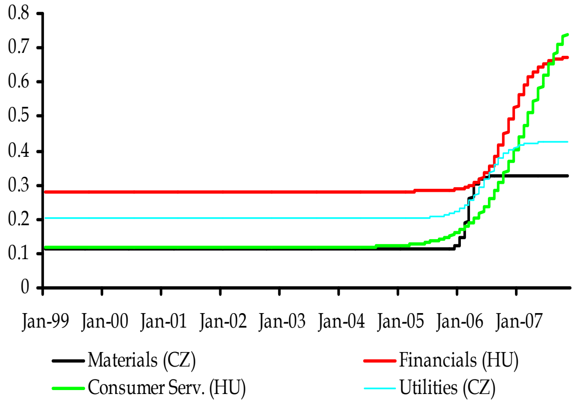


Figure 2: Time-varying (STCC) correlations for industry indices for the Czech Republic, Hungary and Poland with Euro STOXX index from bivariate VGS models

(a) Czech Republic and Hungarian Sectors



(b) Polish Sectors

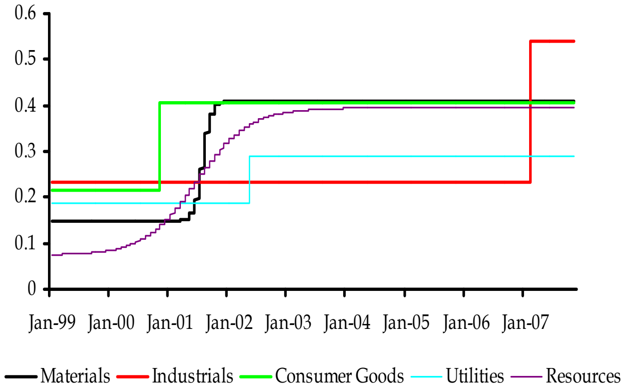
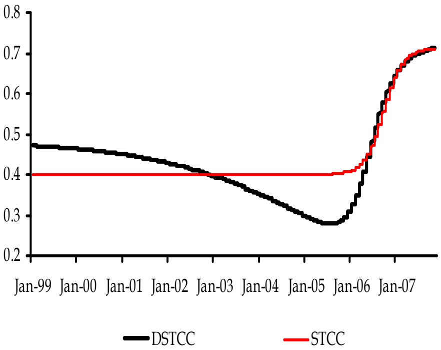
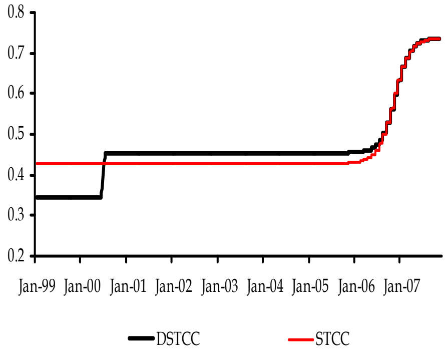


Figure 3: Time-varying (STCC and DSTCC) for various equity market indices with Euro STOXX index from bivariate VGS models

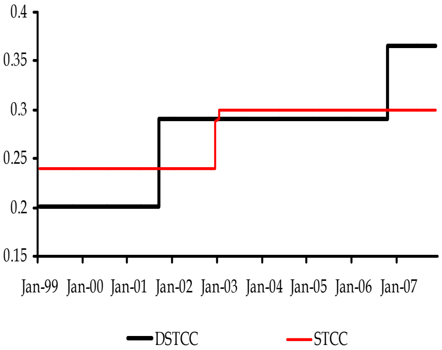
(a) Hungary: Market Index



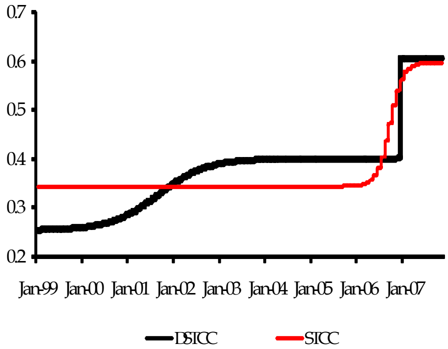
(b) Poland: Market Index



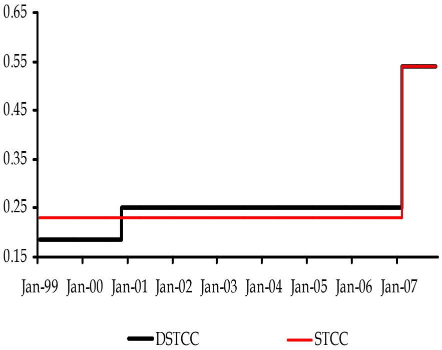
(c) Czech Republic: Financials



(d) Poland: Financials



(e) Poland: Industrials



(f) Poland: Basic Resources

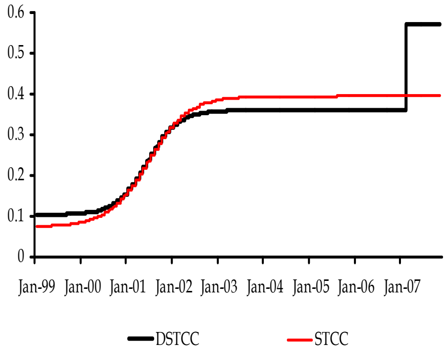
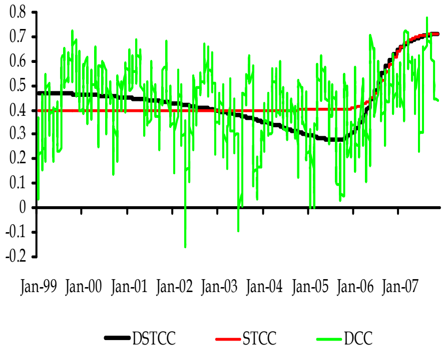
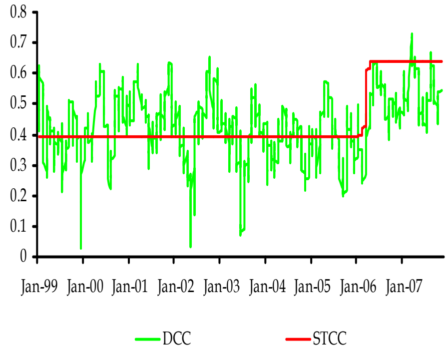


Figure 4: Time-varying correlations for market indices for the Czech Republic, Hungary and Poland with the Euro STOXX index estimated with bivariate STCC or DSTCC versions of the VGS model and DCC.

(a) Hungary: Market Index



(b) Czech Republic: Market Index



(c) Poland: Market Index

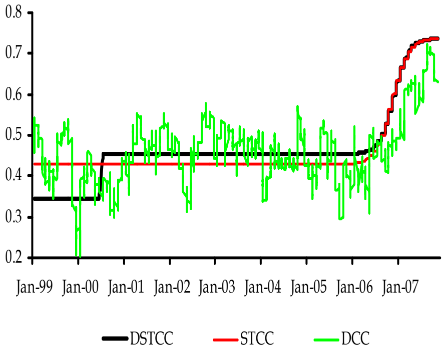
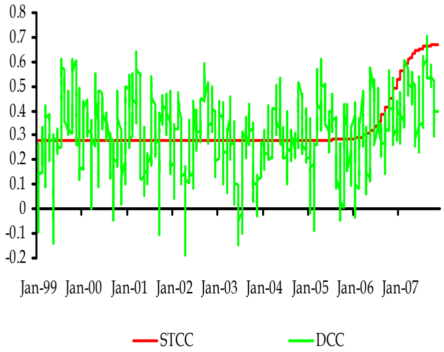
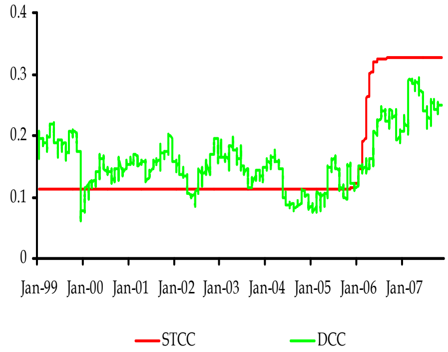


Figure 5: Time-varying (STCC) correlations for industry indices for the Czech Republic, Hungary and Poland with the Euro STOXX index estimated with bivariate STCC or DSTCC versions of the VGS model and the DCC model

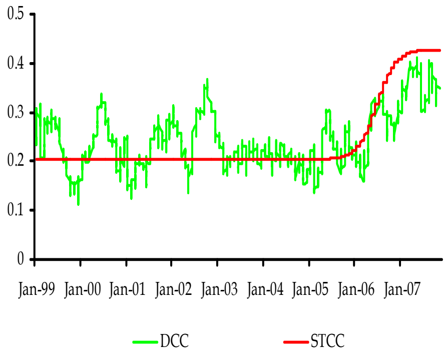
(a) Hungary: Financials



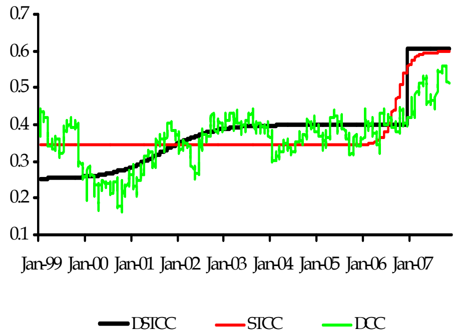
(b) Czech Republic: Materials



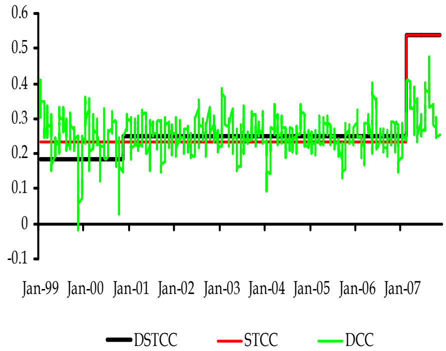
(c) Czech Republic: Utilities



(d) Poland: Financials



(e) Poland: Industrials



(f) Poland: Basic Resources