Are there still portfolio diversification benefits in Eastern Europe? Aggregate versus sectoral stock market data

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Abstract

The advent of the European Union has decreased the diversification benefits available from country based equity market indices in the region. This paper measures the increase in stock integration between the three largest new EU members (Hungary, the Czech Republic and Poland who joined in May 2004) and the Euro-zone. We allow for a potentially gradual change in correlation between stock markets, which seems particularly appropriate to analyse the increasing integration between the Eastern European and the Euro-zone stock markets over the recent years. 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.

JEL classifications: C32; C51; F36; G15

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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, Taylor and Wang (2007) find changes in the relationships for the larger countries in EMU, while Kim, Moshirian and Wu (2005) support greater integration, and greater stability, across a wide range of EMU equity markets.[1] The evidence of 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 from May 1, 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, Gérard, Kadareja and Manganelli (2006), Égert and Kočenda (2007) and Savva and Aslanidis (forthcoming).

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

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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, Jappelli, Padula and Pagano (2004), Hardouvelis, Malliaropulos and Priestley (2006) and Savva, Osborn and Gill (forthcoming).

[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. It is worth noting that higher correlation alone is not a sufficient condition for greater market integration; however it is a very good indication.

(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 is 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.

To capture time-varying correlations in the stock markets we adopt the recently developed smooth transition conditional correlation (STCC) and double STCC models (Silvennoinen and Teräsvirta, 2005, 2007, and Berben and Jansen, 2005). 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 integration between the Eastern European and the Euro-zone stock markets over the recent years.

Our paper is compared to the literature on Eastern European equity market integration in the following way. In our model, where the unconditional correlation is allowed to change over time, we find progress towards financial integration with the EMU amongst the 3 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, Gérard, Kadareja and Manganelli (2006) find mixed evidence for increased integration, finding none for Hungarian

[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.

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 very little evidence of stock market integration for these countries using cointegration, VAR and Granger causality techniques. Instead, the long-run dynamics of financial integration may be better captured by our model where stock market correlations are allowed to change smoothly over time.

It finally extends the work of Savva and Aslanidis (forthcoming) in the following three ways. Firstly, using sectoral market indices in addition to the market aggregate it addresses whether there are still portfolio diversification benefits in Eastern Europe. Secondly, it extends the methodology for the conditional mean (VAR), conditional variance (GJRGARCH) and considers a bivariate student-*t* distribution for the errors. Finally, it employs higher frequency data (daily data instead of weekly). Weekly data interval may be too long for stock prices in relation to market efficiency arguments that suggest news is quickly incorporated into stock prices.

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 confined to a sector (or group of sectors), but 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 organised as follows. Section 2 presents the smooth transition conditional correlation methodology. Section 3 discusses the data and presents the results. In Section 4, we perform robustness checks to validate our results. Finally, Section 6 concludes.

2. Modelling stock market correlations

We review in this section the methodology proposed by Silvennoinen and Teräsvirta (2005, 2007) and Berben and Jansen (2005) and considered in Savva and Aslanidis (forthcoming). We first assume that the mean equation for the two-dimensional vector of stock returns is modelled as a VAR(1) model. Then, each conditional variance is assumed to follow a univariate GJRGARCH(1,1) process. 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 smooth transition conditional correlation (STCC) specification proposed in Silvennoinen and Teräsvirta (2005) and Berben and Jansen (2005).[5] 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

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

The function $G_t(s_t;\gamma,c) = \left(1+\exp(-\gamma(s_t - c))\right)^{-1}$ 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 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 constant conditional correlation (CCC) model (Bollerslev, 1990), whereas the alternative model is a 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 (2007). Under the null hypothesis a single STCC (one change in correlations) is adequate whereas the alternative supports a double STCC (two changes in correlations). If evidence of a

[5] 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.

second change in correlations is found, then we estimate the double smooth transition conditional correlation (DSTCC) given by the following equation

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

The second transition variable is also a function of time ($s_t = t/T$), and hence (2) allows the possibility of a non-monotonic change in correlation over the sample. This is a special case of Silvennoinen and Teräsvirta (2007) 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-*t* distribution. In particular, the likelihood function at time *t* is given by

$$I_t(\theta) = \ln\Gamma(\frac{2+v}{2}) - \ln\Gamma(\frac{v}{2}) - \ln(\pi(v-2)) - \ln|D_t| - 0.5\ln|R_t|$$

$$-\frac{2+v}{2}\ln(1+\frac{1}{v-2}(\varepsilon'_t R_t^{-1}\varepsilon_t)) \quad (3)$$

where v is the number of degrees of freedom, $\Gamma(.)$ is the gamma function, $D_t = diag(h_{11,t}^{1/2}, h_{22,t}^{1/2})$ is a $2x2$ 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, employing numerical derivatives of the log-likelihood.[6]

3. Empirical results

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

The data set consists of daily returns on stock indices for Hungary, Czech Republic, Poland and the Euro-area (using the Euro STOXX index[7]) from January 1, 1999 to November 1, 2007, a total of 2305 observations. All prices are denominated in euros.[8] The sample contains the 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.[9] 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 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.[10] For example, in the GJRGARCH equations the betas are usually between 0.85 and 0.95, although in a few cases they range between 0.60-0.80. 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 constant conditional correlation (CCC) estimates for the aggregate and sector indices.[11] As seen, correlations at the aggregate level are higher

[7] Results with respect to the DAX were qualitatively similar to those presented here.
[8] Estimates using data denominated in local currencies have also been performed with the results remaining qualitatively the same.
[9] 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.
[10] The appropriate order, p was determined using the Schwartz Information Criterion.
[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

than those at the sectoral level. Typically, aggregate correlations are above 0.43, 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 US using aggregate as well as sectoral data during the 1980s and 1990s. Across sectors, financials appear to be the most correlated sector.

As these three 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 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 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

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maximal value of the likelihood function from Normal to *t*-distribution is statistically significant. Consequently the tables report estimates using *t*-distributed errors and the increase in the log-likelihood 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 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 European Union to utilities integration is significantly lower than across Japan, the US, the UK and Germany and this may be a contributing factor. Industrials, basic resources, consumer goods and technology shares only played a limited role in the change in aggregate correlations.

Table 4 reports the estimated STCC for the models that 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.[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 towards the end of the sample. This can be seen clearly in Figure 2(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. So, the increase was effected within a time span of about one year. Furthermore, for the

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compared to the Gaussian specification.

Czech market the increase was almost instantaneous, while for the other two markets it was rather gradual. These findings are comparable to those by Savva and Aslanidis (forthcoming) and Chelley-Steeley (2005). Savva and Aslanidis (forthcoming) also find that the Czech and Polish as well as Slovenian markets have increased their correlation to the Euro-zone in recent years. Chelley-Steeley (2005) investigates the correlation of the stock markets of Hungary, Czech Republic, Poland and Russia with developed markets but for the period 1994-1999. 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, Moshirian and Wu (2005), Batram, Taylor and Wang (2007) and Christiansen and Ranaldo (2009). The authors argue that a monetary union led to stock market integration in the old EU member states. Moreover, in a way this result relates to the finding in Frankel and Rose (1998) that countries which enter a monetary union are likely to experience more correlated business cycles than before. In our context, this may also imply that countries that enter or are about to enter a monetary union are likely to have more correlated stock markets than before. [13]

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

[12] Berben and Jansen (2005) use 400, Silvennoinen and Teräsvirta (2005) use 100.
[13] All new EU members are expected to join the Euro at some point in the near future.

the Czech-EURO model does not take part in the trend towards greater equity market integration. In fact, the correlation decreases in November 2001.

The tendency towards greater equity market integration is not only confined to the financial sector, but 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 most of the 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 and utilities in the Czech market show an increase in correlation towards the end of the sample, although at differing speeds; see Figure 2(b). 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(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.

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 (2007), reported in Table 6. The results 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 the second correlation change in the market index is supported at the 10% level (p-value is 0.053). 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 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 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 Figure 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, comparable to the gradual rise in correlation implied by the STCC specification; see Figure 3(c) and (d). The estimates for Polish industrials and basic resources imply a further (abrupt) increase in correlation in February 2007, shown in Figure 3(e) and (f).

4. Sensitivity analysis

Four robustness checks are undertaken in this section. These are: first, a comparison of the results with a 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,

$$q_{ij,t} = \overline{\rho}_{ij}(1-\alpha-\beta) + \alpha\,\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta q_{ij,t-1}, \quad i, j = 1,2, \tag{4}$$

where $\overline{\rho}_{ij}$ is the (assumed constant) unconditional correlation between $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ (standardised 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.[14]

The correlations implied by various (D)STCC and DCC models are presented in Figures 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, Moshirian and Wu, 2005). 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 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 8 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.[15] 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 is based on previous findings that co-movements are stronger in volatile times than in more tranquil periods (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 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, the STCC

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

[15] 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, Munandar and Hafner (2005).

methodology was applied to equity markets of Russia, China and India for the same sample period. The results rejected this hypothesis for the aforementioned markets supporting the Euro-area driven nature of the increasing integration of the Eastern European data. A similar result has also been found in Cappiello, Gérard, Kadareja and Manganelli (2006) and Savva and Aslanidis (forthcoming). Moreover, the results in Hasousek, Kočenda and Kutan (2008) may also be consistent with ours as they document that the three largest 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 analyze these linkages is the correlation between the estimated variances of two assets

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

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 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 amongst 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 a 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. The transition of the Hungarian and Polish markets has been relatively gradual, while the Czech market shows an abrupt change. This may relate to 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. Further detail from industry level indices supported the broad basis for the increase in correlation with the EU. However, the move to integration in the aggregate indices was not shown to be driven by any particular sector. The results supported that greater diversification opportunities remained within the sectoral indices of these new EU members than demonstrated at the aggregate index level.

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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: 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 some of 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 and value in parenthesis is the increase in the log-likelihood compared to the Gaussian 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: STCC-GJRGARCH-*t* models

	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)	(0.025)	(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)	(0.019)	(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)	(0.063)	(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)	(0.014)	(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)	(0.039)	(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)	(0.038)	(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)	(0.056)	(0.996)		
Consumer Services	0.350	0.140	500	0.324	5.427	13 Nov 01	-7413.3 (219.2)
	(0.032)	(0.028)		(0.007)	(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)	(0.018)	(1.257)		
Industrials	0.231	0.539	500	0.917	7.306	07 Feb 07	-7573.6 (100.4)
	(0.023)	(0.053)		(0.010)	(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)	(0.016)	(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)	(0.025)	(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)	(0.044)	(0.783)		
Utilities	0.188	0.287	500	0.381	10.40	15 May 02	-7692.2 (46.4)
	(0.032)	(0.026)		(0.012)	(1.363)		
Consumer Goods	0.216	0.406	500	0.208	10.89	03 Nov 00	-8071.8 (36.2)
	(0.043)	(0.021)		(0.007)	(1.559)		

Notes: The table presents maximum likelihood estimates of some of 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 and value in parenthesis is the increase in the log-likelihood compared to the Gaussian STCC-GJRGARCH model; 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: 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	10915.1
2005	6390.1	9559.7	7857.3

Notes: The table presents figures 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 DataStream, IMF International Financial Statistics.

Table 6: 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 7: DSTCC-GJRGARCH-*t* models

	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)	(1.380)	(0.051)	(1.036)			
Cz. Rep-EURO											
Financials	0.200	0.290	0.366	1284	500	0.307	0.881	7.654	19 Sep 01	13 Oct 06	-7529.6 (82.9)
	(0.037)	(0.027)	(0.055)	(8309)		(0.002)	(0.001)	(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)	(0.006)	(0.018)	(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)			(0.002)	(0.001)	(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)	(0.129)	(0.010)	(0.846)			
Basic	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)
Resources	(0.055)	(0.027)	(0.046)	(6.378)		(0.047)	(0.001)	(0.784)			

Notes: The table presents maximum likelihood estimates of some of the parameters of 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 DSTCC-GJRGARCH model; 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 8: 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: Asymmetry in volatility--Effects of negative and positive shocks

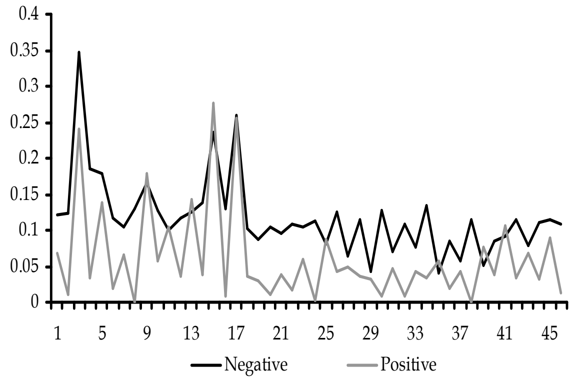
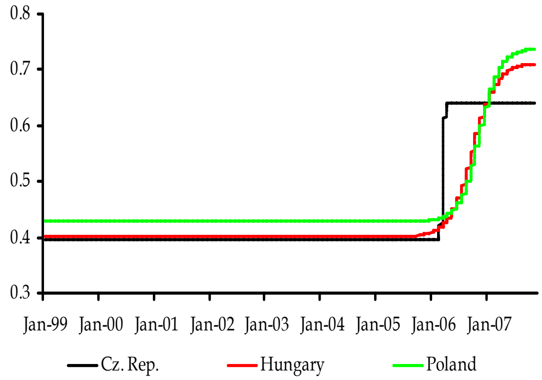
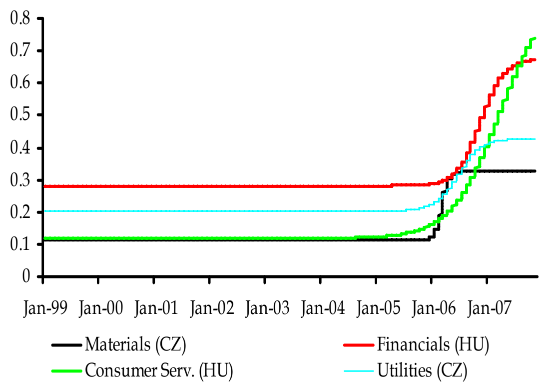


Figure 2: Time-varying (STC) correlations for various indices with Euro STOXX index

(a)



(b)



(c) Poland

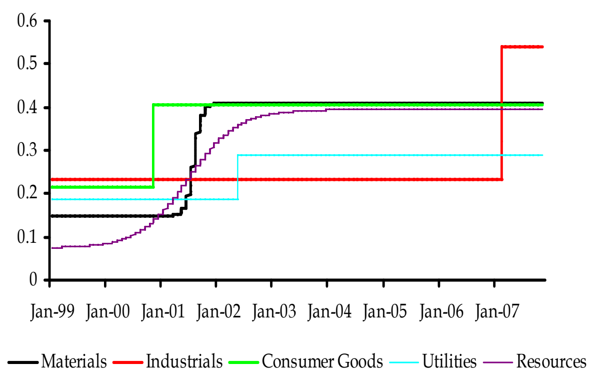
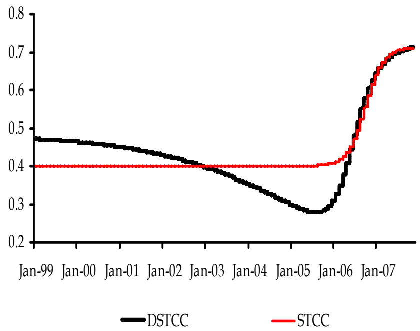
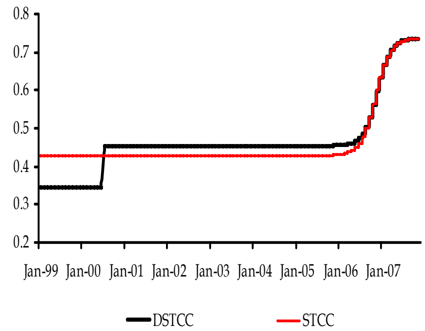


Figure 3: DSTC and STC Correlations for various indices with Euro STOXX index

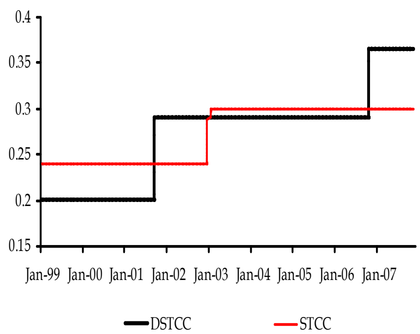
(a) Hungary: Market Index



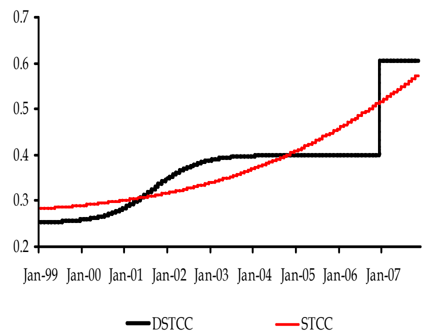
(b) Poland: Market Index



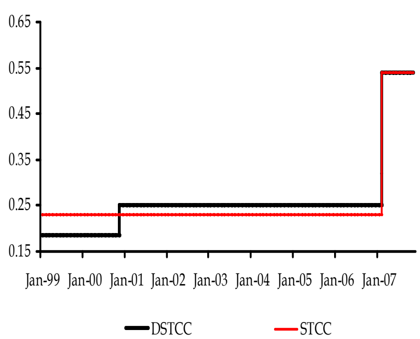
(c) Czech Republic: Financials



(d) Poland: Financials



(e) Poland: Industrials



(f) Poland: Basic Resources

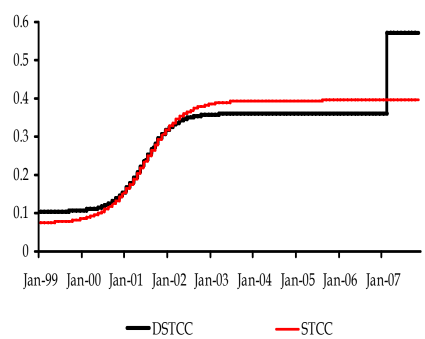


Figure 4: Time-varying correlations with Euro STOXX index for market indices

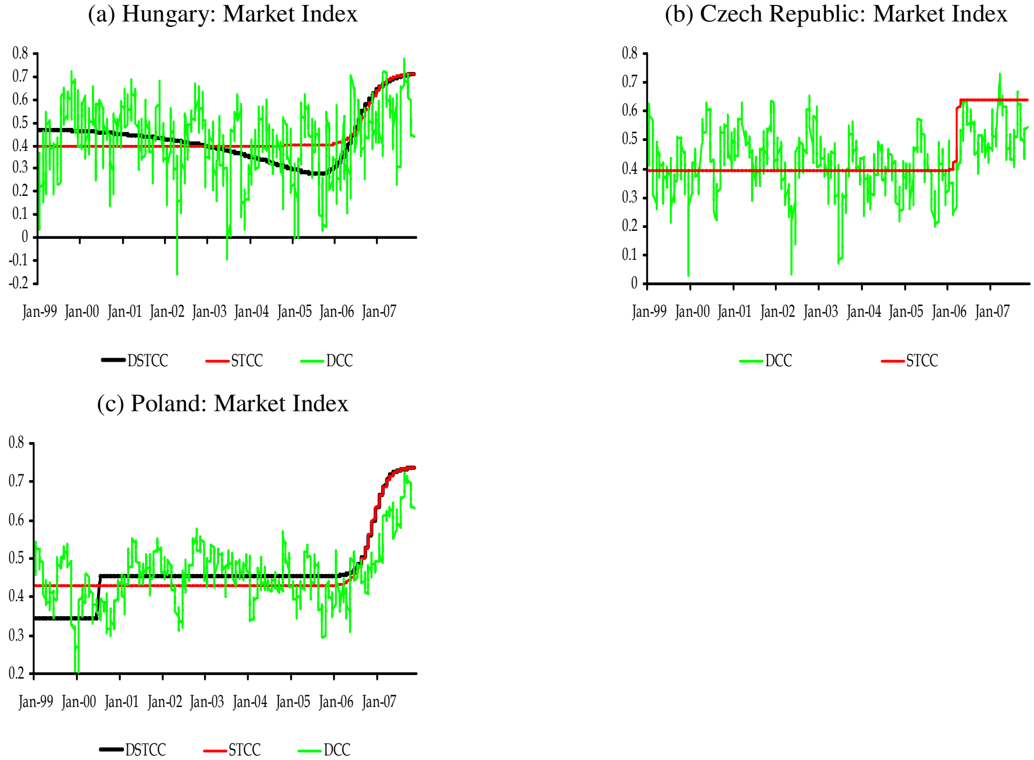


Figure 5: Time-varying correlations with Euro STOXX index for industry indices