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David Büttner and Bernd Hayo

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Coordination: Bernd Hayo • Philipps-University Marburg
Faculty of Business Administration and Economics • Universitätsstraße 24, D-35032 Marburg
Tel: +49-6421-2823091, Fax: +49-6421-2823088, e-mail: hayo@wiwi.uni-marburg.de

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David Büttner and Bernd Hayo

Philipps-University Marburg

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Corresponding author:
David Büttner
Faculty of Business Administration and Economics
Philipps-University Marburg
Universitätsstr. 24
35032 Marburg
Germany
Phone: +49 - (0) 64 21 - 28 - 23 087
Fax: +49 - (0) 64 21 - 28 - 23 088
Email: buettner@wiwi.uni-marburg.de
Web: http://www.uni-marburg.de/fb02/makro

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Determinants of European Stock Market Integration

Abstract

We analyse the determinants of stock market integration among EU member states for the period 1999–2007. First, we apply bivariate DCC-MGARCH models to extract dynamic conditional correlations between European stock markets, which are then explained by interest rate spreads, exchange rate risk, market capitalisation, and business cycle synchronisation in a pooled OLS model. By grouping the countries into euro area countries, "old" EU member states outside the euro area, and new EU member states, we also evaluate the impact of euro introduction and the European unification process on stock market integration. We find a significant trend toward more stock market integration, which is enhanced by the size of relative and absolute market capitalisation and hindered by foreign exchange risk between old member states and the euro area. Interest rate spreads and business cycle synchronisation do not appear to play an important role in explaining equity market integration.

Keywords: Stock Market Integration, European Unification, DCC-MGARCH model

JEL Codes: E44, F3, F36, G15

I. Introduction

The integration of financial markets is important to both market participants and policymakers. In integrated markets, capital flows freely to where it will generate the highest return. Integrated financial markets have easier access to foreign capital, but are also more vulnerable to financial crises occurring in other areas of the world. Moreover, any increase in the degree of global financial market integration decreases the opportunity for diversification. It is thus essential to achieve a better understanding of the factors driving financial market integration. In this study, we analyse determinants of stock market integration using data from European Union (EU) member states.

Our empirical indicator of the degree of integration of European equity markets is the (conditional) correlation of returns between these markets. Taking into account that financial integration is a dynamic process, we allow the estimated correlations to vary over time. We use bivariate DCC-MGARCH (dynamic conditional correlation multivariate generalized autoregressive conditional heteroskedasticity)[1] models (Engle, 2002) to extract the conditional correlations of European stock markets for the period 1999–2007.

Following Engle (2002), we characterise the conditional covariance matrix of stock market returns $r_t | F_{t-1} \approx N(0, H_t)$ as follows:

$$H_t \equiv D_t R_t D_t \,,$$

where $D_t = diag\{\sqrt{h_{i,t}}\}$, and $R_t = diag\{Q_t^{-1}\} Q_t diag\{Q_t^{-1}\}$,

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta Q_{t-1} \,,$$

$$r_{it} = \sqrt{h_{it}}\,\varepsilon_{it} \,,$$

F_{t-1} captures all information up to t-1,

and $\overline{Q}$ is the matrix of unconditional correlations.

We are interested in the elements of the conditional correlation matrix R_t, i.e., the dynamic conditional correlations between stock market returns:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ij,t} q_{ij,t}}} \qquad (1)$$

with i,j=1,2 and $q_{ij,t}$ as elements of Q_t.

[1] For the univariate part of the model, we employ a FIGARCH (fractionally integrated GARCH) model (Baillie et al., 1996).

To assess the impact of political factors on financial market integration, we group the countries based on their European integration status into euro area member (EMU), old EU member states without the euro (OMS), and new EU member states (NMS).[2] The estimated dynamic correlations of European stock markets are explained by variables proxying for the maturity of financial markets, exchange rate risk, the degree of business cycle synchronisation, and seasonal as well as trading day effects.

A number of authors suggest (e.g., Fratzscher, 2002; Baele et al., 2004; Kim et al., 2005) that the introduction of the euro promotes financial market integration by eliminating exchange rate risks and short-term interest rate spreads. We model exchange rate risk by extracting the conditional volatilities of exchange rate returns using a GARCH model. Short-term interest rate spreads are computed using the absolute three-month interest rate differentials of the respective countries.[3]

To account for the current state of financial market development, we include two measures of the depth and size of these markets in our model: the sums of absolute and relative (in terms of GDP) market capitalisation of the two markets under consideration (see Kim et al., 2005).[4]

Erb et al. (1994) find that the degree of business cycle synchronisation has a significantly positive effect on stock market integration. We evaluate the impact of goods market integration on financial market integration by adding two (monthly) lags of an indicator variable for business cycle synchronisation, which take the value 1 if the output gaps (extracted from monthly industrial production) of two countries show the same sign and –1 if they have opposing signs.[5] The cumulated effect of business cycle synchronisation over (almost) one year is captured by a variable that consists of the sum of the business cycle synchronisation indicator from lag 3 until lag 12.[6] Allowing for possible lags in the processing of information on output developments, we include the sum of this indicator variable for up to 12 months. We also examine whether the phase of the business cycles matters by including dummy variables for booms and recessions. Controlling for omitted trending factors, we include a deterministic time trend. Finally, dummy variables capture the financial crisis

[2] Members of the groups are: (1) Euro area: Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, and Spain. Greece is not included, as it introduced the euro only in 2001; nor is Luxemburg, as its markets are small. (2) Old EU member states outside the euro area: Denmark, Sweden, and the United Kingdom. (3) New EU member states: the Czech Republic, Hungary, and Poland. These countries were chosen because they have not yet introduced the euro, but have sufficiently large financial markets.

[3] The data were retrieved from Eurostat and national statistical offices/central banks.

[4] Data sources: ECB and Eurostat.

[5] The data are from the OECD webpage (MEI original release data and revisions database). To extract the output gaps, we derive the trend using a Hodrick-Prescott filter with $\lambda = 14400$ (Hodrick and Prescott, 1997).

following the terrorist attacks on 11 September 2001, as well as deterministic seasonal and trading day effects.

As shown by Orphanides and van Norden (2002), using revised output data to estimate reactions of economic agents can lead to severely biased estimates. Thus, the authors advise employing real-time data that reflect the actual state of information at the time of decision making. To investigate the importance of this distinction in the construction of the data set, we estimate the model using both kinds of data for industrial production.[7]

Using these factors, we explain the conditional dynamic correlations between equity markets in the various groups of countries. Estimation takes place within one large stacked OLS model with group-individual regressors and fixed effects (see Equation (2)). The advantages of this model set-up include an increase in estimation efficiency due to the large number of observations and the possibility of testing for asymmetries across country groups using powerful standard tests; the disadvantages include the assumptions of equal coefficients within the groups and a common error structure. We estimate Equation (2):

$$\begin{aligned}\mathrm{Corr}_{i,t} = {} & \mathrm{Const}_i + \mathrm{Corr}_{i,t-1}\alpha_i + \mathrm{Control}_{i,t}\gamma_i + \mathrm{Exchange\ Rate\ Risk}_{i,\,t\text{-}1}\beta_i \\ & + \mathrm{Interest\ Rate\ Spread}_{i,\,t\text{-}1}\nu_i + \mathrm{Absolute\ Market\ Capitalisation}_{i,\,m\text{-}1}\tau_i \\ & + \mathrm{Relative\ Market\ Capitalization}_{i,\,m\text{-}1}\xi_i + \sum_{r=0}^{2}\mathrm{Boom}_{i,m-r}\mu_{i,m-r} \\ & + \sum_{r=0}^{2}\mathrm{Recession}_{i,m-r}\varpi_{i,m-r} + \sum_{r=0}^{2}\mathrm{Business\ Cycle\ Syncronisation}_{i,m\text{-}r}\eta_{i,m-r} \\ & + \mathrm{Cumulated\ Business\ Cycle\ Syncronisation}_{i,t}\kappa_i + u_t\end{aligned} \tag{2}$$

i = EMU/EMU, EMU/OMS, EMU/NMS, OMS/OMS, OMS/NMS, NMS/NMS,

where $\mathrm{Corr}_{i,t}$ is the bivariate dynamic stock market correlation between two countries belonging to the groups EMU, OMS, or NMS at time t (see Equation (1)), Control includes a deterministic trend as well as dummies for January, Friday, 11 September 2001, and 12 September 2001. m-1, m-2, … refers to the previous 1, 2, … month. All other variables are self-explanatory.

[6] At a preliminary stage we also vary the specification with regard to the underlying sizes of the respective output gaps. However, no substantial changes in estimation results occurred.

[7] The correlation coefficients between real-time and revised output gap estimates are 0.68, 0.62, and 0.75 for EMU, OMS, and NMS, respectively.

II. Estimation Results

Table 1 provides an overview of our results for output gap estimates based on real-time data for industrial production. Tests indicate that there is no statistical difference from estimators obtained with revised output data. Thus, contrary to Orphanides and van Norden (2002), we do not find the data distinction to be important. Note that the estimation takes place within the framework of one large model and the columns in Table 1 refer to the coefficient associated with the observations for each particular country group within this specification. Correlations are normalised to 100 for ease of interpretation.

Table 1: Explaining dynamic conditional correlations of european stock market returns

i =	EMU/EMU	EMU/OMS	EMU/NMS	OMS/OMS	OMS/NMS	NMS/NMS
$Const_i$	0.473 *	0.649 *	1.022 *	0.922 *	1.206 *	0.556 *
$Corr_{i,t-1}$	98.588 *	98.669 *	95.790 *	97.468 *	95.140 *	98.378 *
$Trend_i$*100	0.012 *	0.008 *	0.028 *	0.024 *	0.033 *	0.007
$January_i$	-0.032	0.026	0.005	0.046	0.074	0.047
$Friday_i$	0.008	0.058	0.073	0.087	0.120	0.003
11 09 2001_i	-0.426	0.275	2.049 *	-1.763	1.511	1.101 *
12 09 2001_i	3.341	5.398 *	7.523 *	8.999 *	8.316 *	2.213 *
Exchange rate $risk_{i,t-1}$		-4.224 *	-0.344	7.129	-0.760	-0.329
Interest rate $spread_{i,t-1}$		-0.036	-0.007	0.013	-0.005	-0.010
Market $Cap_{i,m-1}$ (% of GDP)	0.124 *	0.133 *	0.577 *	0.232	0.753 *	0.939
Market $Cap_{i,m-1}$ (Billion €)	0.211 *	0.074 *	0.228 *	-0.010	-0.035	0.030
$Boom_i$	-0.068	-0.055	-0.003	-0.096	0.062	-0.006
$Boom_{i,m-1}$	-0.049	0.039	0.053	-0.155	0.032	0.054
$Boom_{i,m-2}$	-0.074	-0.035	-0.017	-0.016	-0.089	-0.118
$Recession_i$	-0.054	0.017	-0.229 *	0.035	-0.174	0.268
$Recession_{i,m-1}$	-0.034	-0.021	0.016	0.222	0.080	-0.174
$Recession_{i,m-2}$	-0.018	-0.112	0.093	-0.092	0.172	-0.123
Business Cycle $Synchronisation_i$	-0.004	0.014	-0.007	0.034	-0.034	0.004
Business Cycle $Synchronisation_{i,m-1}$	0.006	0.007	0.009	0.042	0.004	0.003
Business Cycle $Synchronisation_{i,m-2}$	-0.008	-0.001	-0.021	0.041	0.021	0.034
Cumulated Business Cycle $Synchronisation_{i,m-3 \text{ to } m-12}$	0.001	-0.003	0.000	0.004	-0.001	-0.002
No. of observations	230,520					
Log-Likelihood	538,428					
Normality test	Chi²(2) = 1,099,400*					
Hetero test	F(165,230230) = 14.0*					
AR 1-2 test:	F(2,230394) = 44.4*					

Note: * indicates significance at a 0.5% level. Stock market correlations are normalised to 100. m-1, m-2 … refer to values of the previous 1,2… month.

As the sample is very large (230,520 observations), making the statistical tests highly sensitive to violations of the null hypotheses, we test at a 0.5% level following Leamer (1983), who recommends adjusting the significance level inversely with the sample size.

Since the estimates exhibit evidence of autocorrelation and heteroscedasticity, we apply robust standard errors based on Andrews (1991).

We discover a significant deterministic trend toward greater stock market integration This trend in integration between old and new member states, as well as between euro area participants and new members, is stronger than the correlation between the new EU member states themselves, which is not significant.

Foreign exchange risk depresses stock market integration among old EU member states and participants in the euro area. The absence of foreign exchange rate risk in the euro area leads to higher equity market integration. These results suggest that adoption of the euro by those EU member countries that are still outside the euro area will foster financial market integration. In contrast, interest rate differentials do not play a role.

We approximate the maturity and depth of equity markets by including relative and absolute market capitalisation. As expected, these indicators exert a positive impact on market integration, implying that the deepening of financial markets (especially in the new member states) will result in enhanced market correlations in the future. The point estimates show that correlations are higher on Fridays and lower during January but, in contrast to the findings of Kim et al. (2005), these seasonal effects are not significant. The downturn of financial markets following the terrorist attacks on 11 September 2001 tightens the correlation of all stock market returns except within the euro area.

Finally, business cycle synchronisation does not play a major role in explaining stock market integration. We find that when euro area and new EU member states are in a recession, their mutual financial market correlation decreases. Moreover, the sum of the boom indicators decreases the intra-euro area correlations ($Chi^2 = 10.22^*$).

III. Conclusion

We analyse the determinants of stock market integration between EU member states using dynamic conditional correlations estimated by DCC-MGARCH models. Our indicator of financial market integration is then analysed by means of a pooled OLS model that groups EU member countries into three categories: euro area members, old EU member countries not participating in EMU, and new member states. We conduct our analysis for both real-time and revised output data and discover no noteworthy differences. Regarding the general development of European stock market integration, we find that for almost all groups of countries there is a significant trend toward more integration. However, foreign exchange risk depresses integration among old EU member states and for participants of the euro area. Therefore, if non-euro area countries adopt the euro, an increase in stock market correlations vis-à-vis the euro area can be expected. The size of relative and absolute market capitalisation also promotes equity market integration. If markets deepen, higher correlations can be expected in the future, especially for the new member states, which are in the process of catching-up. Business cycle synchronisation does not appear to play a major role in determining financial market integration and neither do interest rate spreads. We do not find significant evidence of seasonal or trading day effects. Thus, nominal determinants of stock market integration seem to be more important to this process than real determinants.

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