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The impact of the crisis on the monetary autonomy of Central and Eastern European countries

SUMMARY: Where a country allows the free movement of capital and follows a free floating exchange rate policy, the monetary trilemma would suggest the existence of monetary autonomy, which is prejudiced when external shocks cause a significant decrease (divergence) or increase (contagion) in market co-movements. This study aims to analyse the extent to which daily changes in bond market returns and exchange rates of the Euro area, and the monetary policy measures of the European Central Bank (ECB) influenced the daily changes in the bond market returns and currencies of the Czech Republic, Hungary and Poland between 2002 and 2011. After rejecting the efficient market hypothesis for the capital and money markets under review, a dynamic conditional correlation is fitted to individual market pairs. Whether the differences between these are significant is analysed against extreme and normal daily movements in Euro area indicators. A movement is considered extreme where the empirical movement is an outlier for the theoretical normal distribution applicable to it. Although the objective function of monetary policy in Central and Eastern European countries is mostly aligned with that of the ECB, owing to differences in their fundamentals, collective actions taken on extreme days caused risk premiums to increase. Consequently, Central and Eastern European markets were much harder hit by adverse changes in the Euro area, while the impact of the ECB's measures to enhance liquidity was not necessarily felt. It is doubtful, however, that the introduction of the Euro would eliminate such unfavourable phenomena.*

KEYWORDS: contagion, divergence, yield curve, Central and Eastern Europe, monetary policy autonomy
JEL CODES: C32, G01, G12

INTRODUCTION

This paper aims to explain to what extent monetary autonomy applies in the bond and currency markets of Central and Eastern Europe. As part of its discussion of monetary policy autonomy, our paper considers the confines within which central banks make decisions on base rates and liquidity. Decisions by foreign central banks on monetary policy may influence the steepness of the yield curve and the changes in individual maturities, while a co-movement of certain currencies may also occur. We will consider the impacts of the decisions of the European Central Bank (ECB) on the Hungarian, Czech and Polish bond and currency markets, using logarithmic first differentials of daily closing values between 1 January 2002 and 31 July 2011.

The choice of analysing the selected Visegrád countries is supported by the strong convergence between currency rates as described in *Stávárek* (2009) and *Babetskaia – Kukharchuk et al.* (2008), and by *Farkas*' (2011) claim that this group of countries constitutes a separate economic model in addition to those traditionally

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existing in Anglo-Saxon, Northern, continental and Mediterranean countries within the European Union.

The positive steepness of the yield curve is a result of the time value of money, from which markets typically diverge in the event of severe liquidity shortage or when inflation outlook improves [inverted yield curve, which could develop merely as a result of the Balassa–Samuelson effect, see *García –Solanes et al.* (2007) and *Darvas – Szapáry* (2008)]. Therefore, to start with, we consider it worthwhile to look at how the difference of 10-year and 3-month returns changed in the countries of the sample as a result of the ECB's monetary policy decisions. If ECB action taken in response to the global liquidity shortage of late summer and autumn 2008 caused the difference between 3M and 10Y returns to increase, then a positive external effect is observed.

The temporal stability of co-movement seen in the fluctuation of yield curves and currency rates could also be essential in both the application of the financial innovations required for risk management, and the execution of maturity transformation (Marsili – Raffaelli, 2006; Eisenschmidt – Holthausen, 2010; Ondo – Ndong, 2010; Barrel et al., 2010). As banks in the countries of the region, although to varying extents, used foreign funds to finance the credit expansion of the 2000s (ECB, 2008), changes in currency market co-movements should not be ignored. In the light of *Chen* and *Zhang* (1997), *Goetzmann et al.* (2005), Szegő (2010), and also *Obstfeld* and *Taylor* (2002), it is concluded that there is empirical evidence for an increase, since the 1980s, in the co-movement tendency of the capital markets of real economies globally integrated through convertibility. With the assets reviewed here, account should also be taken of the need for the future Euro accession, which is reflected in institutional harmonisation on the one hand (ECB-compliant monetary policy objectives, exchange rate systems, definitions and methodologies), and in market expectations on the other. Thus, in connection with the co-movement of returns and currencies, it is possible to look at the dynamic changes in their co-movement over the 10-year period, and a comparison is also appropriate to determine whether any significant changes occurred as a result of the crisis. We have taken a dual approach to the phenomenon of crisis: by comparing two time windows, and along the extremity of volatility in Euro area indicators. In the time window approach, we worked on the basis of changes in the ECB base rate, exploiting the fact that the period of interest rate rises from 6 December 2005 to 13 October 2008 is approximately the same length as the period of interest rate cuts accompanying the crisis, starting on 14 October 2008 (745 and 738 trading days, respectively). With the volatility of Euro area indicators, the distribution function of the logarithmic first differentials of daily values were separated into 'normal' and 'extreme' states. Then we searched for traces of significant changes in correlations; it is precisely such dramatic hikes that risk management seeks protection against. The most convenient arrangement would be the total absence of considerable changes in correlation on such extreme days; however, both monetary policy makers and other market players could face a challenge from either weakening or strengthening co-movement.

Our approach to the theoretical background of the issue is based on the findings of *Bonanno et al.* (2001) concerning the three key levels of market complexity. According to those findings, market returns and standard deviations are only approximately stationary (covariance stability), while the autocorrelation of returns shows a monotonic decrease prolonged for at least 20 trading days. On the other hand, cross-correlation exists within industries and time series, allowing for event-based trading due to the synchronous interactions created. From that follows the third rule, positing the phenomenon of collective behaviour during extreme market events, three special varieties of which are presented in the paragraphs below: interdependence, contagion and divergence.

Contagions referred to in literature could be analysed following the World Bank's[1] three approaches. According to the broad definition, contagion is the cross-country transmission of shocks or the general cross-country spillover effects, whether in good times or crises. Under the restrictive definition, contagion leads to higher than normal correlation which is underpinned by fundamental links (financial links, links resulting from cross-border production chains, and political links) among the countries. According to the very restrictive definition, contagion occurs when cross-country correlations increase significantly during crisis times relative to correlations during tranquil times.

This approach is based on an observation of the asymmetric nature of capital market returns (Campbell et al., 2002; Bekaert et al., 2005) according to which *assets and countries* with similar characteristics (geographical location, sector, rating by rating agencies, etc.) are considered *homogeneous* by market players, who seek to escape from the entire homogeneous category in the event of a problem. The opposite of that could be *heterogenisation* as described in *Bearce* (2002), where market players start to pay attention to *unique characteristics* within a group previously considered homogeneous, and they also price this in risks. The disintegration of a group that was previously considered homogeneous, i.e. converging, will involve a reduction in co-movement; consequently, this phenomenon will be referred to as divergence below.

It is appropriate therefore to define this threefold concept in more depth.

Definition 1: Capital market contagion (1) is defined as a significant increase in the correlation $\rho^{m_k m_j}$ between the markets m_k, m_j as a result of external or internal shock $r_{n/x}$ (Forbes – Rigobon, 2002; Campbell et al., 2002; Bekaert et al., 2005):

$$r^{m_i}_{\frac{n}{x}} \neq 0 \rightarrow \rho_n^{m_k m_j} \leq \rho_x^{m_k m_j} \qquad (1)$$

According to Wong et al. (2010), when the equilibrium is disrupted between the demand and supply sides in the event of contagion, capital flows in the same direction will become international in scale, which, combined with increased correlation, will undermine any defensive diversification effort (Campbell et al., 2002). *Van Royen* (2002) and *Markwat et al.* (2009) go even further, finding in connection with the crises of 1997 in the Far East and of 1998 in Russia, and the 2001 dotcom crash, that the spread of contagion does not depend on the macroeconomic fundamentals of the country concerned, rendering even geographical diversification powerless against sudden shocks. In any case, the Russian crisis drew attention to *high-leverage financing* as a possible cause of contagion, since the shortage of market liquidity led to financing problems then as well, and high-leverage funds withdrew simultaneously from geographical regions which were apparently not related in any way. In the crisis starting in 2007, the contagion of developed financial markets was largely owed to the market of structured products, the interbank market, and, through de-leveraging, the liquidity channel.

It is thus appropriate to define the previously mentioned phenomenon of divergence as follows. In his book, Bearce (2002) traces the monetary policy background of the phenomenon back to the 1973 failure of the Bretton Woods system, citing, as a starting point, the monetary trilemma of Mundell–Fleming: monetary policy autonomy, free capital movement and floating exchange rates allow interest rates to converge over a period that is shorter than a decade at most.

DEFINITION 2: Capital market divergence (2) is defined as a significant decrease in the correlation $\rho^{m_k m_j}$ between the markets m_k,m_j as a result of external or internal shock $r_{n/x}$:

$$r^{m_i}_{\frac{n}{x}} \neq 0 \rightarrow \rho_n^{m_k m_j} > \rho_x^{m_k m_j} \qquad (2)$$

The conditional nature of interest rate convergence could pose a serious challenge to the countries in the sample, because risk premiums may easily increase between individual countries precisely as a result of a crisis.

To the extent that no significant change occurs in correlations as a result of external shock, interdependence can be defined in line with *Forbes* and *Rigobon* (2002).

DEFINITION 3: Capital market interdependence (3) is defined as no significant change in the correlation $\rho^{m_k m_j}$ between the markets m_k,m_j as a result of external or internal shock $r_{n/x}$ (Forbes – Rigobon, 2002):

$$r^{m_i}_{\frac{n}{x}} \neq 0 \rightarrow \rho_n^{m_k m_j} \approx \rho_x^{m_k m_j} \qquad (3)$$

However, determining changes in correlation requires an organising principle, i.e. a definition of shocks. Using the definition provided by *Jentsch et al.* (2006), the extremity of events is defined on the basis of their low probability and high impact. An endogenous approach to extremity involves the analysis of the impact which an extreme event occurring in a given market at a given time has on other markets; thus our model is established without taking into account exogenous factors[2]. In order to view heavy-tailness (Alderson, 2008; Albeverio – Piterbag, 2006) as an endogenous process resulting from the interaction of markets, markets should be assumed to be complex. Heavy-tailness occurs when, with daily exchange rates observed in the market, the differences between the probability of movements of any size and of those one magnitude larger are much smaller than could be expected with normal distribution.

HYPOTHESIS 1: *As a result of monetary policy autonomy, the divergence (4) of bond and currency markets will be observed:*

$$r^{m_i}_{\frac{n}{x}} \neq 0 \rightarrow \rho_n^{m_k m_j} > \rho_x^{m_k m_j} \qquad (4)$$

Our analysis therefore aims to assess the various forms of collective actions that affect monetary policy (contagion, divergence, interdependence), and our hypothesis concerns the phenomenon of divergence as explained by Bearce (2002).

THE ECB'S MONETARY POLICY MEASURES

In the period under review, from 1 January 2002 to July 2011, it is possible to distinguish eight main stages in the ECB's monetary policy *(see Figure 1)*. The ECB responded to the crisis following the burst of the dotcom bubble in spring 2001 by cutting its base refinancing rate, as a result of which in 25 months the base rate dropped by 275 basis points from the initial rate of 4.75 per cent. This is Stage *A*, with the start of the period under review in the first third. The 2.00 per cent base refinancing rate achieved by the end of the rate cuts, subsequently maintained for 30 months (Stage *B*), was a means of monetary stimulus.

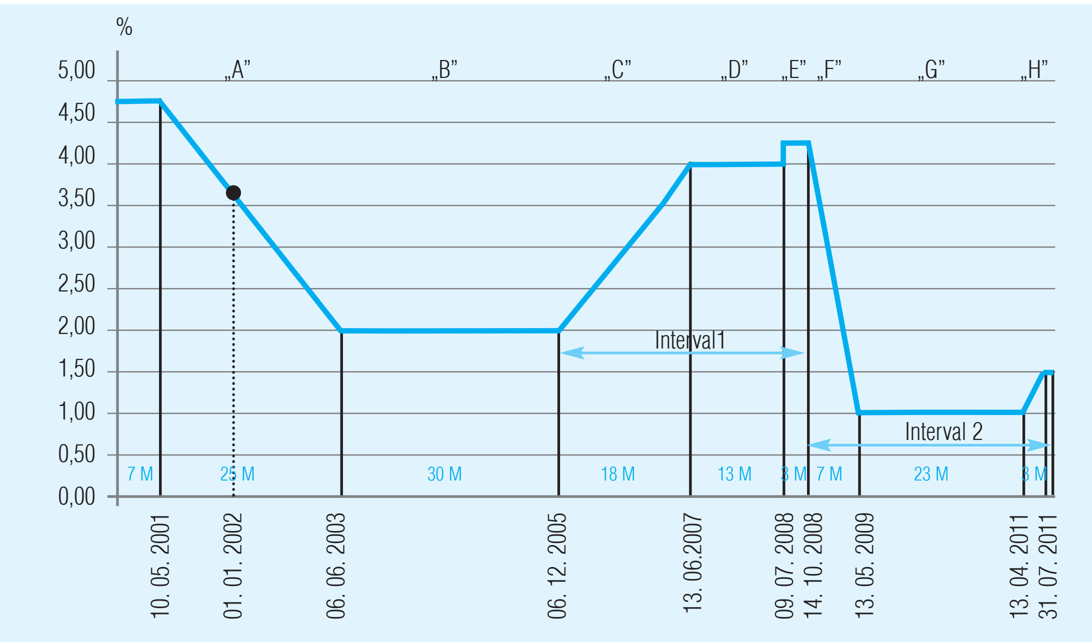
In Stage *C*, the ECB raised the base refinancing rate by 200 basis points to 4.00 per cent in nine steps; these 18 months were marked by rising commodity prices and recovering growth as well as an excessive take-off in the real estate sector. In Stage *D*, the ECB maintained the base refinancing rate at a high 4.00 per cent for 13 months, responding to banks' insufficient liquidity and fears of dollar devaluation and inflation, then, as of 3 July 2008, raised its rate by 25 basis points to 4.25 per cent, while the FED had been gradually decreasing its rate since September 2007. It is appropriate to consider these three months as a separate Stage *E* owing to uncertainties surrounding the bankruptcy of Lehman Brothers.

During the crisis following that bankruptcy, the ECB implemented extremely rapid interest rate cuts, reducing its base refinancing rate from an initial high of 4.25 per cent to a historic low of 1.00 per cent in eight successive steps in a mere seven months. The monetary policy measures responding to the crisis also included means other than interest rate cuts. For example, with a view to reducing high interest rate volatility, the Central Bank's interest rate corridor for refinancing operations was narrowed from 200 to 100 basis points (maintained for a few months until late January 2009), while the extension of the range of collateral assets accepted for lending operations across the Euro system also served to enhance liquidity. At the same time, to facilitate longer-term refinancing, the US provided liquidity denominated in USD via currency swap arrangements. Stage *E* was clearly about saving banks and the increased sovereign debt of Euro area countries. The base rate was not cut any further after 13 May 2009; in the 23 months (Stage *G*) leading up to the end of the period under review, the ECB kept its base rate at the level of 1.00 per cent, while also announcing longer-term refinancing operations maturing in one year to provide liquidity. As a unique form of monetary stimulus, as of 8 July 2009 the ECB declared the European Investment Bank (EIB) to be an approved partner in the monetary policy operations of the Euro system. Since then, the EIB has had access to refinancing funds under equal terms with any other contracting party. According to estimates by the EIB, this additional funding may have resulted in up to EUR 40 billion worth of additional investments. The Euro crisis intensified over that period.

In 2010, in the field of monetary policy, the ECB continued the practice of tendering at fixed interest rates without quantitative restric-

Figure 1

CHANGES IN THE ECB'S BASE RATE



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tions. Then, in May 2010, responding to tensions in the financial markets, the ECB intervened in the secondary market sovereign bonds and other debt securities issued in the Euro area. At the end of the period (Stage *H*), from 13 April 2011, the base rate was raised to 1.50 per cent in two steps as a result of uncertainties about the Euro (note, however, that as of 14 December 2011 the rate has since been lowered again to 1.00 per cent).

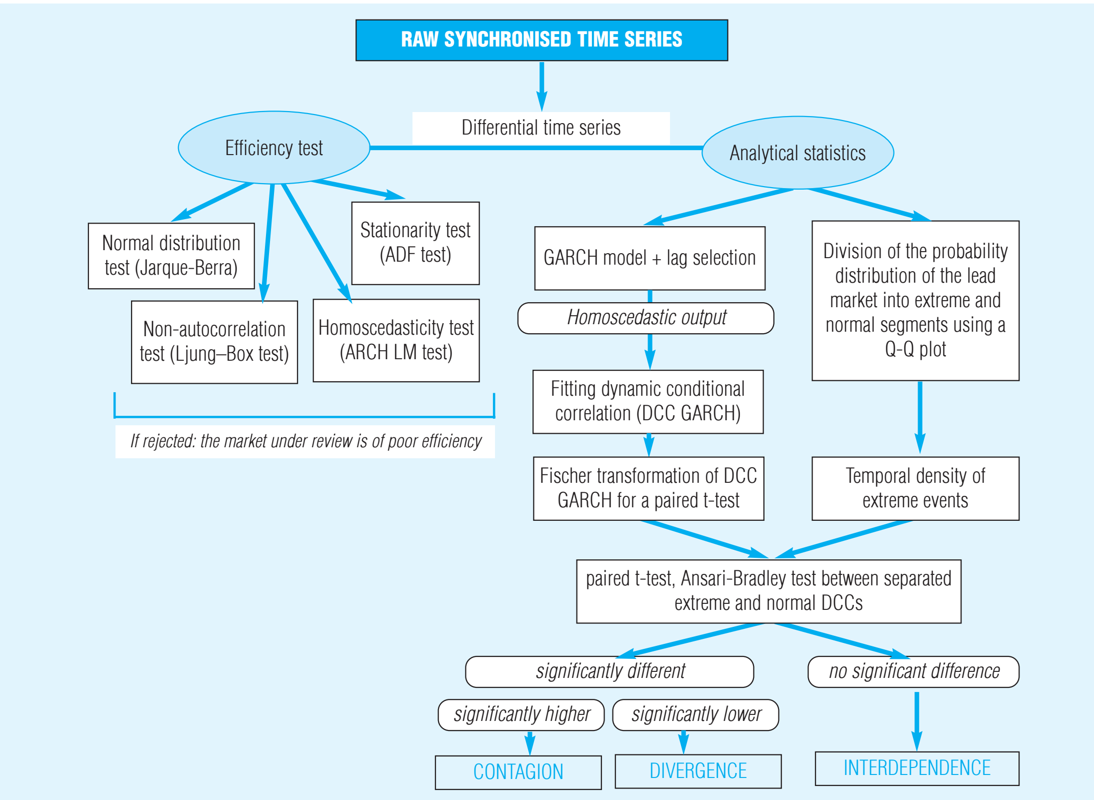
To test the impact of the ECB's monetary policy, we chose two intervals out of the eight stages discussed above, both of which are approximately the same length. The first comprises the 34 months from 6 December 2005 to 14 October 2008 (corresponding to Stages *C*, *D* and *E*), clearly characterised by liquidity absorption. The second selected interval is linked to the financial crisis of 2008, covering the 36 months of monetary easing from 14 October 2008 to July 2011.

METHODOLOGY – STATISTICAL EVIDENCE FOR CONTAGIONS

To draw conclusions concerning the statistical and dynamic properties of extreme events, $r_{n/x}$ and the alternative market model allowing for the occurrence of contagions are introduced, following which statistical evidence is considered for or against contagions in the markets under review. In each case, the lead market m_v is represented by the German (Euro area) pattern (m_v), while the follower markets are the selected Central and Eastern Europe markets.

Figure 2

STRUCTURE OF THE RELATIONSHIPS CONSIDERED BETWEEN MARKETS IN THE SAMPLE



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The calculation process is summarised in *Figure 2.* In performing descriptive statistics, the sample is used to highlight the problems arising from poor market efficiency, limited rationality and scale-free networks. As part of GARCH fitting, which represents the first part of analytical statistics, the distortions revealed by descriptive statistics (autocorrelation and heteroscedasticity) are eliminated; then, following the calculation of dynamic conditional correlation, extreme and normal events are separated, and the hypothesis is tested.

Our work is based on the Matlab software, in which we carried out time series analysis using the UCSD GARCH and Oxford MFE[3] packages developed by *Dr. Kevin Sheppard* (Oxford).

Testing market efficiency

In our analysis of the interaction of markets, we first verify the efficiency of the markets under review using the definition provided by *Fama* (1970). If only poor market efficiency were to be observed, we could not use past prices to draw conclusions about future changes. Then, from a statistical perspective, future prices would be best predicted on the basis of present prices, which is called *random walk* (5):

$$r_t = r_{t-1} + \varepsilon_t, \qquad (5)$$

where ε_t represents the impact of new information (information shock), and r_t represents the pricing of the asset at t point in time. This is to assume that returns have a normal distribution, are stationary, non-autocorrelated and homoscedastic.

The Jarque–Bera test was used to test normal distribution, the augmented Dickey–Fuller test (ADF) to test stationarity, and the Ljung–Box and ARCH–LM tests to demonstrate autocorrelation and heteroscedasticity based on *Jentsch et al.* (2006), *Alexander* (2008) and *Lütkepohl* (2004).

Fitting dynamic conditional correlation following elimination of heteroscedasticity

According to *Forbes* and *Rigobon* (2002), correlation in a specific time window or rolling correlation could be distorted by heteroscedasticity; to eliminate such distortion, based on *Bollerslev* (1990) and *Tsay* (2005), univariate or multivariate GARCH models can be applied, the standardised error terms of which can already be used to calculate distortion-free, temporally constant and unconditional correlation (Chan, 2002).

In the generalised ARCH (GARCH) model (6), lag length is represented by p, the ARCH process by σ^2 and q, the impact of present news on conditional variance by ε^2, α_i, while volatility persistence, i.e. the shock of recent news to old information, by β_i (Davidson – MacKinnon, 2003):

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \qquad (6)$$

A distinction is made between symmetric and asymmetric models, and nonlinear responses can also be incorporated[4]. *In our work, we relied on the interdependency of the APARCH–GJR-GARCH–TARCH–GARCH models* in order to use a variety of parameters to fit these to the time series considered, then to select the model with the best fit suitable for eliminating autocorrelation and heteroscedasticity from error terms. Each model and its application is explained in more detail in the Appendix to this paper. Once heteroscedasticity is eliminated, it becomes possible to use the DCC–GARCH model constructed by Engle (2002).

The DCC model (7, 8) relies on the returns (r_t) of asset k, which have the expected value of

0 and a normal distribution, as well as a covariance matrix marked H_t.

$$r_t \mid \Phi_{t-1} \sim N(0, H_t) \tag{7}$$

$$H_t \equiv D_t R_t D_t \tag{8}$$

where r_t is a $K \times 1$ vector; H_t is a conditional covariance matrix; R_t is a $k \times k$ time-variable correlation matrix; and all information available at a t–1 point in time is contained in Φ_{t-1} whereas D_t represents a $k \times k$ diagonal matrix containing the time-variable standard deviations of a univariate GARCH model (Kuper–Lestano, 2007; Wong-Li, 2010).

To compare the correlations registered in normal and extreme periods, we used a variance test, the Ansari–Bradley test. To ensure that the test can be carried out, we performed, based on *Lukács* (1999), Fischer transformations (9) on the correlations:

$$z_i = 0{,}5 \times \frac{ln(1+rho_i)}{1-rho_i} \tag{9}$$

As part of the Ansari–Bradley test, we compare two independent samples of different length, assuming that they are from the same probability distribution, in contrast with the alternative hypothesis, under which they only have similar medians and forms, but distributions with different variances. If $H=0$, the two samples are similar, whereas if $H=1$, they are significantly different.

Separation of extreme and normal values

In connection with the statistics of extreme values, *Jentsch et al.* (2006) raise the question of where to draw a limit of probability beyond which a given event is considered extreme. To test our hypothesis, we need some organising principle which enables the correlations in our sample to be separated (10) into 'normal' and 'extreme' groups based on the extremity of the relevant returns as the swing point:

$$\rho^{m_j m_k} = \begin{cases} \rho_x^{m_j m_k} & r > r_{x+}, r < r_{x-} \\ \rho_n^{m_j m_k} & r_{x-} < r < r_{x+} \end{cases}, \tag{10}$$

where ρ is the value of correlation fitted to daily closing returns, r_{x+} is the lowest extreme return (positive swing point), r_{x-} is the highest extreme return (negative *swing point*), while ρ_x and ρ_n represent the correlation grouped according to extreme and normal returns.

To that end, an evaluation is needed first as to whether the generally accepted and used methods described so far are suitable for the test, which is followed by an explanation of the organising principle created based on the above *(see Table 1)*.

Therefore, to allow for a definition of the swing points for returns r_x^+ and r_x^- which we are seeking, it appears appropriate to resort to the original idea of mixed distributions involving the subdivision of the underlying distribution model. A certain extent of heavy-tailness of empirical distributions has been demonstrated, only we have no general form that is well fitted to any capital market. Nevertheless, the near-equilibrium of the capital market can still be described using average oriented models; assuming normal distribution in such a case is probably not very wide of the mark. Ultimately, the separation of extreme events r_x corresponds to the definition of tails, which, from the perspective of average oriented models, is done by separating the tails upwards and downwards from the sections of theoretical and actual distributions after fitting a theoretical normal distribution. Heavy-tailed distribution is characterised by tails consisting of outlier elements which are separated from 'normality', referred to in this paper as 'extreme events'.

In the case of asymptotic stationarity, the periods observed may have differing characteristics, i.e. volatility could become compressed, while the existence of such 'unexpected' periods is also confirmed by power-law distribution. On those grounds, it is pertinent to raise the question whether the

$r_{\frac{n}{x}}^{m_v}$

state of a focal, or m_v lead market influences the co-movement of the other markets.

The research question is ultimately concerned with determining a market the normal and extreme *(n/x)* states of which are suitable to identify contagion under our definition, where the notable events *E*1, *E*2 and *E*3 are defined. Additionally, suppose that ρ^{m_k,m_j} represents the set of combinations situated above the main diagonal from the matrix comprising all the possible combinations of the markets 1…,*j*,*k*,…*n*, which in the case of $\rho_n^{m_k,m_j}$ and $\rho_x^{m_k,m_j}$ have been separated by normal and extreme returns. As a first step, let us assume that output can only be situated between the extremes of significantly different correlations [contagion and divergence – *E*1(11)] and not significantly different correlations [interdependence – *E*2(12)]:

$$E1:\ r_{\frac{n}{x}}^{m_i} \neq 0 \rightarrow where\ \rho_n^{m_k m_j} \neq \rho_x^{m_k m_j} \qquad ,(11)$$

$$E2:\ r_{\frac{n}{x}}^{m_i} \neq 0 \rightarrow where\ \rho_n^{m_k m_j} \approx \rho_x^{m_k m_j} \qquad ,(12)$$

where r^{mi} is the movement of market i, and ρ^{m_k,m_j} is the correlation of markets *k* and *j* along normal and extreme groups. That is, the emergence of either contagion/divergence or interdependence is observed, depending on the normal and extreme state of the lead market selected.

It follows from the foregoing that the separation of a finite number of discrete correlations *(co-movements of market pairs)* available, i.e. classification as *E*1 or *E*2, should be

Table 1

DISTRIBUTIONS AND METHODS GENERALLY ACCEPTED AND USED TO DESCRIBE EXTREME EVENTS

Name of distribution/method	Description of distribution/method	Limitations in defining extreme events
Normal distribution	light tail, complex=random	light tail
Families of power-law and stable distributions	suitable for capturing heavy-tailness and extreme events	does not offer an organising principle to determine the point beyond which events are considered extreme
EVT, GEV, Fisher-Tippet	definition of groups within an ordered population, selection of minimum and maximum values within each group	the number and size of the groups are determined on an arbitrary basis
VaR	a probabilistic approach in general use, a procedure generally accepted by capital market players and the Basel II Regulations	it aims to minimise potential loss rather than to define extreme events, as a result of which the definition of the probability limit is arbitrary
POT-GPD	returns must be above/below a limit, marked by u, to be considered extreme	parametrisation is ambiguous
Q–Q plot	a graphical representation of the goodness of fit of normal distribution fitted to empirical distribution, allowing identification of a point beyond which movements registered in the market are seen as outliers for expected normal distribution	the method is not used to identify extreme events

Source: own editing based on Tsay (2005), Kotz and Nadarjah (2000), Jajuga and Papla (2005) done relative to the total number of variations of the markets in the sample. For that purpose, it is useful to introduce a third case [*E*3 (13)] halfway between the extremes, which is not classifiable. Owing to 'non-classifiability', the case comprises significantly different correlations (to the extent that the correlations of markets $i=1 \ldots k \ldots l \ldots n$ are compared depending on the n/x state of the lead market: $\rho_n^{m_l m_k}$, $\rho_x^{m_l m_k}$) and correlations suggesting interdependence which are not significantly different ($\rho^{m_l m_k}$), at 50 per cent each.

$$E3:\ r^{m_i}_{\frac{n}{x}} \neq 0 \rightarrow \textit{where one half of the combinations satisfy } \rho_n^{m_k m_j} \neq \rho_x^{m_k m_j}\textit{, and the other helf satisfy } \rho_n^{m_k m_j} \approx \rho_x^{m_k m_j} \qquad (13)$$

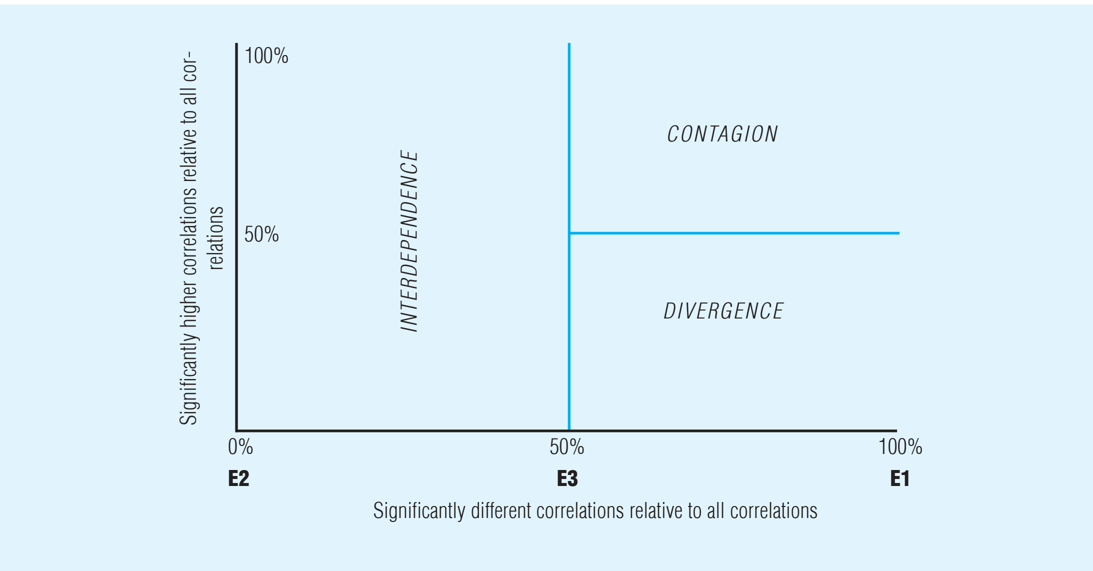
It is important to underline that in reality, the tailed[5] nature of extreme events will yield 'negative extreme and normal' and 'positive extreme and normal' correlation pairs.

Practical applicability also requires that once correlations separated by the lead market have been compared, we should not insist on an extreme definition of contagion or interdependence according to *E*1 and *E*2, but perform a more general classification *(see Figure 3)*, which allows contagions and divergences to be construed in the interval [*E*3, *E*1], and interdependence on interval [*E*2, *E*3]. This makes it possible to rank the output of correlations separated by the n/x states of the lead and other markets.

Subsequently, as a final step, the interval [*E*3, *E*1] characterised by significantly different correlations should be further subdivided to separate contagions and divergences. Under the definition of contagion, the ratio of significantly higher correlations to all correlations should reach at least 50 per cent. Cases below 50 per cent will be considered divergence.

Figure 3

CLASSIFICATION OF A GIVEN MARKET INTO THE CATEGORIES OF 'CONTAGION', 'DIVERGENCE' AND 'INTERDEPENDENCE' BASED ON THE SIGNIFICANT DIFFERENCE OF CORRELATION PAIRS SEPARATED BY NORMAL AND EXTREME EVENTS OF THE MARKET



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TESTING THE MODEL ON THE MARKETS UNDER REVIEW

In this section, we seek to present our findings concerning the impact which the synchronous effects resulting from collective behaviour have on the monetary policy environment in each type of market, to establish homogeneity or heterogeneity within each type of market, and to determine whether lead and follower markets exist. Following the presentation of descriptive statistics, we explain how each GARCH model can be fitted. After that, dynamic conditional correlations (DCC) between markets are calculated, which is followed by an assessment of the tendency of each market for extreme volatility so that the capital market contagions and divergences in the periods under review can be identified and described using the method which we explained previously. At the end of the section, we evaluate the hypothesis of our work.

Liu et al. (1998), *Chen-Zhang* (1997) and *Heathcote – Perri* (2004) all point out that in real economies, capital markets are subject to a regional segmentation which is similar to that described by Viturka et al. (2009) and Lengyel (2006). In our analysis of contagion in capital markets, therefore, we followed a hierarchical logic based on the dominant role of international focal points to select the range of markets to review. The use of USD to express exchange rates in analyses of interactions between markets is suggested by Babetskaia – Kukharchuk et al. (2008) and Stavárek (2009).

Rejecting market efficiency

The efficiency of the markets under review can be rejected, as they do not show the statistical properties described in section 3.1: normal distribution, non-autocorrelation, and homoscedasticity *(see Table 2)*. Clearly, the probability distribution of logarithmic returns does not follow a normal distribution in any of the cases, while leptokurtosis is far from the expected value of 3, which suggests heavy-tailness and a great number of extreme movements. The negative value of asymmetry represents a left slant in probability distribution, which indicates a higher ratio of foreign currency gains in currency markets, and, through reduced returns, of monetary relief in the bond market. In bond markets, with most 3M returns, there is more room for monetary easing, except for the Hungarian market. Conversely, in the 10Y market values approximate 0 or are positive, a sign of monetary tightening. In currency markets, overall gains are observed, which could be construed as an impression of trends preceding 2008.

The ADF test suggests that logarithmic returns are stationary; however, most of the time series considered show signs of both heteroscedasticity and autocorrelation, which confirms the necessity of using GARCH models. The presence of heteroscedasticity indicates clustered market volatility[6], underlining the importance of the phenomena resulting from the occurrence of extreme returns.

Fitting dynamic conditional correlation

Once the poor efficiency of markets has been confirmed, it is appropriate to explain the GARCH models that have been fitted successfully to eliminate at least heteroscedasticity from the time series considered. The methodology section describes 21 compositions of four models.

As shown in *Table 3,* more serious asymmetric models were needed mostly for the bond markets, whereas with currency markets, simpler models using less lag were sufficient to eliminate adequate goodness of fit and het-

Table 2

DESCRIPTIVE STATISTICS OF LOGARITHMIC RETURNS REGISTERED IN THE MARKETS UNDER REVIEW

Markets under review	Asymmetry	Leptokurtosis	Normal distribution test (Jarque–Berra	Stationarity test (ADF-test) 1 lag		Heteroscedasticity (ARCH-LM) 1 lag	Autocor (Ljung–Box) 1 lag
			p	*t* value	critical value	*p*	*p*
EURO 3M	–0,0200	42,0711	0,001	–51,223*	–1,9416	0,0000	0,2245***
HU 3M	1,3047	85,5834	0,001	–50,208*	–1,9416	0,0000	0,8346***
CZ 3M	–3,9396	63,4792	0,001	–46,990*	–1,9416	0,8460**	0,0033
PL 3M	–0,7997	37,5076	0,001	–44,166*	–1,9416	0,0334	0,0000
EURO 10Y	0,0321	4,9600	0,001	–46,933*	–1,9416	0,0000	0,0016
HU 10Y	0,3541	14,6869	0,001	–47,682*	–1,9416	0,0000	0,0171
CZ 10Y	–1,6999	63,9912	0,001	–49,120*	–1,9416	0,0000	0,3756***
PL 10Y	0,6234	16,2843	0,001	–42,228*	–1,9416	0,0000	0,0000
DAX	0,1070	8,2694	0,001	–52,259*	–1,9416	0,0000	0,0276
BUX	–0,0930	9,9225	0,001	–47,662*	–1,9416	0,0000	0,0178
PX	–0,5618	17,8663	0,001	–46,496*	–1,9416	0,0000	0,0003
WIG	–0,2971	6,2382	0,001	–46,363*	–1,9416	0,0000	0,0002
EUR/USD	–0,1148	5,2043	0,001	–49,713*	–1,9416	0,0000	0,8173***
HUF/USD	–0,4760	7,2750	0,001	–50,685*	–1,9416	0,0000	0,4640***
CZK/USD	–0,2709	5,5867	0,001	–48,062*	–1,9416	0,0000	0,0573***
PLN/USD	–0,1601	8,5734	0,001	–50,046*	–1,9416	0,0000	0,9433***

*: Stationary time series, **: Homoscedasticity, ***: Non-autocorrelation
Source: own editing

Table 3

FITTING GARCH MODELS TO THE TIME SERIES CONSIDERED

Asset under review	AIC	GARCH-model	Parameters								ARCH-LM
EUR 3M	1,6261	aparch112	0,0210 ω	0,1985 $\alpha(1)$	–0,2413 $\gamma(1)$	0,2612 $\beta(1)$	0,5401 $\beta(2)$	2,1090 δ			1*
HU 3M	1,3282	aparch222	0,2087 ω	0,2031 $\alpha(1)$	0,2864 $\alpha(2)$	0,3180 $\gamma(1)$	–0,3249 $\gamma(2)$	0,0000 $\beta(1)$	0,5103 $\beta(2)$	0,7890 δ	1*
CZ 3M	1,2870	aparch111	0,0547 ω	0,0157 $\alpha(1)$	–0,9995 $\gamma(1)$	0,9371 $\beta(1)$	0,4887 δ				1*
PL 3M	0,7049	aparch112	0,1502 ω	0,3115 $\alpha(1)$	–0,2915 $\gamma(1)$	0,1940 $\beta(1)$	0,3894 $\beta(2)$	0,6995 δ			1*
EUR 10Y	1,5155	gjr111	0,0036 ω	0,0115 $\alpha(1)$	0,0403 $\gamma(1)$	0,9666 $\beta(1)$					1*
HU 10Y	1,5723	aparch112	0,0836 ω	0,2116 $\alpha(1)$	0,2014 $\gamma(1)$	0,2997 $\beta(1)$	0,4807 $\beta(2)$	1,4632 δ			1*
CZ 10Y	1,4797	aparch112	0,5358 ω	0,0056 $\alpha(1)$	0,9994 $\gamma(1)$	0,0502 $\beta(1)$	0,4051 $\beta(2)$	3,9999 δ			1*
PL 10Y	0,9395	garch23	0,0001 ω	0,2796 $\alpha(1)$	0,0000 $\alpha(2)$	0,2645 $\beta(1)$	0,0807 $\beta(2)$	0,3750 $\beta(3)$			1*
EUR/USD	0,9431	garch11	0,0023 ω	0,0468 $\alpha(1)$	0,9490 $\beta(1)$						1*
HUF/USD	1,3254	gjr112	0,0449 ω	0,0548 $\alpha(1)$	0,1098 $\gamma(1)$	0,1467 $\beta(1)$	0,6939 $\beta(2)$				1*
CZK/USD	1,1220	garch11	0,0036 ω	0,0436 $\alpha(1)$	0,9512 $\gamma(1)$						1*
PLN/USD	1,2732	aparch112	0,0240 ω	0,1140 $\alpha(1)$	-0,3081 $\gamma(1)$	0,3790 $\beta(1)$	0,4950 $\beta(2)$	1,462 δ			1*

Note: *: the standardised error term is homoscedastic
Source: own editing

eroscedasticity. Another unique result is the major role of volatility persistence, symbolised by β.: in a large part of the sample; a far greater number of past terms had to be involved with a definitely larger weight than in the case of novelties, symbolised by α. Monetary policy therefore must cope in a market where uncertainty, measured by the volatility of indicators, reinforces itself in times of crisis.

The dynamics of correlation are different for each type of market *(see Figure 4):* 3M markets fluctuate around non-correlation, whereas with 10Y markets, varying degrees of co-movement are observed between market pairs. In the context of currency markets, we can capture exchange rate convergence, considered in more depth by Stavárek (2009) and Babetskaia–Kukharchuk et al. (2008), which continued even after the 2008 crisis. With 3M returns, correlation fluctuates around an expected value approximating 0, while swings also remain outside the range of stronger co-movement or retrograde movement. This means that in such a case, the behaviour of yield curves is fairly autonomous, and a diversified portfolio can be successfully created. On the other hand, there is no sign at all of convergence by Central and Eastern European countries (albeit even the convergence stipulation of the Maastricht criteria applies to 10Y maturities).

With 10Y returns, a certain degree of volatility is already seen between non-correlation and co-movement in respect of the entire sample. Hungary is an outlier; its previous slight co-movement with the Euro area turned into retrograde movement as a result of the crisis. Previously, the Czech and Polish markets showed some form of weaker or stronger co-movement prior to the crash of Lehman Brothers (marking the onset of the crisis); however, this has been negated by global liquidity shortage. The co-movement of the three Central and Eastern European markets fluctuates around 0.1–0.2. Overall, it is concluded that the 10Y maturity does produce the crisis-induced divergence referred to in the introduction; that is, in the EU, previously considered homogeneous to some extent, fundamental differences lead to the heterogenisation of market pricing. This, of course, also means that the measures taken by developed countries to increase liquidity failed to take effect in the bond markets of Central and Eastern Europe; there was no co-movement in the 3M market anyway, and it became looser in the 10Y market.

The credibility of future Euro accession is confirmed by converging long-term returns as well as a closer co-movement of currencies; so that since March 2008, none of the Central and Eastern European countries has had an ERM 2 type exchange rate regime. Despite that, the HUF has shown a surprisingly stable co-movement with the EUR, CZK and PLN.

It can thus be concluded that market co-movement clearly fluctuates around some special value; however, the multitude of outlier values underlines the question of what happens in the event of extreme market volatility.

In the section explaining the statistical properties of extreme events, we highlighted their insignificant proportion to the size of the entire sample, and their temporal clustering. *Table 4* shows that the weight of returns on the tails of probability distribution, which we identified as extreme, does not exceed 5 per cent in any of the markets.

With 3M returns, the greatest number of extreme events occurred on the positive side as a result of monetary easing. Within this type of market, the Hungarian market was the most sensitive, having the highest ratio of extreme contraction, followed by the Euro area and Poland. The American data could be misleading in this case, as some of the fluctuations seen here are rather extreme. It is appropriate to treat the data for the Euro area and Poland separately because in the former, only spikes of

Figure 4

DYNAMIC CONDITIONAL CORRELATION (DCC) IN THE TIME SERIES CONSIDERED

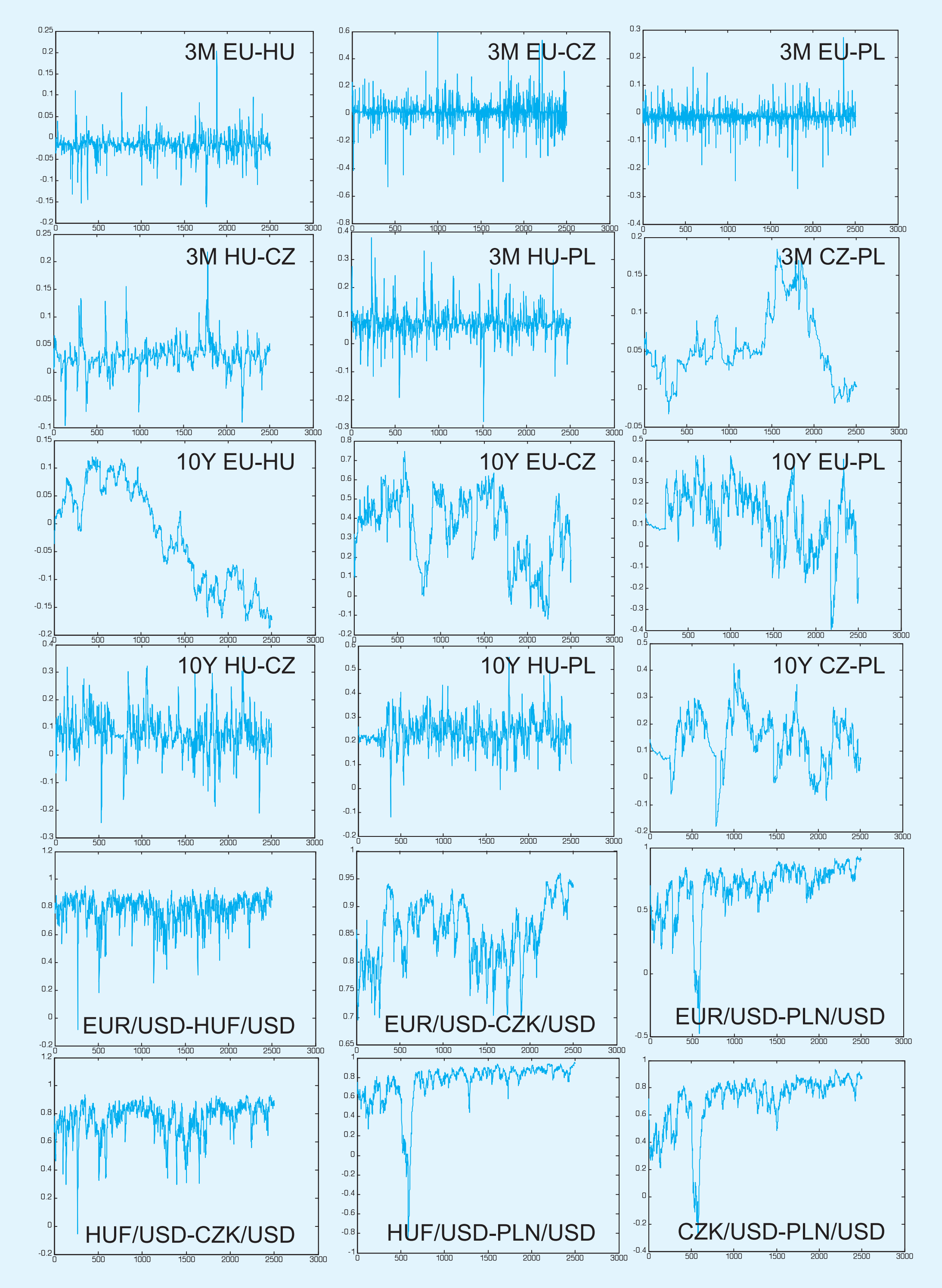

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Table 4

PROPERTIES OF NORMAL AND EXTREME EVENTS

Market under review		EUR 3M	HU 3M	CZ 3M	PL 3M	EUR 10Y	HU 10Y	CZ 10Y	PL 10Y	EUR/USD	HUF/USD	CZK/USD	PLN/USD
	number	60	73	23	60	103	91	33	85	29	34	29	39
extreme „+"	%	*2.40*	*2.92*	*0.92*	*2.40*	*4.12*	*3.64*	*1.32*	*3.40*	*1.16*	*1.36*	*1.16*	*1.56*
	r	6,201	3,054	2,278	1,192	2,144	2,559	2,628	1,57	1,555	2,309	1,966	2,227
normal		2,395	2,399	2,457	2,356	2,334	2,357	2,439	2,344	2,395	2,353	2,367	2,359
	number	48	31	23	87	66	55	31	74	77	114	105	103
extreme „–"	%	*1.92*	*1.24*	*0.92*	*3.48*	*2.64*	*2.20*	*1.24*	*2.96*	*3.08*	*4.56*	*4.20*	*4.12*
	r	–6,694	–3,164	–2,028	–1,143	–2,433	–2,895	–2,647	–1,616	–1,239	–1,738	–1,401	–1,748

Note: yields: number of yields; % ratio of yields compared to total yields; r: yield interpreted as a threshold of extremity

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over six per cent are considered extreme, whereas one-sixth of that size counts as extreme in the Polish market. All this casts a new light on Hungarian vulnerability; in Hungary, an event is considered extreme if it reaches three times the volatility registered in the Polish market and twice that registered in the Czech market, i.e. this market is much more volatile to begin with, and also has tails with a larger weight of extreme returns.

The markets of 10Y returns are already less exposed to monetary policy and the flow of short-term liquidity; however, the Hungarian market shows a weight of extreme movements similar to that in lead markets, which, owing to an asymmetry similar to that of 3M returns, primarily take the form of monetary tightening. As in the 3M market, the threshold of extreme volatility is the highest in the American market with 3.2 per cent, although the differences are smaller here; in the Czech market the threshold is 1.57 per cent, whereas in the Hungarian and Polish markets the values on the positive side are higher than those of the Euro area.

Currency markets are dominated by extreme gains with all four pairs, which could be attributed to the lows of the dollar in the 2000s. Indeed, in the period preceding the 2008 events, the currencies of Central and Eastern European countries also gained against the Euro, while in the crisis they lost within a rather short time, i.e. a smaller number of declining returns are registered. Another characteristic is that the swing points of Central and Eastern European countries tend to coincide, distributed around 1 per cent on the positive side, and around 4 per cent on the negative side.

Table 5 shows the diagnostics of extreme-normal separation, comparing, based on *Pukthuanthong* and *Roll* (2011), the leptokurtosis of the full sample to that of the population which is considered normal. As 'normal' has been defined as volatility within the normal distribution, it is not surprising that the leptokurtosis of this sub-sample approximates the value of three, which is considered ideal.

Difference in market characteristics before and during the crisis

Table 6 compares the changes of the markets in the sample on the basis of two time windows, one characterised by rising and the other by falling base rates. In the course of crisis management, the level of short-term returns fell substantially only in the Euro area and the Czech market, while in the Hungarian and Polish markets it failed to do so even with a higher standard deviation. With longer maturi-

Table 5

LEPTOKURTOSIS OF NORMAL AND EXTREME EVENTS

	EUR3M	HU3M	CZ3M	PL3M	EUR10Y	HU10Y	CZ10Y	PL10Y	EUR/ USD	HUF/ USD	CZK/ USD	PLN/ USD
full sample	42,0711	85,5834	63,4792	37,5076	4,9600	14,6869	63,9912	16,2843	5,2043	7,2750	5,5867	8,5734
normal state	7,7186	6,4723	6,1227	4,7224	2,6747	3,7812	4,3682	3,4725	2,7427	2,8684	2,7738	2,8646

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Table 6

AVERAGE RETURNS AND CURRENCY MARKET VOLATILITY BEFORE (INTERVAL *A*) AND DURING THE CRISIS (INTERVAL *B*)

		EUR	HU	CZ	PL
3M returns	Average in interval *A*	3,5003	7,5218	3,0487	4,8834
	Standard deviation in interval *A*	*-0,361*	*0,7361*	*0,5813*	*0,8121*
	Average in interval *B*	0,7093	6,9252	1,8194	4,2992
	Standard deviation in interval *B*	*0,2983*	*3,5459*	*0,7010*	*0,5364*
10Y returns	Average in interval *A*	4,0302	7,2212	4,2229	5,5631
	Standard deviation in interval *A*	*0,0954*	*0,3768*	*0,2221*	*0,1818*
	Average in interval *B*	3,0693	8,0788	4,2510	6,0088
	Standard deviation in interval *B*	*0,1264*	*1,6655*	*0,2821*	*0,0931*
10Y–3M spread	Average in interval *A*	0,5298	-0,3007	1,1743	0,6798
	Standard deviation in interval *A*	*0,1770*	*0,4704*	*0,1673*	*0,3369*
	Average in interval *B*	2,3600	1,1537	2,4316	1,7095
	Standard deviation in interval *B*	*0,2867*	*0,9540*	*0,5249*	*0,5545*
Foreign exchange	Average in interval *A*	1,3660	0,0054	0,0506	0,3692
	Standard deviation in interval *A*	*0,0138*	*0,0000*	*0,0001*	*0,0028*
	Average in interval *B*	1,3664	0,0050	0,0537	0,3352
	Standard deviation in interval *B*	*0,0052*	*0,0000*	*0,0000*	*0,0006*

Source: own editing

ties, none of the Central and Eastern European countries had its returns reduced; in this case, the countries were already unable to leverage the monetary easing implemented in the Euro area. The extent of market liquidity and the sustainability of maturity transformation can be inferred indirectly from the 10Y–3M spread, which provides a good expression of the time value of money. That will cast a new light on our previous impression, with increased steepness in the yield curves of Central and Eastern European countries (and reduced standard deviations in spreads) during the ECB's monetary easing. It is thus concluded that although the level of base rates is not directly influenced by the ECB's monetary policy, its role in increasing liquidity is felt to a certain extent.

In interval *B*, the EUR continued to gain on average, in contrast with the losses of the HUF and the PLN; surprisingly, the standard deviation of the currencies was reduced during the crisis. It should be added that before the crisis, the currencies of the region gained against the EUR, while during the crisis, they sustained occasionally abrupt losses, which, however, is not reflected in this form of the data.

The co-movement of returns did not necessarily change significantly as a result of the crisis, which could make the job of the central banks and market players concerned easier, as shown in *Table 7*. Typically, this insusceptibility developed mostly for the less liquid 10Y maturity and within the region, while, with one exception, there is always a significant difference from Euro area returns. The 3M market mostly remained uncorrelated, coupled with higher variance, i.e. in the short term, positive or negative co-movement at 0.4 could easily occur, as shown previously in connection with dynamic conditional correlation. With 10Y returns, the market apparently did not price in interest convergence for each Euro candidate; indeed, as a result of the crisis, even the previous limited co-movement of the Czech market, considered a safe haven, became looser. Consequently, divergence should rather be expected to occur in the case of 10Y maturities.

The situation is even more dramatic with respect to the co-movement of currency markets, where an increase in the previously strong correlation is observed. Overall, the crisis led to disintegration in regional bond markets and to integration in regional currency markets. Therefore, with sovereign risks, the emphasis shifted from catching up and convergence to the differences in local fundamentals.

Difference in market characteristics before and during the crisis

Following the definition of extreme events and the calculation of correlation between markets, it is worth addressing the demon-

Table 7

REARRANGEMENT OF CORRELATIONS BETWEEN MARKETS BEFORE (INTERVAL *A*) AND DURING THE CRISIS (INTERVAL *B*)

	EU-HU	EU-CZ	EU-PL	HU-CZ	HU-PL	CZ-PL
3M returns						
Ansari–Bradley test between intervals *A* and *B*	0	1	1	1	0	1
Average in interval *A*	–0,017	0,0110	–0,014	0,0357	0,0757	0,0875
Standard deviation in interval *A*	*0,0005*	*0,0029*	*0,0005*	*0,0003*	*0,0016*	*0,0019*
Average in interval *B*	–0,015	0,0171	–0,010	0,0305	0,0702	0,0520
Standard deviation in interval *B*	*0,0006*	*0,0060*	*0,0007*	*0,0009*	*0,0014*	*0,0033*
10Y returns						
Ansari–Bradley test between intervals *A* and *B*	1	1	1	0	0	0
Average in interval *A*	–0,044	0,4480	0,1575	0,0757	0,2271	0,1826
Standard deviation in interval *A*	*0,0026*	*0,0107*	*0,0143*	*0,0037*	*0,0032*	*0,0073*
Average in interval *B*	–0,129	0,1697	0,0197		0,2441	0,0991
Standard deviation in interval *B*	*0,0009*	*0,0229*	*0,0220*	*0,0047*	*0,0038*	*0,0072*
Foreign exchange						
Ansari–Bradley test between intervals *A* and *B*	0	0	0	1	0	0
Average in interval *A*	0,7444	0,8305	0,7537	0,7168	0,8326	0,7642
Standard deviation in interval *A*	*0,0105*	*0,0026*	*0,0066*	*0,0141*	*0,0049*	*0,0059*
Average in interval *B*	0,8102	0,8800	0,7996	0,8292	0,8718	0,8356
Standard deviation in interval *B*	*0,0060*	*0,0039*	*0,0068*	*0,0046*	*0,0028*	*0,0030*

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stability of collective actions (contagion and divergence) *(see Figure 5)*. Assuming extremity in the volatility of Euro area assets, the full sample will show divergence in the case of increasing returns and losing currencies. With the sub-samples described earlier (intervals *A* and *B*), the already close correlation was significantly reinforced on days when the EUR lost significantly, that is, a loss of confidence affected the Euro area and its orbit at the same time.

In the case of returns, dried up markets were coupled with a significant reduction in correlation for both maturities. It is a different issue that with 3M, divergence was not demonstrable before the crisis, while it was during the crisis. However, with 10Y, no significant correlation change can be demonstrated that is coupled with extreme monetary tightening either before or during the crisis. That is, irrespectively of our previous finding of considerable co-movements between 10Y returns, extreme hikes do not lead to synchronous effects on a daily basis.

On days of extreme EUR gains, only interdependence is observed over the entire period; however, the two sub-samples already show divergence. The sudden EUR gain thus did not pull the other currencies; the positive shock failed to spill over *(see Figure 6)*. At times of

Figure 5

DEMONSTRABILITY OF CONTAGION, DIVERGENCE AND INTERDEPENDENCE WITH THE NORMAL AND EXTREME STATES OF THE MARKETS UNDER REVIEW, CONSTRUING EXTREMITY ONLY IN THE POSITIVE RANGE OF PROBABILITY DISTRIBUTION

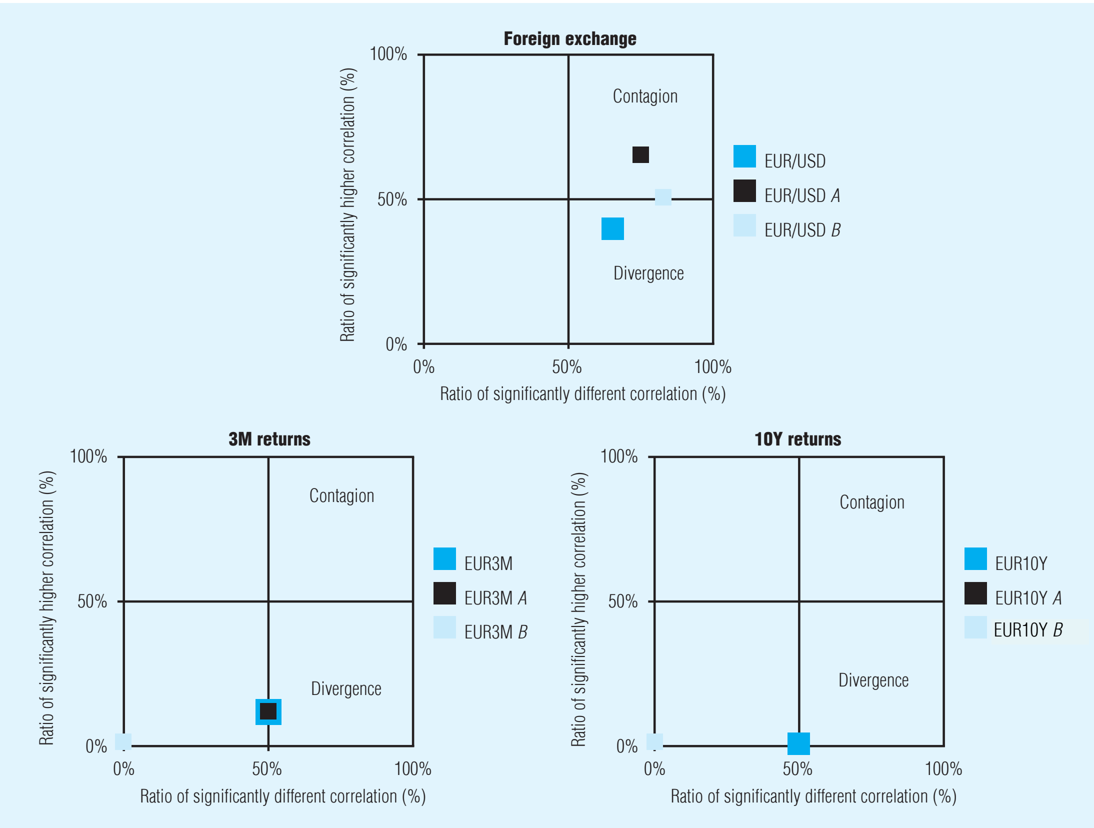

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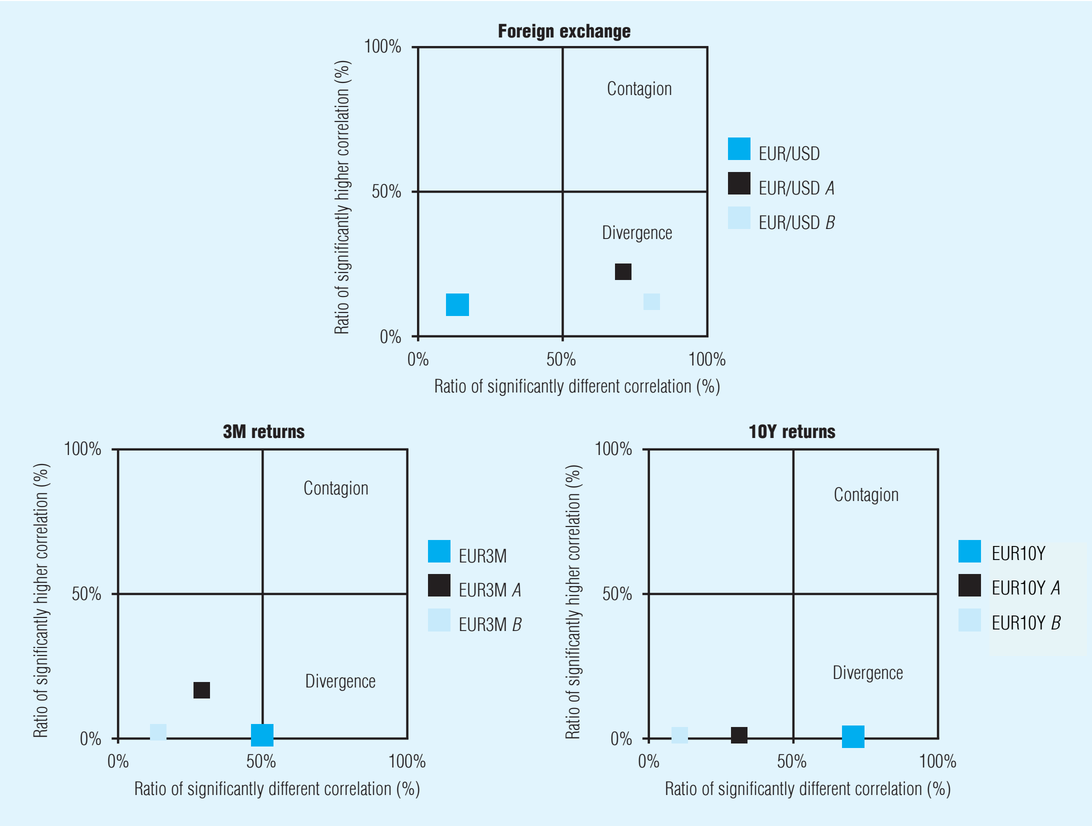
Table 6

DEMONSTRABILITY OF CONTAGION, DIVERGENCE AND INTERDEPENDENCE WITH THE NORMAL AND EXTREME STATES OF THE MARKETS UNDER REVIEW, CONSTRUING EXTREMITY ONLY IN THE NEGATIVE RANGE OF PROBABILITY DISTRIBUTION



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monetary easing, divergence is seen only on the entire sample, whereas sub-samples failed to produce the same effect. That is, despite a sudden increase in liquidity in the bond markets of the Euro area, there was no co-movement between Central and Eastern European markets on that day.

SUMMARY

The autonomy of monetary policy becomes limited when, as a result of collective action evolving in the markets, co-movements of significantly varying degrees occur. We have constructed a diagnostic model for such observations, as part of which first we reject the principle of market efficiency and random walk by testing the normal distribution, non-autocorrelation and homoscedasticity of market movements. In the second step, we compared the conditional correlations of market movements derived from various GARCH *(Generalized Autoregression Heteroscedasticity)* models and obtained through Fischer transformation, in the extreme and normal states of the lead market. There are two main approaches to the analysis of financial time series; average oriented models look at the expected value and variance of probability distribution, whereas extreme value models are concerned with the tails *(fat-tailness or heavy-tailness)* of the distribution[7], and its maximum and minimum values. In this paper, we sought to offer a diagnostic analysis of the latter.

The bond market, compared to either currency or equity markets, is more of an oligopolistic and regulated market owing to the dominance of institutional actors and the actions of monetary policy (this is also confirmed by differences in leptokurtosis). Nevertheless, the interaction of markets largely depends on the period selected for review, and the extremity of daily movements. A summary of key results is therefore appropriate.

Over the entire time series, 3M markets were found to be uncorrelated, while extreme movements were found to be symmetric. Ten year returns fluctuated between weak correlation and non-correlation, and extreme movements were more typical in cases of increased returns (liquidity shortage). Currency markets are strongly correlated, and on days of extreme EUR gains, the co-movement of currencies intensified more than at times of extreme losses. In general, Czech markets produced a far lower number of extreme movements than the rest of the sample.

In the sub-samples characterised by the ECB base rate rising before the crisis *(A)*, and falling in the course of crisis management *(B)*, only the Czech markets produced a decrease in 3M returns as a result of the ECB's measures. Meanwhile significant changes occurred in market co-movement, which nevertheless remained uncorrelated on average, although with a higher standard deviation. With the 10Y maturity, the Central and Eastern European sample showed a uniform increase in returns, while correlations between countries of the Euro area and the region were significantly reduced. However, the difference between long and short term returns increased in all cases, indicating a general improvement in maturity transformation. In currency markets, the losses of Central and Eastern European currencies during the crisis are tangible, while the previous strong correlation between markets also remained.

Assuming extremity in the daily changes of Euro area indicators, divergence in bond markets is mostly observed over the entire period, with no significant change resulting from extreme movements of EUR returns in correlation between markets in the sub-samples comprising the respective intervals before and during the crisis. The extreme gain of the EUR against the USD was suitable to demonstrate a significant reduction in correlation on the full sample, while crisis-induced contagion could also be observed. The extreme EUR loss before and during the crisis was an indicator of divergence.

Based on a comparison of the entire period and the sub-samples taken before and during the crisis, two conclusions are drawn; on the one hand, there is no substantive difference between the collective behaviours observed in the ECB's periods of interest rises and cuts, while the results of the sub-samples differ from what is seen in the full sample.

Monetary policy autonomy in Central and Eastern European countries was rearranged so that the voluntary harmonisation of institutional frameworks supported by the market in the form of convergence was replaced, as a result of dented market confidence, by individual strategies aligned with different fundamentals. The ECB's decisions spilled over only to the Czech bond market, while their influence was limited to the steepness of the yield curve in other countries. Thus, in the course of managing the crisis, central banks in Central and Eastern Europe were left to their own devices in the market, which, paradoxically, entailed an unexpected increase in monetary policy autonomy, thus confirming our hypotheses.

Appendix

FITTING DYNAMIC CONDITIONAL CORRELATION FOLLOWING ELIMINATION OF HETEROSCEDASTICITY

In the generalised ARCH (GARCH) model (6), lag length is represented by p, the ARCH process by σ^2 and q, the impact of present news on conditional variance by ε^2, α_i, while volatility persistence, i.e. the shock of recent news to old information, by β_i (Davidson – MacKinnon, 2003):

$$\sigma_t^2=\omega+\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2+\sum_{i=1}^{p}\beta_i\sigma_{t-i}^2 \qquad (6)$$

The most general description of *the family of asymmetric GARCHs* is offered by the *APARCH(p,o,q) – Asymmetric Power ARCH* – model (7) explained in a joint paper by *Ding*, *Granger* and *Engle* (1993):

$$\sigma_t^2=\omega+\sum_{i=1}^{q}\alpha_i(|\varepsilon_{t-i}|-\gamma_i\varepsilon_{t-i})^{\delta}+\sum_{j=1}^{q}\beta_j\sigma_{t-j}^{\delta} \qquad (7)$$

where $\delta>0$ and $-1<\gamma_i<1$, and $e_t\sim N(0,1)$ introducing heavy-tailness are obtained as the ratio of the error term and standard deviation. The APARCH can be used to express other models, such as *the GJR GARCH and threshold ARCH (TARCH)* models constructed by *Glosten*, *Jarannathan* and *Runkle* (1993), subject to the restrictions below. The latter allow a comparison of simpler symmetric approaches (ARCH, GARCH) and, within the asymmetric approach, solutions operating with squared (GJR)(15) and absolute value (TARCH) (16) innovations. Asymmetric responses are captured by means of an S indicative dummy (binary) variable (14):

$$\begin{cases} S_{t-i}^{-}=1,\ \text{if}\ \varepsilon_{t-i}<0 \\ S_{t-i}^{-}=0,\ \text{if}\ \varepsilon_{t-i}\geq 0 \end{cases} \qquad (14)$$

$$\text{GJR GARCH: } \sigma_t=\omega+\sum_{i=1}^{p}\alpha_i\varepsilon_{t-i}^2+\sum_{i=1}^{o}\gamma_i S_{t-i}^{-}\varepsilon_{t-i}^2+\sum_{i=1}^{q}\beta_i\sigma_{t-i}, \qquad (15)$$

$$\text{TARCH: } \sigma_t^2=\omega+\sum_{i=1}^{p}\alpha_i|\varepsilon_{t-i}|+\sum_{i=1}^{o}\gamma_i S_{t-i}^{-}|\varepsilon_{t-i}|+\sum_{j=1}^{q}\beta_i\sigma_{t-i}^2, \qquad (16)$$

where $\alpha_i>0(i=1,\ldots,p)$, $\gamma_i+\alpha_i>0(i=1,\ldots,o)$, $\beta_i\geq 0(i=1,\ldots,q)$, $\alpha_i+0{,}5\gamma_j+\beta_k+<1(i=1,\ldots,p,$ $j=1,\ldots,o,$ $k=1,\ldots,q)$.

With squared innovation and $o=0$, the model can be reduced to symmetric GARCH (which can be further reduced with $q=0$ to ARCH). If $o>0$, the use of squared innovation will produce a GJR model, while the use of absolute value innovations will produce a TARCH model. The significance of asymmetry lies in capturing a stronger response to negative news; this preference for negative novelties is represented by the combined use of α_i and γ_i , in contrast with positive news, where only α_i can be taken into account.

Mindful of the above, the appropriate GARCH model was selected as follows:

❶ With the appropriate parametrisation of TARCH/GJR, GARCH and APARCH models, the following models were made to compete while applying a variety of lags:

- GARCH (p,q) (1,1)(2,1)(1,2)(2,2)(3,2)(2,3),
- GJR GARCH (p,o,q) (1,0,1)(1,1,1)(2,1,1)(1,2,1)(1,1,2),
- TARCH (p,o,q) (1,1,1)(2,1,1)(1,2,1)(1,1,2)(2,2,2),
- APARCH (p,o,q) (1,1,1)(2,1,1)(2,2,1)(1,1,2) (2,2,2);

❷ We calculated the standardised error terms associated with each model: ;

$$\varepsilon^{\#}_{it} \frac{\varepsilon_{it}}{\sigma^2_{it}}$$

❸ Standardised error terms were tested for homoscedasticity using the ARCH-LM test with a lag of 1;

❹ Out of the competing models, we chose the one the standardised error term of which was homoscedastic;

❺ In step 4, the sample is narrowed further to select the model with the lowest value of the Akaike information criterion[8].

The DCC model (17,18) relies on the returns of asset k (r_t), which have an expected value of 0 and a normal distribution, as well as a covariance matrix marked H_t.

$$r_t \mid \Phi_{t-1} \sim N(0,H_t), \qquad (17)$$

$$H_t \equiv D_t R_t D_t, \qquad (18)$$

where r_t is a $K \times 1$ vector; H_t is a conditional covariance matrix; R_t is a $k \times k$ time-variable correlation matrix; and all information available at a $t-1$ point in time is contained in Φ_{t-1}. Naturally, returns can also be the error terms of a time series. D_t is a $k \times k$ diagonal matrix, comprising the time-variable standard deviations of a univariate GARCH model, with $\sqrt{h_{it}}$, which is item i of the main diagonal. Converting this into the GARCH form, (19) can thus be expressed (Kuper – Lestano 2007; Wong – Li, 2010):

$$h_{it}=\omega_i+\sum_{p=1}^{P_i} \alpha_{ip} r^2_{t-p} + \sum_{q=1}^{Q_i} \beta_{iq} h^2_{it-q} \qquad (19)$$

NOTES

1 This is the most restrictive definition of contagion offered by the World Bank, see: http://go.worldbank.org/JIBDRK3YC0

2 Under the very restrictive definition of contagion, in the context of the yield curve our analysis is limited to changes in the ECB base rate and changes in the yield curves of other countries, and does not consider changes in other macroeconomic variables such as per capita GDP, international reserves or fiscal policy.

3 UCSD GARCH: http://www.kevinsheppard.com/wiki/UCSD_GARCH; Oxford MFE: http://www.kevinsheppard.com/wiki/MFE_Toolbox

4 For better clarity, the formulae associated with asymmetric GARCH models are described for cases with a lag of 1, i.e. (1,1) and (1,1,1).

5 Extreme events are situated on the tails of the probability distribution; therefore with any time series, there will be a negative extreme and a positive extreme population in addition to the set which is considered normal.

6 Volatility is high in certain periods and lower in others.

7 Based on Király et. al (2008) and Feller (1978), the original of this paper uses the Hungarian term vastagfarkúság as an equivalent of fattailness and heavytailness.

8 The Akaike information criterion (AIC) tests the deviation of a model from a given distribution, with which MLE methods will produce the overestimation of LL: the lower the AIC value, the smaller the difference between the estimate and the 'actual model'. $AIC = -\frac{2}{\text{number of data}} \{1n(LL) + number\ of\ parameters\}$ (Lovric 2009).

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