Zalán Kocsis and Dénes Nagy: Variance decomposition of sovereign CDS spreads*,[1]

In this paper we analyse the information content of correlations between daily changes in CDS spreads. Using factor analysis, we can break down the variance of CDS spreads into global, regional and country-specific components. Our results confirm the finding of other studies, namely that there is a strong global factor underlying credit risk spreads. Comparison of different time samples reveals that the global correlation of spreads has become stronger during the financial crisis; at present, the global factor universally affects emerging and developed countries. CDS spreads are most strongly correlated with other countries in geographically interpretable regional country groups. The Hungarian CDS spread generally follows the global factor; in recent years, the escalating crisis on the periphery of the euro area has also affected the country's spreads. From the summer of 2010 until the end of the year, country-specific events led to a considerable deterioration in Hungary's risk assessment. However, the shift in the government's fiscal policy stance in early 2011 restored most of the lost investor confidence.

INTRODUCTION

This paper analyses correlations between CDS spreads of major developed and emerging countries in order to study the behaviour of the Hungarian CDS spread. Analysis of the correlations of spreads and their segmentation into global, regional and country-specific components reveals the relative importance of factors in the case of individual countries and allows a better understanding of the driving forces behind changes in the market's assessment of sovereign credit risk.

Comparisons can work in various ways. For each country, we can calculate the relative impact of various components (e.g. we can estimate and compare the effect of global, regional and idiosyncratic factors on the Hungarian CDS spread). This is performed on the whole sample period and on shorter time samples as well. Segmentation also allows for international comparisons. For example, the sensitivity of the Hungarian CDS spread to global or regional shocks can be compared against similar indicators in other countries.

The paper first provides a brief discussion of the information content of CDS spreads. Then the global, regional and country-specific factors of CDS spreads are presented. Next, correlations between countries and factors and the sensitivities of countries to those factors are compared. Finally, based on the results of the last subsample, the Hungarian CDS spread is segmented into factors, and we present how these factors contributed to changes in the risk indicator over different time periods.

ON CDS SPREADS IN GENERAL

The information content of CDS spreads

A CDS (credit default swap) is a derivative transaction, the payoffs of which depend on a bond issuer fulfilling its debt obligations or defaulting. If the default event specified in the contract occurs, the seller of the CDS protection has a payment obligation vis-à-vis the buyer of the CDS protection. The seller meets this obligation either by paying the notional of the reference bond in exchange for the bond's physical delivery, or by paying the difference between the notional and the market value. In both cases, in effect, the seller of CDS protection compensates the buyer for losses arising from the credit event.

Thus, the buyer of the CDS can theoretically cover credit risk exposure to an issuer by using a sovereign CDS transaction, provided that the seller remains solvent. Essentially, the buyer of the sovereign CDS obtains a kind of insurance for the referenced sovereign's default event, for which a fee is

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paid at regular intervals. The magnitude of the fee is determined as a percentage of the nominal value of the underlying instrument and is called the CDS spread.[2]

Theoretically, the magnitude of the CDS spread has to be in line with the risk of the investor's expected loss arising from the potential default event. The value of this risk is the product of the probability of default and the loss expected in this case (the difference between the notional and the market value). If the CDS spread is too high compared to the credit risk (i.e. the difference between the notional value and the market value is relatively low), it is worth entering the market as a CDS seller, because the expected value of the fees collected on the transaction exceeds the expected value of the conditional disbursement. If many market players recognise this opportunity, their entrance into the CDS market and underbidding of the market price will result in a decline in the CDS spread.

The fundamental value of CDS transactions for sovereign issuers is determined by the product of the probability of default of the given country and the loss suffered in such a case. This fundamental value is related to macroeconomic conditions of the reference country, since the probability of default depends mainly on these factors. Political factors are also important, since non-payment of the debt obligation and its specific form are usually the result of political decisions.

In addition to fundamentals, market confidence is also important in terms of the creditworthiness of the issuer. Market confidence may be a considerable factor both in terms of the long-term sustainability of the debt of the sovereign and its short-term financeability. Increasing wariness about a sovereign's creditworthiness reduces demand for its bonds, which may result in an increase in yields and exchange rate depreciation, as well as a failure of bond auctions. Thus, market confidence by itself – independent of the endogenous changes in the fundamentals – can affect the solvency of the sovereign. This may also influence CDS spreads, and therefore both the seller and the buyer of the CDS must take into account how other investors assess market confidence and, accordingly, the expectations of other investors. This provides a game theoretic aspect for the determination of CDS spreads, and may be a possible answer to the dilemma that the empirical literature faces when it finds that the volatility of CDS spreads is far larger than what fundamentals can explain.

Decomposition of CDS spreads

There are many ways of segmenting CDS spreads into different factors.[3] The extensive empirical literature focuses on identifying a component that can be explained by fundamentals and separating a component above that (the latter is known by different names: market sentiment component, risk aversion/appetite, risk premium). Most papers use a linear regression on panel data for this purpose, where the credit spreads of several countries are dependent variables. The fundamental part is then attributed to fundamental variables in the regression (macroeconomic variables expressing solvency and liquidity or sometimes even variables relating to the political situation), while the risk premium is either simply the error of the regression or proxied by variables capturing global market confidence (VIX index, TED spreads).[4] In certain cases, the fundamental part of the credit risk is captured with credit ratings or historical default frequencies[5] instead of macro variables.

Instead of using simple OLS regressions, several authors apply instrumental variables and 2SLS procedures in order to avoid endogeneity. Error correction models assuming cointegration are also found in the literature, while other authors apply factor analysis or a similar method of principal component analysis.[6]

Factor or principal component analyses typically establish that (1) a significant proportion of the spreads of the countries included in the analysis has a strong positive correlation with the first principal component (this is why it is called a global component), (2) this factor is mainly explained by global investor sentiment, as it also strongly correlates with related variables (for example, the VIX index). Usually, the (in general, relatively low) variance proportion remaining in addition to the global component is identified as the local (regional or country-specific) and typically fundamental factor.[7]

Our paper also confirms the existence of a global factor and its important role in common variance. The novelty here is that in addition to the global factor, we elaborate on the

[2] A more detailed description of the transaction is provided by Varga (2008).

[3] This may also include the analyses of other credit risk variables besides CDS spreads (foreign exchange bond spreads or ratings), as the concept is the same: all of them deal with the decomposition of the sovereign credit risk.

[4] Some studies that are often referred to in this field: Edwards (1984, 1986), Cantor and Packer (1996), Eichengreen and Mody (1998).

[5] Kamin and Kleist (1999), Sy (2001), Kocsis and Mosolygó (2006).

[6] A few examples for the above: 2SLS: Benczúr (2001), Remonola et al. (2008), cointegration: Rosada –Yeyati (2005), principal component analysis: Kisgergely (2008), McGuire and Schrijvers (2003), Broto et al. (2011)

[7] Westphalen (2001), McGuire and Schrijvers (2003), Longstaff et al. (2010).

factors associated with smaller groups of countries as well. As we will see, factor analysis arranges CDS spreads into groups on a regional basis. That we can deal with these additional country groupings is partly made possible by the choice of the sample: the inclusion of a wide cross-section (which comprises several regions) and of the period of the crisis. In earlier samples, changes in CDS spreads were not arranged into such regional groups. Our analysis also addresses changes in factor structure over time, which is an important, albeit less discussed, topic in the literature.

VARIANCE DECOMPOSITION OF SOVEREIGN CDS SPREADS

Data and method of analysis

Our data set consists of time series of daily changes in the 5-year CDS spreads available on the Bloomberg system. Our sample runs from May 2006 to July 2011 and includes the data of 37 (developed and emerging) countries[8] in the cross-sections. The resulting roughly 5-year-long time series contains 1,375 temporal observations (1,374 for CDS differences). This number of observations allows us to perform analysis on three main subsamples (pre-crisis: May 2006–December 2007;[9] financial crisis: January 2008–August 2009; sovereign crisis: September 2009–July 2011) even with the examined large cross-section.

Analysis is conducted on the daily changes of CDS spreads. Stationarity is not a condition in the factor analysis procedure; the method can be applied to CDS levels and CDS changes alike. (The relevant literature is divided in this respect; there are examples for analysing both the levels and the changes.) Nevertheless, correlations between changes may better express the direct relations between countries (and country groups), whereas indirect responses given in relation to a third variable, as well as common trends, may play a greater role in the levels; therefore, in our opinion, examination of changes is more justifiable.

The method applied in the paper is factor analysis. The essence of factor analysis is that it allows segmentation of the common variance of a large number of variables (the CDS spreads include nearly 40 countries in this case) into a few factors. It is important that factor analysis deals only with the common part of the variance rather than the total variance.[10]

Factor analysis establishes the factor matrix, which is the table of correlation coefficients (or factor loadings) between variables and factors. In the case of each variable (CDS spread), the factor loadings express the correlation with different factors. If the value of the loading is 1, it implies a perfect positive correlation between the factor and the variable; a 0 value shows that the variable and factor are uncorrelated, whereas a −1 value represents movements in opposite directions.

In a mathematical sense, there are an infinite number of ways to divide the common part of the variance among the factors. However, some have a more notable role in applications. This paper uses three methods of segmentation (Chart 1).

In terms of explaining the variance of CDS spreads, the (unrotated) factors extracted in the first step of factor analysis have a hierarchical order: the first factor explains the greatest part of the common variance, the second one explains the greatest part of the remaining common variance, etc. Of these first-step, unrotated factors, only the first factor is used in this analysis. This will be our global CDS factor, and its role in different countries may be examined by means of an international comparison. We do not use other factors of the unrotated factor solution.

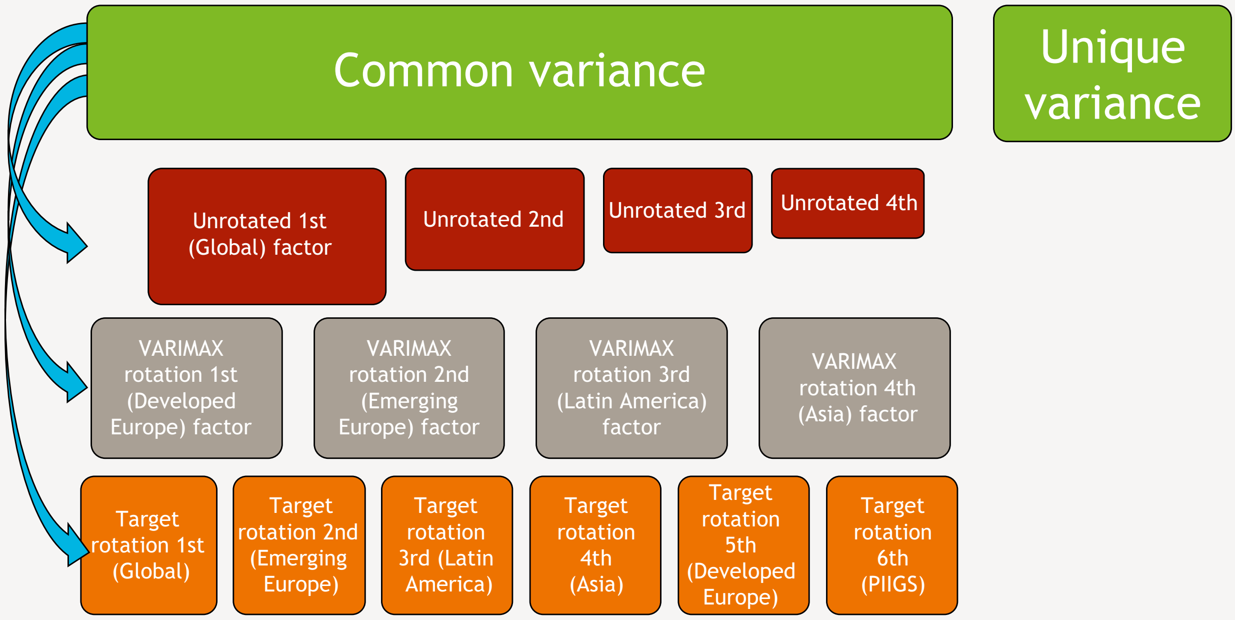
The factors that express the correlation of country subgroups are obtained during the rotation phase of the factor analysis procedure. The first rotation method used here is the varimax rotation, which is an optimisation procedure minimising a complexity function. The objective function reaches a minimum value if the variables are well separated by the factors. Technically, this separation means that for each variable there will be one factor with a high factor loading (the variable correlates with this factor), but its loadings will be low in the case of other factors. This is useful in most applications using factor analysis, because it allows a clear linking of variables to factors and usually provides an intuitive interpretation of what different factors mean. In this analysis as well, the varimax rotation

[8] Developed countries: Austria, Belgium, France, Greece, the Netherlands, Ireland, Japan, Italy, Portugal and Spain. Emerging countries: Bulgaria, Czech Republic, South Africa, Estonia, Croatia, Kazakhstan, Poland, Lithuania, Hungary, Russia, Romania, Slovakia, Turkey, Ukraine, Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela, South Korea, Indonesia, China, Malaysia, Thailand and Vietnam.
In the second and third subsamples, data on Denmark, Lithuania, Great Britain, Germany, Sweden and the USA were also available; for the sake of comparability of the samples, the findings regarding the narrower cross-section are discussed.

[9] A more realistic pre-crisis period, with a sample ending in July 2007, exhibits a factor structure that is more difficult to explain; this is why the end-2007 period, which can be considered as relatively calm compared to the events experienced in the later financial crisis, was also attached to the first subsample. The next chapter draws the conclusion that correlations between countries were weaker and individual groups were less separated from one another in the pre-crisis period. This is even more true for the narrower sample of 2006 to mid-2007.

[10] In contrast, principal component analysis distributes the total variance among the components.

Chart 1
Three possible segmentations of the common variance



Source: MNB.

creates factors that allow a good identification of which of the variables (CDS spreads) belong to which factors (regions). Thus, the regional factors used in the analysis are created by the varimax solution.

A third segmentation is carried out in the last part of the paper, which deals with the Hungarian CDS spread. In this section, a target pattern rotation is used, as it allows the simultaneous segmentation of the common variance into (uncorrelated) global and regional factors. For this method, however, a factor structure (i.e. which variable belongs to which factor) has to be established a priori; to that end, the conclusions drawn from the varimax rotation are used.[11]

Factor structure

The conditions usually checked prior to starting factor analysis are met by the whole sample and by all subsamples of our data set.[12] The optimum number of factors indicated by various statistical methods[13] was, however, different across subsamples and methods. Finally, we decided on extracting four factors, which was justifiable for the full sample both on interpretational and statistical grounds. In the four-factor case, the countries in the varimax rotation form an emerging European bloc, a Latin American bloc, an emerging Asian bloc and a developed European bloc.[14]

Table 1 contains the unrotated global factor loadings, the loadings of the varimax rotated factors and the unique variances for the full sample (May 2006–August 2011). (The unique variance is the same in the case of the unrotated and rotated solutions.)

The first column of the table presents the correlation coefficients (factor loadings) with the global factor for each country. As mentioned above, this is the first factor of the

[11] See the Appendix for more details about factor analysis.

[12] The anti-image correlation matrix almost exclusively contains close-to-zero elements, whereas the complete correlation matrix contains mostly high values. The correlations between variables are significant on the basis of the formal Bartlett test as well (the p value is less than 0.001). The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (MSA) value is also adequately high: 0.9617 for the complete sample; it is 0.89 even for the pre-crisis subsample, which has a weaker factor structure (an MSA value of 0.7 is already considered good, and a value above 0.9 signals an extremely suitable data set for factor analysis).

[13] Eigenvalue greater than 1, cumulated variance proportion greater than 60 per cent and the minimisation of the average partial correlations.

[14] Most methods indicated a larger number of factors to be extracted for the pre-crisis subsample. After rotation, these factors usually made up groups that were difficult to interpret; even the higher loadings were relatively low, compared to loadings of later subsamples. For this sample, the factor structure was weak and indicated that the co-movements of CDS spreads of individual countries were less easy to separate, although the correlations of the global factor of the unrotated solution were adequately high in the case of most emerging countries (mainly Latin American and Asian countries). In the sovereign crisis subsample, adding a fifth regional factor is acceptable on statistical grounds and would separate the group of the euro-area peripheral countries (PIIGS) from the other developed European countries. However, because this was only characteristic of the last period we applied the four factor solution in this phase of the analysis.

Table 1
Correlations between credit default swaps and factors, including the unique variance

		Factors (common variance)					Unique variance
		Unrotated 1st factor	Varimax rotation factors				
Region	Country	Global	Developed Europe	Emerging Europe	Latin America	Emerging Asia	share of variance
Emerging Europe	Hungary	0.642	0.326	0.680	0.296	0.239	32.5%
	Poland	0.647	0.357	0.501	0.265	0.309	30.2%
	Czech Republic	0.678	0.221	0.607	0.351	0.254	31.9%
	Slovakia	0.692	0.227	0.632	0.356	0.302	32.7%
	Romania	0.639	0.224	0.762	0.315	0.193	31.3%
	Croatia	0.626	0.231	0.736	0.279	0.253	34.4%
	Bulgaria	0.711	0.238	0.708	0.353	0.276	23.1%
	Latvia	0.540	0.124	0.572	0.261	0.248	55.9%
	Estonia	0.589	0.115	0.358	0.235	0.350	42.4%
	Ukraine	0.275	0.066	0.569	0.121	0.153	88.4%
	Russia	0.774	0.081	0.620	0.421	0.525	25.6%
	Turkey	0.829	0.117	0.298	0.600	0.383	28.9%
	South Africa	0.805	0.147	0.608	0.464	0.448	23.0%
	Kazakhstan	0.710	0.070	0.612	0.449	0.347	41.5%
Emerging Asia	China	0.655	0.143	0.250	0.296	0.764	27.8%
	Thailand	0.679	0.124	0.242	0.337	0.764	26.1%
	Malaysia	0.699	0.115	0.288	0.296	0.850	13.2%
	Indonesia	0.799	0.038	0.102	0.478	0.634	22.8%
	Vietnam	0.743	0.069	0.235	0.406	0.739	22.6%
	Korea	0.681	0.103	0.190	0.249	0.838	14.5%
Latin America	Mexico	0.920	0.076	0.311	0.857	0.292	11.2%
	Brazil	0.943	0.082	0.271	0.936	0.234	2.1%
	Argentina	0.434	0.112	0.364	0.336	0.157	80.8%
	Peru	0.901	0.081	0.065	0.914	0.195	8.6%
	Venezuela	0.568	0.129	0.270	0.452	0.194	67.2%
	Chile	0.709	0.080	0.274	0.531	0.379	48.7%
	Colombia	0.940	0.088	0.299	0.867	0.332	7.7%
Developed	Spain	0.325	0.871	0.102	0.099	0.072	20.7%
	Portugal	0.238	0.835	0.105	0.057	0.041	29.5%
	Ireland	0.255	0.791	0.094	0.059	0.050	35.8%
	Italy	0.373	0.873	0.241	0.099	0.133	17.2%
	Greece	0.182	0.634	0.205	0.046	0.008	59.3%
	Austria	0.429	0.526	0.211	0.112	0.229	51.1%
	France	0.352	0.704	0.288	0.091	0.146	42.4%
	Belgium	0.334	0.783	0.284	0.089	0.090	32.8%
	Netherlands	0.367	0.543	0.296	0.093	0.196	57.5%
	Japan	0.286	0.190	0.220	−0.004	0.378	75.8%

Note: factor loadings in the table denote the correlation between a given country's CDS spread and a factor. Values close to 1 indicate strong positive correlation; values close to 0 suggest that the given factor has an insignificant effect on the spread. (Only the 1st factor of the unrotated solution is shown.)

four-factor unrotated loading matrix, the factor that explains the greatest share of common variance of the CDS spreads. The factor loadings are positive in the case of each country and are highly significant (i.e. not close to 0 in most cases). Therefore, it can be asserted that a dominant global factor does exist, making it possible to explain a significant proportion of the changes of CDS spreads of most countries. The global factor shows the highest correlations within emerging countries, while loadings are the highest for certain Latin American and Asian countries. The remaining three columns of the unrotated factor matrix are not shown in the table.

The next four columns display the values of the factor loading matrix following the varimax rotation step. These factors create country groups which are easy to interpret and are separated along geographical units. It must be emphasised that this structure is not at all evident. Based on much of the literature, it would be just as reasonable to expect credit spreads to form groups on the basis of macro variables instead of regional units. Debt ratios, GDP dynamics or yield levels could form equally plausible criteria for creating country groups.

Although the emergence of regional factors may partly be justified by common macro-economic and political conditions within regions, the common structure of investors' portfolios may also play a greater role in the larger regional CDS correlations. Large international financial organisations, as well as the economic-financial media and analysts that thematise the markets, also think along such regional lines.

Correlation coefficients show that the first regional factor basically constitutes developed European countries. The factor does not correlate strongly with Japan (and neither with the USA in the second and third subsamples, based on data not presented here), so it does not represent developed countries in general. The second factor groups emerging European countries in a wider sense. In this group, Bulgaria, Croatia and Romania have the highest factor loadings of the full sample. The loadings of Hungary and Poland are lower for this factor, because a relatively greater part of the variance in these countries is explained by the developed European factor. The third and fourth factors aggregate the Latin American and emerging Asian countries, respectively. Russia, Turkey, South Africa and Kazakhstan, which are generally included in emerging Europe in regional analyses, have strong correlations with the Asian and Latin American factors as well (in addition to the emerging European factor), which suggests their higher shares in global investment portfolios. It is also possible that although on a regional portfolio investment basis these countries are more linked to Europe, their foreign-exchange rates are usually taken into account compared to the dollar and not to the euro, which, in the case of a major shift in the euro/dollar exchange rate, also changes the perspective of the risk assessment of these countries compared to the Central and Eastern European ones.

The last column shows the unique variance for each country (i.e. the share of the variance that cannot be linked to common factors). In the factor analysis procedure, variables with a high unique variance (above 50 per cent, as a rule of thumb) are usually removed and the analysis is repeated; here, however, we present the original results for two reasons. First, in this way an international comparison can be made for the same set of countries across various time samples. Secondly, the traditional procedure eventually leads to the same factor structure, with very similar factor loadings for the countries remaining in the sample.

Unique variance is typically higher in countries that experienced a major country-specific risk shock in one of the periods: Argentina, Ukraine, Venezuela and, to a lesser extent, Greece and Latvia as well. Outside of periods of country-specific shocks, these countries had high factor loadings and low uniqueness. It is only in the case of Japan that the higher unique variance is a consequence of the country not belonging to any of the CDS regions.

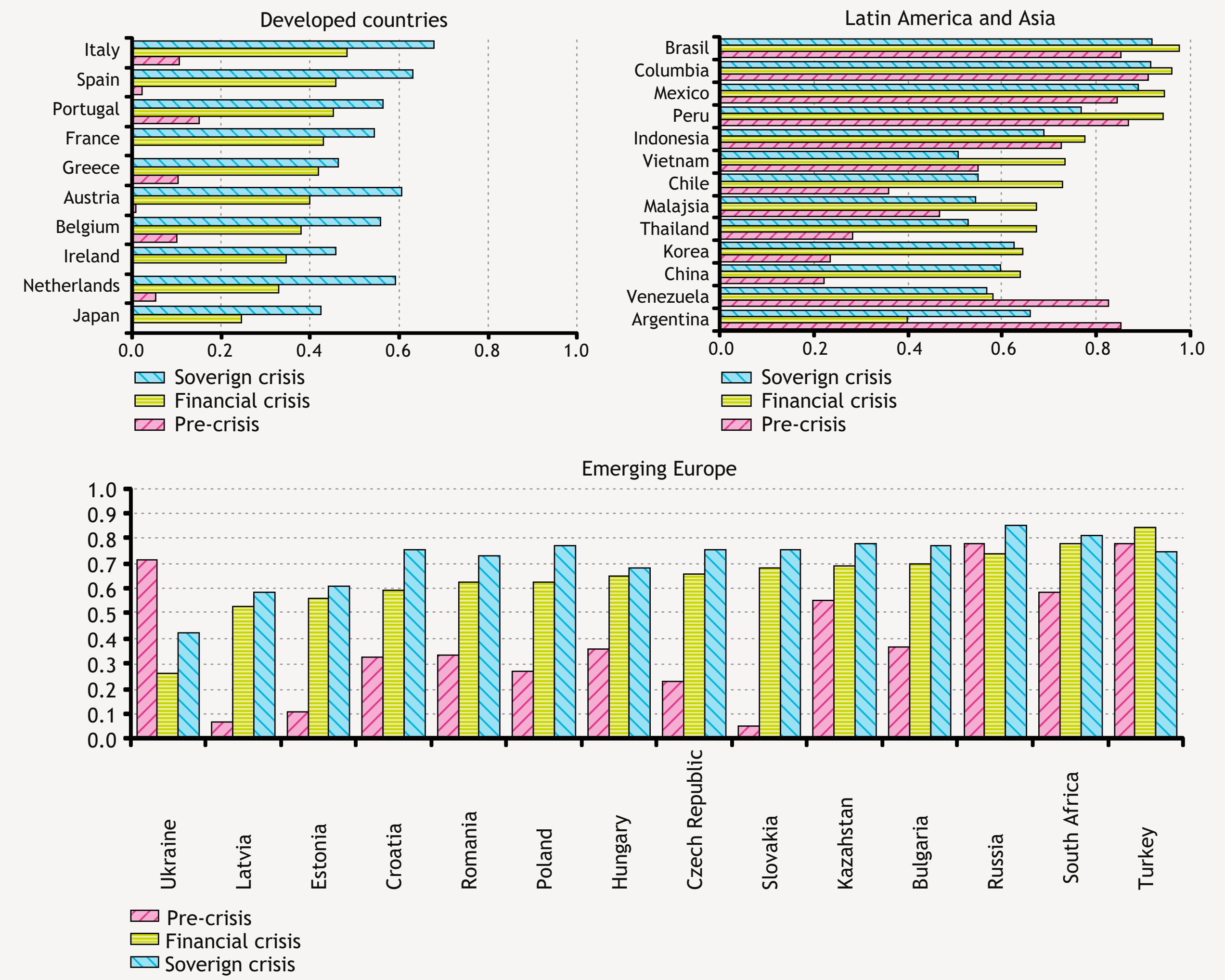
Characteristics of the global factor

The (daily changes in) CDS spreads of the majority of sovereigns – and especially of emerging countries – demonstrate high positive correlation with the global factor, which is shown by the factor loadings of the first factor of the unrotated solution (first column of Table 1). The squares of loadings show the proportion of CDS spreads' variance explained by the global factor. Based on the Hungarian factor loading of 0.64, the changes in the Hungarian sovereign CDS were 41 per cent, related to the global factor in the full sample. In terms of an international comparison, this ratio can be considered average; the ratios were generally lower in developed countries, but higher in emerging Asian and Latin American countries.

However, an inspection of the subsamples reveals that factor loadings changed considerably over time (Chart 2). In the pre-crisis period, the loadings of most countries were much lower than those experienced in the full sample; coefficients of around 0.5–0.6 were already considered high, even though that accounts for only 25–36 per cent of the variance. Regional or local, country-specific factors accounted for the remaining variance. Hence, in the pre-crisis period the general co-movement of emerging sovereign spreads was less strong, while the correlation with developed countries was negligible.

Chart 2 also shows that correlation with the global factor varied across countries. Prior to the crisis, it was mostly the CDS spreads of Latin American and certain Asian countries that correlated with the global factor. Therefore, a relatively smaller fraction of emerging European spreads, and accordingly the Hungarian CDS spread, was attributable to global developments. In the sample for the financial crisis

Chart 2
Factor loadings of the global factor



period, the co-movement between CDS spreads increased significantly in most countries. The significance of the global factor also became considerably more general by covering most of the variance of both emerging and developed countries.

In the period following the financial crisis (sovereign crisis subsample), correlation with the global factor declined in many of the emerging countries. However, in the case of the emerging European countries and developed European countries, the correlation coefficients stagnated or even increased. This highlights the increased importance of investor concerns related to the euro area periphery, which has become an increasingly dominant issue in sovereign credit risk changes and a factor that has affected sovereigns worldwide.

Thus, the global factor has had different connotations in different periods. Underlying this phenomenon is the time-varying correlation structure between financial variables, as investors re-interpret common risks from time to time. In the period preceding the financial crisis, the widest concept of sovereign risk premium shocks may instead have meant changes in general investor confidence related to emerging bond markets. The financial crisis resulted in the global re-evaluation of fiscal paths and an increase in perceived systemic risks, which linked sovereign credit risks worldwide to more universal, general global market and macroeconomic factors. Daily news about the outlook for the duration and depth of the crisis have simultaneously affected the assessment of economic policy prospects for most (developed and emerging) countries. With the decline in the intensity of the crisis, the role of individual or local factors may have increased again, but the sovereign crisis of the euro area also came to the fore and gained in global importance.

Another group of indicators – the 'betas', which reflect the sensitivity of CDS spreads to factors – are worth elaborating on. Changes in the global sovereign risk factor have had a different impact on different countries' CDS spreads. The relation with the correlation coefficient is direct: the value of the beta is the product of the correlation coefficient and the standard deviation of the given variable (on a given sample). Accordingly, the higher beta can be the outcome of both a greater correlation with the global factor or the relatively high volatility of the CDS spread changes. A comparison of the emerging European countries makes it clear that the relatively high sensitivity of the Hungarian CDS is caused by the latter fact, higher volatility, while the magnitude of the correlation coefficient of Hungary is similar to that of other countries in the region.

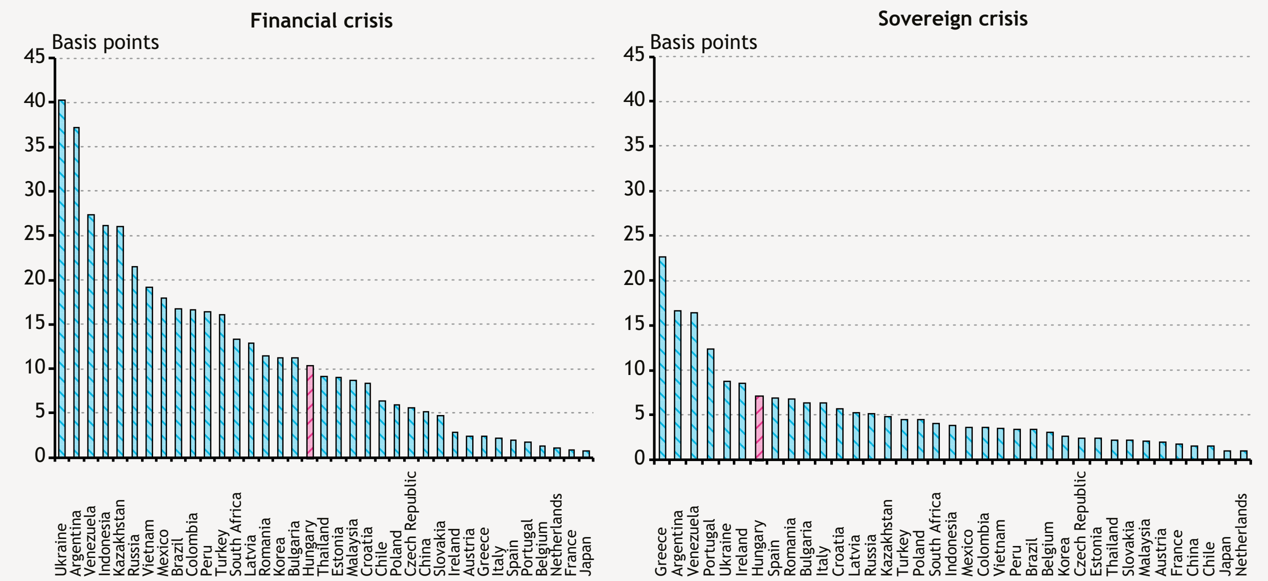
The value of the beta is the magnitude of CDS response to a unit of factor shock. Thus, the size of global betas expresses how sensitively the CDS spreads of individual countries react to a shock of a global origin. The sensitivity of CDS spreads has also changed over time. With the exception of the euro area peripheral countries, betas have declined in each country since the financial crisis, but the degree of this decline was not the same everywhere. Although the sensitivity of the Hungarian CDS spread also fell to nearly one half, the Hungarian beta increased, comparatively speaking. In the sovereign crisis subsample, the Hungarian CDS spread was the second most sensitive to global developments of all the emerging European countries (preceded only by Ukraine), although the Hungarian beta did not materially exceed that of Romania or Bulgaria.

The ranking of betas for international comparison is very similar to the ranking of the levels of CDS spreads. Comparing the two components of the betas (the correlations and the standard deviations) to CDS levels, we find that this similar ranking is due to levels of CDS spreads being correlated with the standard deviation of spread changes. Hence, riskier countries have both a higher level of CDS spreads and a greater volatility of CDS spread changes. Because there is less difference in factor loadings, it is this higher volatility of spreads in riskier countries that leads to their higher sensitivity to global shocks.

The regional factors

The varimax rotation produces the aforementioned four regional factors on the full sample (developed Europe – emerging Europe – Latin America – emerging Asia). For the subsamples, the range of optimum factor numbers varies greatly across statistical methods and samples. For the pre-crisis sample, different methods estimate the ideal number of factors to be between 2 and 11. For nearly all factor numbers, the rotated solutions contain an emerging Latin American, emerging European and Asian factor, though the developed countries form different groups depending on the different solutions. For the financial crisis and sovereign crisis subsamples, the number of factors recommended by different methods is between 2 and 5. The first four factors create well-separated regional groups for these subsamples (in the case of two factors, CDS spreads separate into emerging and developed groups; in the case of three factors Latin America is additionally separated from other

Chart 3
The sensitivity of CDS spreads to global shocks
(betas)



emerging countries; with four factors, the structure aligns with that on the full sample presented earlier).

The correlations (loadings) with the regional factors also change from sample to sample, as observed in the case of the global factor. This can be interpreted in two ways: from the aspect of a certain country, a greater correlation coefficient means that the country's credit risk assessment is more strongly impacted by CDS spreads of that region. On the other hand, viewed from the factor's aspect, a higher loading usually means that the spread of the given country has a larger influence on the factor. If the correlation coefficient changes relative to the other countries the interpretation of the regional factor will also change.

Looking at the individual factors, all of the regional factors' loadings significantly increased in the last two subsamples compared to the first (pre-crisis) sample. This is primarily the consequence of the aforementioned increase in global CDS spread correlations, which affected most countries, and especially those in the developed and emerging European regions. (The regional factors of the varimax rotation partly contain the information of the global factor.) The developed European factor emerges only in the financial crisis; factor analysis on the first subsample extracts a fourth factor that separates the four countries of Kazakhstan, Turkey, South Africa and Russia from the rest of the emerging European region.

Romania, Bulgaria, Croatia and Hungary had the largest correlation with the emerging European factor in the pre-crisis sample. In subsequent samples, the regions' factor loading increased and became more homogeneous. On the last subsample, the Romanian, Bulgarian and Croatian factor loadings were somewhat higher than correlations of other regional countries. Therefore the emerging European factor also had a different interpretation on different samples.

In the case of Asian and Latin American factors, the last subsample exhibits slightly lower correlations with emerging countries outside the region compared to the financial crisis subsample. Accordingly, the co-movement within all emerging countries increased considerably throughout the crisis, but before and after that the Asian and Latin American regions constituted more separated groups.

THE FACTORS OF THE HUNGARIAN CDS SPREAD

To investigate the components of the Hungarian CDS spreads, another method, the aforementioned target pattern rotation is used. Its result is a factor structure in which global and regional factors appear simultaneously (in the previous methods the common variance was either decomposed into a global and three other, unrotated factors, or in the varimax case it was distributed between four regional factors).

There are two important differences in the factors' interpretation compared to previous sections. First, the developed European countries are divided into two groups, which creates an additional regional factor, the group of euro-area peripheral countries (PIIGS). Second, the interpretation of each regional factor changes, as in this procedure the regional factors represent only the part of CDS variances that excludes the global component. Therefore, the regional factor loadings will generally be lower. Of course, the sum of the squares of factor loadings (common variance) plus the unique variance share still adds up to 100 percent, the total variance in each country's case. However, this time the factors decompose the common variance into one global and five regional components.

Chart 4
Component shares of the Hungarian CDS spread's variance

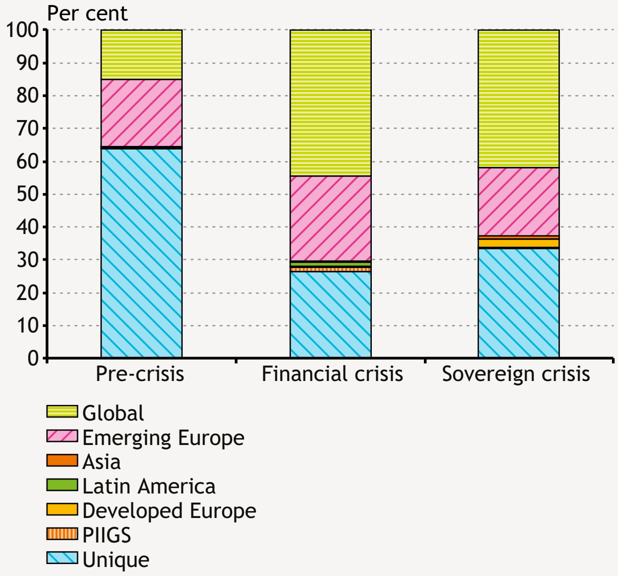
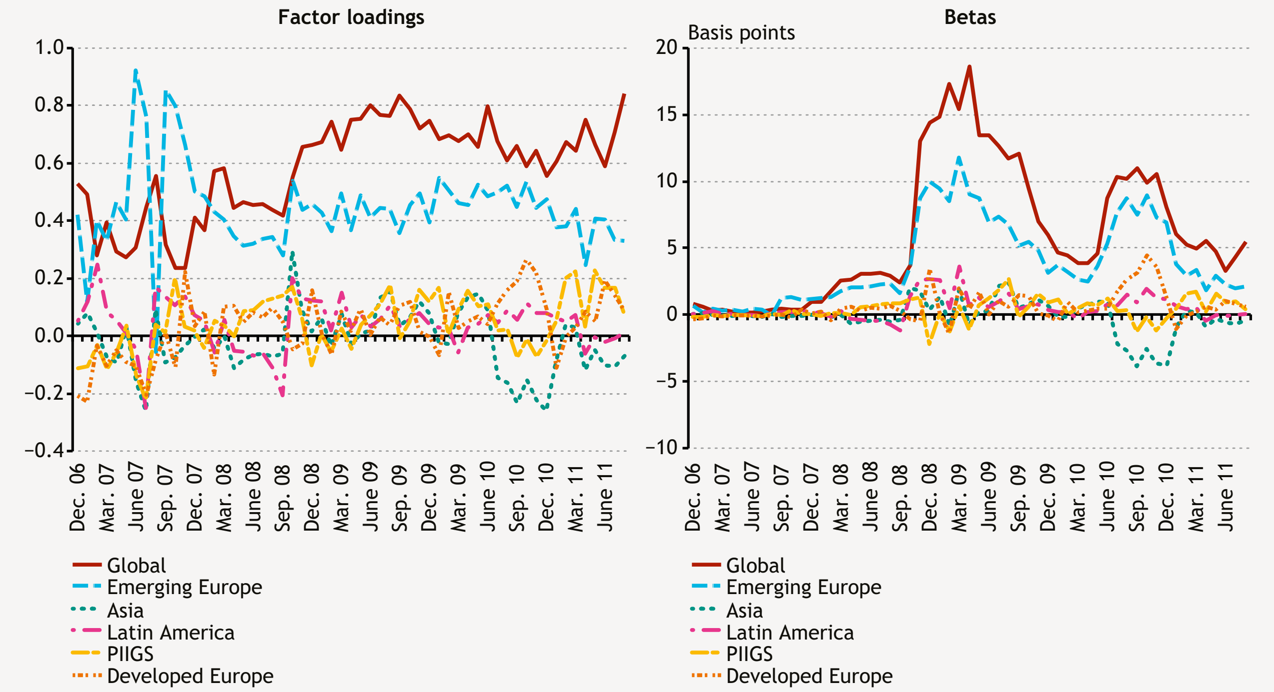


Chart 4 depicts the variance shares attributed to each component in the case of the Hungarian CDS spread for the three subsamples (pre-crisis, financial crisis, sovereign crisis). In Hungary, just like in CDS spreads elsewhere, the global component's weight increased and that of the unique component declined during the financial crisis. The emerging European factor also increased in this period. In the third subsample (September 2009–July 2011), during the sovereign crisis, the developed European and unique

Chart 5
Changes in factor loadings and betas of Hungarian CDS spreads
(betas)



components gained share, while the emerging European factor decreased. The effect of other regional components was insignificant. Therefore, the impact of euro-area periphery's crisis also mostly affected the Hungarian CDS spread through the global factor. Hungarian risk assessment did not correlate with this region directly. A minor contagion effect may have occurred via the developed European region.

Changes in factor loadings and betas over time

The analysis on half-year moving windows also shows that the global factor was consistently the most significant component in Hungarian CDS spreads (Chart 5). The emerging European effect (net of the global effects) was typically somewhat more moderate. Thus, the Hungarian spread was significantly influenced not only by global shocks but also by developments in the region. In the case of the regional factor, the direction of causality was probably two-way. Times of higher factor loadings may occasionally have meant that Hungarian events affected the risk assessment of other East European countries and this has been the source of a larger correlation with the region.

The correlation vis-à-vis other factors was practically insignificant, though the increase of the developed European factor's loading in the spring-autumn of 2010 should be mentioned. This increase indicates that the euro-area periphery's problems at that time partly affected the Hungarian CDS spreads through this factor.

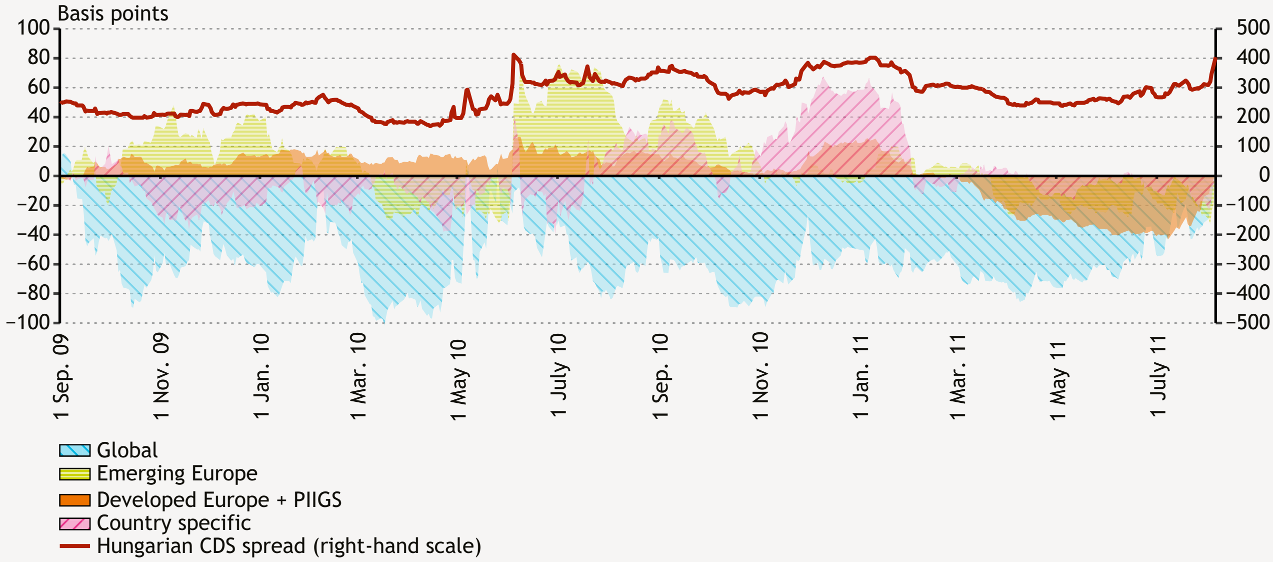
Hungary's risk assessment in the sovereign crisis period

Next we turn to changes in the Hungarian CDS spread in the two years of the sovereign crisis period (September 2009 – July 2011). We use the target pattern rotation result on this sample in generating the components of the Hungarian CDS spread. Sample selection is important, as we have seen that factor loadings change across samples, and thus the factors themselves also have different meanings.

The choice of a longer sample represents correlations between CDS spreads that are relevant over a longer period. This has both advantages and disadvantages. The results of factor analysis will be more robust to the arrival of new data, but it will be less able to capture the latest trends. Shorter samples represent the correlations that are valid at a given point in time, but new data may significantly overwrite these. The sovereign crisis period is nearly two years long, and is a relatively homogeneous period in that correlations in this period were mainly thematised by sovereign risks with the centre of attention on the euro-area periphery.

One important feature of this period is that the global factor universally incorporates emerging and developed and

Chart 6
Components of the Hungarian CDS spread in the sovereign crisis subsample



Note: the chart depicts the Hungarian CDS spread and cumulated components. An increase in component values indicates that the component raised the CDS spread. A decreasing component, in turn, means an improvement in the risk assessment of Hungary, a factor contributing to the decline in the CDS spread.

PIIGS sovereigns; nearly all countries have high loadings on the global factor. Because the global, emerging European and unique factors are the key components affecting the Hungarian spread, the shocks of the peripheral countries are mostly propagated through the global factor and, to a much lesser extent, through the developed European factor.

Chart 6 depicts the cumulated components of the changes in the Hungarian CDS spread (net of the trend). The daily changes in these cumulated series represent the magnitude of daily shocks that a component causes in the Hungarian CDS spread. Factor analysis deals only with the variance of the changes (the deviations from the mean) and not the mean change, which in this case constitutes an approximately 50 basis point increase for the whole sovereign sample. Thus factor analysis separates the relatively favourable/unfavourable time periods in terms of each factor and reveals the extent (either in a positive or a negative direction) that these periods contributed to the variance of the CDS spread.

Regarding the global factor, the end of 2009 and the beginning of 2010 was a period of a relatively steady recovery from the financial crisis. During that period, the global factor gradually contributed to a decline in the Hungarian CDS spread. However, in January 2010, prior to the ECOFIN meeting and the EU summit in early February, the first wave of Greek contagion was reflected in the increase in the developed European component, and the global factor was also rose temporarily (the extent of its negative contribution to the Hungarian CDS spread declined). Thereafter, however, a favourable global atmosphere resumed until mid-April, which is also seen outside of the CDS market in this period's large increases in leading stock exchange indices and improvements in main global risk indicators. From April on, however, the global CDS factor increased as concerns relating to Greece escalated, and the favourable (negative) global effect on the Hungarian CDS spread nearly disappeared by the beginning of May. The first framework of the IMF–EU assistance was able to reduce the sovereign concerns, which was reflected in the decline in the global factor until August.

The global factor reduced the Hungarian CDS spread as well from mid-May, although in this period, barely a few weeks after the favourable European announcements the unfortunate communication of the Hungarian government, which compared the Hungarian fiscal situation to that of Greece, resulted in a sharp spike in the country-specific component. This surge was nonetheless temporary, as foreign investors quickly realised that the statements were related more to domestic political rhetoric than new information on the fiscal position.

The emerging European factor also increased simultaneously with the statements. Based on the coincidence in time, it is likely that in this case the Hungarian events spilled over to cause a regional increase of CDS spreads. In addition, the

Chart 7
Components of the Hungarian CDS spread
(April–October 2010)

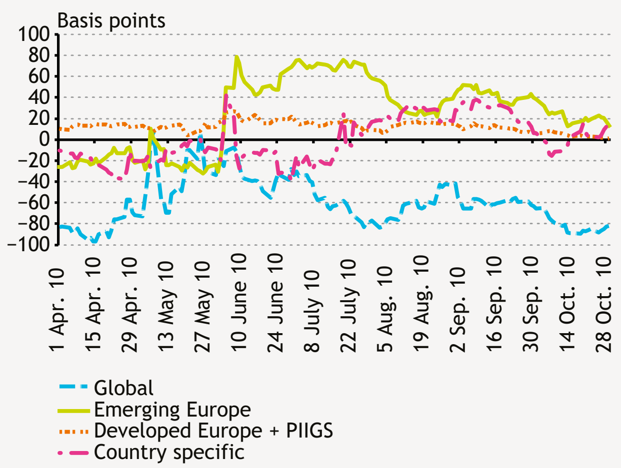
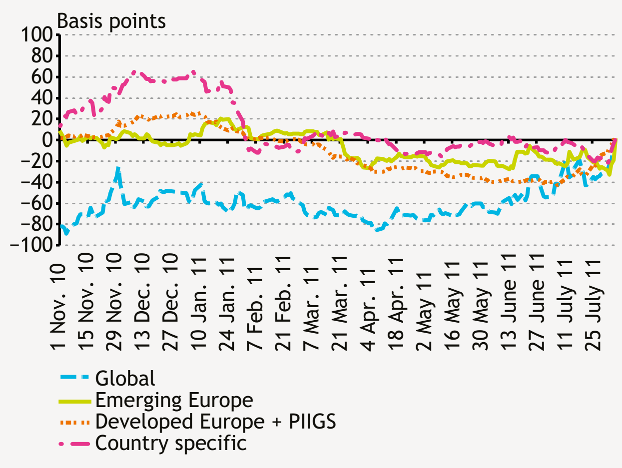


Chart 8
Components of the Hungarian CDS spread
(November 2010–July 2011)



more persistent nature of this increase suggests that the event turned investors' attention to Eastern Europe's fiscal problems. During this period, analyses related to Eastern Europe mostly pondered the possible outcomes of Romanian and Ukrainian IMF negotiation rounds. Following the successful closure of these negotiations in July, the region's CDS spreads generally declined, which also resulted in a decline in the emerging European part of the Hungarian risk spread.

Again, an increase in the country-specific factor, which proved to be permanent this time, prevented the Hungarian CDS spread from declining together with those of other countries in the region. Presumably, this was a result of the deteriorating IMF relations, the bank tax and other measures that were unpopular among investors.

The country-specific component continued to deteriorate until mid-January 2011, which by then was also reflected in actions of credit rating agencies. In the final weeks of January, however, Hungary's risk assessment took a favourable turn, which can be attributed to the anticipation of the Széll Kálmán Plan. Government officials' statements suggested that the plan would mark a shift in the fiscal policy path. The country-specific factor, which raised the CDS spread by nearly 100 basis points from the beginning of the sample fell by the same amount within a couple of weeks. In early 2011, the decline in the Hungarian CDS spread was also supported (to a lesser extent) by favourable changes in the developed European and global risk factors.

The increase in the Hungarian CDS spread in June-August 2011 was primarily related to global developments and was triggered again by investor concerns related to the euro-area periphery. Investor anxiety was a consequence of an increased perceived probability of an imminent Greek sovereign default and its potential consequences, at the worst a spillover to either the euro-area financial sector or major euro-area countries, to Italy, in particular. In this case the Hungarian CDS spread was affected relatively more through the developed European factor as well, although the global factor's increase still caused the largest share of the CDS spread movement.

CONCLUSIONS

The general and significant positive correlations between sovereign CDS spreads confirm the existence of a global factor. The information content of the global factor changed over time. Prior to the crisis, it mostly represented investor confidence related to emerging countries, but by the end of our sample it became a much more universal factor, which also affects the risk assessment of developed European sovereigns as well.

CDS spreads' correlations form groups that can be well interpreted on a regional basis. Regional factors became more defined during the crisis and their content also changed over time. The four groups identified on the full time sample are the developed European, emerging European, Latin American and Asian regions.

The Hungarian CDS spread was most influenced by the global factor in the full sample and in all subsamples. This is the factor through which the fiscal crisis of the euro-area periphery has the greatest effect, although some of the shocks were to a smaller extent propagated through the developed European and peripheral regions.

In addition to the global factor, the emerging European and the country-specific factors had a time-varying, but still important impact on Hungarian sovereign credit risk. Between summer 2010 and January 2011, the country-specific factor caused a considerable increase in the CDS spread; in 2010, the Hungarian events could have also contributed to a worsening assessment of other countries in the region. During January 2011, however, the shift in the government's fiscal policy stance strengthened investor confidence, which was reflected in the decline in the CDS spread.

REFERENCES

Benczúr, P. (2001), 'Identifying Sovereign Bond Risks', *CEU-Economics Working Paper,* no. 9.

Broto, C. and G. Pérez-Quiros (2011), 'Sovereign CDS premia during the crisis and their interpretation as a measure of risk', *Economic Bulletin,* April, Banco de Espana.

Cantor, R. and F. Packer (1996), 'Determinants and impact of sovereign credit ratings', *Economic Policy Review,* October, pp. 37–53., Federal Reserve Bank of New York.

Edwards, S. (1984), 'LDC Foreign Borrowing and Default Risk: An Empirical Investigation, 1976–80', *American Economic Review,* vol. 74 (4), September, pp. 726–34, AEA.

Edwards, S. (1986), 'The Pricing of Bonds and Bank Loans in International Markets: An Empirical Analysis of Developing Countries' Foreign Borrowing', *NBER Working Papers,* 1689, NBER.

Eichengreen, B. and A. Mody (1998), 'What Explains Changing Spreads on Emerging-Market Debt: Fundamentals or Market Sentiment?', *NBER Working Papers,* 6408, NBER.

Hair, J. F., W. C. Black, B. J. Babin and R. E. Anderson (2009), *Multivariate Data Analysis*, 7th ed., Pearson Education.

Hair, B. and A. Mody (1998), 'What Explains Changing Spreads on Emerging-Market Debt: Fundamentals or Market Sentiment?', *NBER Working Papers,* 6408, NBER.

Kamin S. B. and K. Kleist (1999), 'The evolution and determinants of emerging market credit spreads in the 1990s', *International Finance Discussion Papers,* 653, Board of Governors of the Federal Reserve System (US).

Kisgergely, K. (2009), 'What moved sovereign CDS spreads in the period of financial turbulence?', *Report on Financial Stability. Update,* November, MNB.

Kocsis Z. and Mosolygó Zs. (2006), 'A devizakötvény-felárak és a hitelminősítések összefüggése – keresztmetszeti elemzés', [The relationship of international bond spreads and sovereign credit ratings — a cross-section analysis], *Közgazdasági Szemle,* szeptember, pp. 769–798.

Longstaff, F. A., J. Pan, L. H. Pedersen and K. J. Singleton (2007), 'How Sovereign is Sovereign Credit Risk?', *NBER Working Papers,* 13658, NBER.

McGuire, P. and M. A. Schrijvers (2003), 'Common factors in emerging market spreads', *Quarterly Review,* December, BIS.

Remolona, E. M., M. Scatigna and E. Wu (2008), 'A ratings-based approach to measuring sovereign risk', *International Journal of Finance & Economics,* vol. 13 (1), pp. 26–39.

Rozada, M. G. and E. L. Yeyati (2006), 'Global Factors and Emerging Market Spreads', *RES Working Papers,* 4445, Inter-American Development Bank.

Sy, Amadou N. R. (2002), 'Emerging market bond spreads and sovereign credit ratings: reconciling market views with economic fundamentals', *Emerging Markets Review,* vol. 3 (4) December, pp. 380–408.

Varga, L. (2008), 'The information content of Hungarian sovereign CDS spreads', *MNB Occasional Papers,* 78.

Varga L. (2009), 'Hungarian sovereign credit risk premium in international comparison during the financial crisis', *MNB Bulletin,* July, pp. 43–51.

Westphalen, M. (2001), *The Determinants of Sovereign Bond Credit Spread Changes,* manuscript, Universite de Lausanne.

APPENDIX: THE DECOMPOSITION METHOD (FACTOR ANALYSIS)

Factors analysis is used in the paper to identify components of CDS spread changes. Factor analysis allows the representation of the information content of a high number of variables (the 37 sovereign CDS spreads in our case) with a few estimated, latent variables called factors. In general, one of the advantages of factor analysis is data reduction, i.e. the substitution of the large number of variables in the analysis with much fewer factors. If the data set is suitable for factor analysis, little information (a small proportion of the variance) is lost due to this substitution, while the small number of factors allows a considerably simpler interpretation of the data set's full information, which may be useful in further analyses.

Another advantage of the method, however, which is more relevant in our case, is that the factors that are extracted help in identifying an unobserved (latent) structure shaping the variables. The correlations between the latent factors and the original variables show the extent to which factors explain each of the variables. This allows us to learn more about the original variables and their interrelatedness as well.

The technique uses the variance–covariance matrix of the variable data set (time series). It separates the variance of the variables into two major parts: a common variance part that can be explained by other variables (this is called *communality)* and a unique, idiosyncratic component. The method extracts the factors[15] from the common variance, so that the common variance of each variable is a linear combination of the factors. The standardised form (deducting the mean and norming the variance to 1) of a given variable *(x_i)* is thus decomposed into two main factors: the linear combination of the n factors (the common component) and the unique component. The importance of a factor in forming a variable's variance is expressed by the factor loading ($l_{i,j}$, *or loading),* which take values between −1 and +1.

$$z_i = \frac{x_i - \mu_{x_i}}{\sigma_{x_i}} = \sum_{j=1}^{n} l_{i,j} F_j + \varepsilon_i \tag{1}$$

If the factors were interpreted as observed variables, equation (1) would actually be a multiple linear regression, where the standardised variables (in our case the CDS spread of the *i*-th country) are explained with the factors, and where the regression coefficients are the factor loadings. The error of the regression would then represent the unique component.

If the factors are not correlated with one another and the error term, (1) can be rewritten as a decomposition of the variable's variance:

$$var(z_i) = \sum_{j=1}^{n} l_{i,j}^2 var(F_j) + \sigma_i^2 \tag{2}$$

This formula shows the decomposition of the examined variable's variance (CDS spreads in our case). The explanatory power of the factors are expressed by the squares of the factor loadings *($l_{i,j}^2$),* when the variance of the factors are 1 (the variables in this representation are standardised so: *[$var(z_i)=1$]).* The weight of the unique (country-specific) component is expressed by the error variance *(σ_i^2).*

One of the basic issues in factor analysis is the choice of the number of factors to be extracted. The literature recommends several methods and the examination of several indicators in order to determine the number of factors. The essence of these recommendations is that the number of factors should be sufficiently large to explain a relatively large proportion of the total variance (especially if data reduction is the main objective), but should be small enough to aid in the interpretation of the factors. In the standard iterative procedure of factor analysis the analyst extracts factors choosing their number based on several criteria, and then eliminates variables with large unique variance from the sample (thus facilitating that fewer factors explain a greater proportion of the total variance). Even at the end of the iteration it is not always clear what number of factors are worth using. In this case it is sensible to take into account the objective of the analysis (data reduction: as few factors as possible or latent structures: all factors that can be well-interpreted).

The first step of factor analysis extracts factors in a hierarchical order of explained variance. The first factor receives the greatest possible share of the common variance, the second factor the greatest part of the remaining variance, etc. This structure usually does not create factors that are easy to interpret. Therefore, in the next step of the analysis a rotation is applied, which produces a mathematically equally valid factor loading matrix (with the same communalities – unique variances by variables), but one that is easier to interpret. Most rotation procedures minimise a complexity function, which penalises if variables are associated with more than one factor (variable complexity), or if the factors' correlate with the several variables in a similar way (factor complexity). Therefore, the rotation usually produces a factor structure, where variables are more clearly linked to one specific factor, and thus the factors separate the variables into groups. Typically, the rotated factors distribute the variance much more evenly than the original solution.

[15] On this point factor analysis differs from the other popular data reduction technique, the principal component analysis, which distributes the complete variance of variables, not only its common component, among the components. The advantage of the principal component analysis is that it leads to an unambiguous solution, whereas in the case of factor analysis the common-individual decomposition has to be estimated first, which may result in different solutions depending on the estimation technique. At the same time, the decomposition used in factor analysis is usually easier to justify theoretically than the total variance decomposition of the principal component analysis. In practice, the principal component analysis is a preferred method when the primary objective is data reduction, whereas the factor analysis is mostly used when the primary goal is exploring the latent variable structure.

There are two basic types of rotations; the orthogonal and the oblique rotation methods. The former maintains uncorrelatedness among factors, which is advantageous if the factors are included in subsequent regressions. In this case, multicollinearity will not be an issue and the factors' partial effects can be well identified. On the other hand, the oblique method allows factors to correlate and creates factors that can be interpreted even more easily.[16]

The two rotations applied in this paper are both orthogonal. The first is the varimax method, which is one of the most popular methods in various applications. The varimax rotation minimises factor complexity by finding the minimum of the following objective function:

$$f(L) = \sum_{j=1}^{n} (\sum_{i=1}^{m} \sum\nolimits_{k \neq i}^{m} l_{ij}^2 * l_{kj}^2) \qquad (3$$

where m and n are the numbers of variables and factors, respectively, whereas l denotes factor loadings. This method assembles variables (the CDS spreads) into well separated groups. It is well suited to explore the latent correlation structure among the variables, to discover which CDS spreads move together with each other the most, and to indicate which the relative importance of spreads in the factors.

The second method we apply is the target pattern, or Procrustes, rotation. With this procedure, we find a factor matrix that, while keeping factors uncorrelated, differs least from the target matrix. Therefore, the rotations' objective function is the Euclidean distance between the elements of the target matrix and the factor matrix. This method is able to produce a factor structure with uncorrelated global and regional factors. More common rotation types, e.g. the varimax rotation, cannot achieve that because those methods aim to create a structure that links variables to only one factor where possible. Our goal is, however, different, we would like to link two factors to each of our variables; the global factor and the regional factor indicated by the varimax method. In the target pattern matrix the first (global) column will be a vector of 1s, while the regional factors will have cells of 1s for countries that belong to the region and values of 0 for countries outside of the region. For example, the target value of the Hungarian CDS spread is 1 on the global and 1 on the emerging European factor, and 0 on the Latin American, Asian, developed European and PIIGS factors.

[16] See Hair et al. (1998) for more details of the factor analysis procedure and rotation types.