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(Pénzügyi piaci mutatók globális, regionális és országspecifikus komponensei: dekompozíciós módszer és alkalmazásai)

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Contents

Abstract

This paper presents a variance decomposition method - factor analysis with Procrustes rotation - that is capable of separating the global, regional and idiosyncratic components of various financial market indicators. The method is applied to indicators of five key financial markets: sovereign CDS spreads, stock indices, exchange rates, EMBI Global bond spreads and 10-year reference yields of domestic government bond markets. The results support the finding of the literature of a significant global component in most markets, but also point out the importance of regional correlations. Based on the method two practical applications are proposed: one, which is useful in the daily monitoring of financial markets to identify magnitudes of risk premium shocks of global, regional and country-specific origins; and another one, which gauges channels of risk propagation from the eurozone periphery.

JEL: G15, C38, E44.

Keywords: variance decomposition, factor analysis, Procrustes rotation, spillover, cross-country correlations, cross-asset correlations.

Összefoglalás

A tanulmány egy variancia dekompozíciós módszert mutat be (faktoranalízis Prokrusztész-rotációval), amelynek segítségével pénzügyi változók idősorait globális, regionális és idioszinkratikus tényezőkre lehet bontani. A módszert az elemzés öt kulcsfontosságú pénzügyi piac indikátoraira alkalmazza: szuverén CDS-felárakra, tőzsdeindexekre, devizaárfolyamokra, EMBI Global kötvényfelárakra és 10 éves belföldi állampapír-piaci referenciahozamokra. Az eredmények alapján a legtöbb piacon szignifikáns a globális komponens, ami összhangban van a szakirodalom általános tapasztalatával. Emellett azonban a regionális korrelációk is fontosak. A publikáció a módszer két praktikus alkalmazását mutatja be. Az egyik a pénzügyi piacok napi elemzése szempontjából hasznos: a napi pénzügyi piaci sokkok globális, regionális és országspecifikus komponenseinek mérését teszi lehetővé. A másik az eurozóna perifériája felől érkező sokkok csatornáinak erősségét állapítja meg.

1 Introduction

Identification of the source of shocks affecting financial markets has been a basic theme in the finance literature. It has been central to research aiming to explain the drivers of key indicators of various asset classes: risk premia in bond yields and foreign exchange rate movements, credit default swap spreads and excess returns of equity prices.

Besides the descriptive academic interest, this field has had significant normative implications for both financial practitioners and policymakers. For financial practitioners explaining the sources of asset price movements has been important from both a risk management and an asset management perspective. Knowledge of the sources of shocks allows inference on the magnitudes of potential price variations due to specific risk types; whereas identifying dependence between asset prices is important in portfolio allocation decisions. For policymakers the key implication is that observing adverse financial market movements necessitates different policy responses according to what the reasons behind those movements are.

A large body of literature attempted to identify common and idiosyncratic components within financial indicators' movements. Such segmentation of indicators had several applications in finance from the identification of the common part as co-movements in equities (CAPM and APT frameworks) to analyzing cross-country, inter-market or sectoral co-movements of various indicators in order to gauge systemic risks in financial markets. Research studying the nature and changes in cross-country dependency patterns (spillover and contagion) also expanded significantly in recent years due to the crisis.

The contribution of this paper is in presenting a method, factor analysis with Procrustes rotation, for the decomposition of financial time series, which is useful in policy-relevant applications: it aids interpreting financial market developments, it is simple to use and update, and it produces results consistent with intuition. Procrustes rotation has been widely used in confirmatory factor analysis in various disciplines: the quantitative strands of psychology, chemistry and biology. Despite its advantages I am not aware of its application in the fields of economics and finance.

The existing empirical literature proceeded to identify common and idiosyncratic components in a number of ways. A line of literature has used observed financial and macroeconomic variables as proxies for the common and/or the country-specific factors, for instance US interest rates or the VIX index for the former, and local fiscal variables for the latter. (A few recent examples are Basurto et al., 2010; Santis, 2012; Fratzscher, 2011; Longstaff et al., 2011; Remolona et al., 2008; Schuknecht et al., 2009; Zoli and Sgherri, 2009). Another segment has instead turned to explicit market aggregates, such as portfolio returns or composite indices, to proxy the common component (Beirne et al., 2010; Bekaert et al., 2011; Ejsing and Lemke, 2011; Diaz Weigel and Gemmill, 2006).

Another strand of the literature has extracted latent common variables instead of using observable proxies. The advantage of this approach is that it captures the systemic component of co-movements in a more complete manner, while the obvious drawback is that it loses the explanation for co-movements. Several papers therefore have proceeded to explain extracted latent factors by regressing them on observed variables. The two more generally used latent variable methods have been dynamic latent factor models (Ang and Longstaff, 2011; Diebold and Nerlove, 1989; Martin and Dungey, 2007; King et al., 1994) and static principal components analysis (Collin-Dufresne, 2001; Berndt and Obreja, 2010; Kim et al., 2010; Kisgergely, 2009; Murphy and Murphy, 2010).

In terms of methodology this paper is closest to those in the literature, which choose a third latent variable method, static factor analysis (McGuire and Schrijvers, 2003; Kocsis and Nagy, 2011; Broto and Perez-Quiros, 2011). Compared to dynamic factor models this method has the advantage of being more convenient to estimate. The estimated factor score series, being linear combinations of the original series, are able to exhibit the underlying series' empirical properties (e.g. heavy tails, volatility clustering) without the need to explicitly include these in the model specification. Compared to principal components static factor analysis assumes a data generating process that is more consistent with the theory of having systemic and idiosyncratic components in financial indicators, although in most applications the two methods produce very similar results.

Nonetheless, factor analysis also has several drawbacks. Being a statistical, latent variable method it cannot be used for causation-type of analysis and extracted factors might be hard to interpret. The causality issue will be discussed later. To mitigate the interpretation problem rotation methods can be applied. In this analysis two different types of such rotations are used, the varimax and the Procrustes rotations. Also, there is a need to a priori specify the number of common factors, and although there are a number of methods that help the researcher in this decision, often the results of these methods are ambiguous. Finally, without additional restrictions imposed, the factors are not identified. The rotation techniques mentioned, however, deal with this problem by setting objective functions that have unique optima up to a choice of loading signs.

The Procrustes rotation used in the paper relies on prior information about the factor structure. In the current case: the notion that financial indicators are affected by global, regional and idiosyncratic shocks. While this breakdown is generally in line with how market participants, analysts and policy usually think of financial market events' effects and there are both theoretical (e.g. Allen and Gale, 2000; Calvo, 2002; Corsetti et al., 2005) and empirical studies (e.g. Beirne et al., 2010; Dasgupta et al., 2011; Martin and Dungey, 2007; Kaminsky and Reinhart, 2000) underpinning the global and the regional propagation of shocks, the concrete choice of regional classification may not be straightforward and the prior's consistency with the data's structure needs to be verified.

Several steps are taken to ensure a prudent specification of the prior. First, the existence of a global factor is verified for all asset classes except for government domestic bond yields. Second, it is shown that more than one factor is needed to adequately explain the common part of time series' variances. While some studies have pointed this out (Longstaff et al., 2011; Kim et al., 2010), these do not apply rotation techniques and so the interpretation of the extracted components other than the first one are not straightforward. Thus, in a third step, exploratory factor analysis is performed to interpret the factor structure. While there are considerable differences across assets the geographical clustering seems important in general. In two markets, foreign exchange rates and government bond yields, where the regional classification is not evident a rule-based output from the varimax rotation is used to create the prior. As a final step, the Procrustes rotation's solution is checked how closely it corresponds with the prior and it is compared how this relates to alternative choices of priors.

Factor analysis with Procrustes rotation has several advantages over alternatives. It produces a solution that is mathematically as valid a representation of the data as other factor extraction techniques, but in the set of valid factor solutions it is the one that best fits the prior knowledge about the data's latent structure. The technique does not impose a hierarchy between global and regional factors, which, in my view, is more consistent with market participants' thinking. An orthogonal factorization is applied, which helps a clear separation of different types of shocks and reduces the risk of spurious fit. Importantly, if the data demands so, loadings will deviate from the prior target, e.g. countries will usually have non-zero loadings on other regions' loadings even if the prior is set to zero. This is beneficial since the prior might be too restrictive or wrong altogether: the market may consider a country in some way belonging (at least partly) to another group as well, so in this case there is a way for a data-driven correction. Also, there are borderline cases where even the prior selection is not clear and in this respect the data helps decide. Non-zero loadings also have significant implications regarding general intercorrelation with other regions and, of particular interest currently, with the group of crisis countries.

The paper belongs to the relatively smaller group of studies, which deals with cross-country co-movements using data of multiple asset classes (Forbes and Chinn, 2004; Martin and Dungey, 2007; Ehrmann et al., 2005; Longstaff et al., 2011). One advantage of this approach is that the analysis of cross-country correlations in several markets allows identification of a "country-specific" factor, which is the common component of various markets' idiosyncratic shocks. This is a major improvement on approaches that identify the idiosyncratic factor as being country-specific, because the former is arguably contaminated by market-related noise.

Finally, some thoughts on causation. Clearly, the method used here is purely statistical. It extracts unobserved factors from the variance-covariance matrix of the data sets and the factors (or their priors) are not guided by fundamental variables. This has two important consequences. First, between countries (and between countries and factors) it is only correlations, which are revealed, not the direction of causation. For example, a shock stemming from Hungary and fully reverberating throughout the Eastern European region will be considered as a regional shock by the model and not a country-specific one (since co-movements will be observed). There will be no way of knowing from this method alone that the original source of the shock was Hungary. Second, shocks of either type will not be interpreted by the model if they are liquidity or default risk shocks, if they are due to fundamentals or risk aversion, or how they relate to macroeconomic, fiscal, political, financial or other types of variables.

Still, when paired with knowledge of actual news, the applications based on this method provide valuable insights on how different types of shocks impact financial markets. For analysts, policy-makers and market participants who follow the developments of financial indicators on a regular and high-frequency (daily-weekly) basis the cardinal question is not which macroeconomic or political factors has impacted indicators, because this is obvious just by following the financial media. Rather, the main question is by how much the major news of the day of global, regional and country-specific origins have affected the indicators. The method applied here can address this issue. It can be an important tool to disentangle shocks on those days when seemingly important events happen both domestically and abroad. It can also be used to assess how shocks of different sources cumulated in financial market indicators, and so relatively how significant these were on longer horizons.

Paradoxically, this purely statistical approach paired with knowledge of actual news is often more efficient in interpreting market developments than structural, causal models, which aim to explicitly quantify effects of macroeconomic and other fundamental factors. For one, most news items that have a market impact are hard to proxy by available macroeconomic and financial statistics: for instance, political announcements or expectations of announcements often have large market impacts. And even regarding macroeconomic factors, it is often the expectations on future values or the distribution of such expectations that matter more than observable published data. While structural models will often fail to grasp such fundamental-related factors and lead to biased estimates due to variable omission, the statistical method presented here used together with knowledge of current news will help to quantify these effects.

The next section describes the methodology and data set used. Section 3 presents general results regarding the factor structure of data sets in various asset markets. Section 4 turns to applications on the Hungarian sovereign CDS market's example: a monitoring application is presented, which shows how the evolution of the CDS spread can be attributed to global, regional and idiosyncratic factors. Section 4 also provides an extension to other markets and explains how this can be used to improve inference on both international and country-specific components in Hungarian financial indicators. Finally, channels of risk propagation from the eurozone periphery are briefly examined. Section 5 concludes.

2 Methodology and data set

This section first presents the methodology, factor analysis with Procrustes rotation, and related methodological issues. The second subsection introduces the data set. Then, in light of the data, Section 2.3 turns to the discussion of the priors regarding each asset class, which serve as the input for the Procrustes rotation.

2.1 FACTOR ANALYSIS WITH PROCRUSTES ROTATION

The following description mostly relies on Anderson and Rubin (1956) and Browne (2001). Refer to Hair et al. (2009) for an intuitive exposition of static factor analysis.

Static factor analysis assumes that the data generating process of the standardized form, Z_i, of each variable X_i (e.g. a financial indicator of country i) is represented by:

$$\frac{X_i - \mu_i}{\sigma_i} = Z_i = \sum_{j=1}^{p} l_{i,j} F_j + \epsilon_i \tag{1}$$

where l_i, j is the loading of country i's indicator on the j-th factor given p, the number of common factors. The time series Z_i can therefore be thought of as a linear combination of the factor time series and an (uncorrelated) residual term, ϵ_i. In the case of orthogonal factors (which are used throughout this paper) the variance-covariance matrix of $\mathbf{Z}$ is given by:

$$\mathrm{Cov}(\mathbf{Z}) = \mathbb{E}\left[(\mathbf{LF}' + \epsilon')(\mathbf{LF}' + \epsilon')'\right] = \mathbf{LL} + \mathbf{\Psi} \tag{2}$$

where $\mathbf{L}$ is the $n \times p$ matrix of loadings for n countries and p factors, $\mathbf{F}$ is the $T \times p$ matrix of factor time series with T observations, ϵ is the $T \times n$ matrix of idiosyncratic shocks, $\mathbf{\Psi}$ is an $n \times n$ diagonal matrix of idiosyncratic variance components and $\mathbb{E}$ is the expectations operator. For individual series this can be re-written as:

$$1 = \sigma^2_{Z_i} = \sum_{j=1}^{p} l^2_{i,j} + \epsilon^2_i \tag{3}$$

Thus the (unit) variance of the (standardized) variable Z_i is simply the sum of squared factor loadings and the variance of the idiosyncratic term.

A loading close to $+/-1$ on any factor yields a high l^2 indicating that the given factor is important in explaining the variable's variance. Conversely, for those variables that do not co-move with any factors, the idiosyncratic term will dominate the information content and loadings will be close to zero.

Loadings can also be used to assess how two different assets are correlated, i.e. which are the important channels of co-movements. For a given factor, j, the loadings $l_{1,j}$ and $l_{2,j}$ represent correlation with the factor. Hence the product of the two loadings will be attributable to correlation between the two assets through factor j. Summing loading products for all factors equals the total correlation between the two assets if common factors truly capture all commonality. This property will be used in a later application in Section 4.

Estimation of $\mathbf{L}$ and $\mathbf{\Psi}$ requires knowledge of the number of factors to extract. While several methods are available for arriving at this quantity, these usually give a range of factor numbers to consider. In the current study the criteria of scree plots, minimum eigenvalues, cumulated variance ratios and the minimum average partial methods were taken into consideration (see references listed in the beginning of the subsection).

Given the number of factors to extract, maximum likelihood estimation is commonly applied to arrive at the estimates of $\mathbf{L}$ and $\mathbf{\Psi}$, which minimize the distance between the observed and estimated covariance matrix of $\mathbf{Z}$. The common - idiosyncratic breakdown of total variance is determined by the method uniquely, but the loading matrix is not. To see this, the common component of the standardised observations, $\mathbf{Z}$, can be written as a matrix of initial loadings post-multiplied by a respective initial factor score matrix, as well as the rotated loadings matrix and a respective rotated factor score matrix for any orthonormal rotation matrix, $\mathbf{R}$. Both are mathematically equally appropriate representations of the data set's information content:

$$\mathbf{Z}_{common} = \mathbf{L}_{initial} \times \mathbf{F}'_{initial} = \mathbf{L}_{initial} \times \left(\mathbf{R}'^{-1}\right)' \mathbf{R}' \times \mathbf{F}'_{initial} = \mathbf{L}_{rotated} \times \mathbf{F}'_{rotated} \tag{4}$$

The initial loading solution reported by statistics software (extracted via singular value decomposition) impose a hierarchical structure between the factors analogously to principal components analysis, so that the first factor will explain maximum possible common variance, the next factor will explain most of the remaining variance and so on.

Rotation methods commonly applied in (static) factor analysis impose an objective function, whose optimisation generates a unique solution and an interpretable factor structure. One of the most frequently used methods, the varimax rotation, minimizes a complexity function that sums the products of different variables' loadings for each column of the loading matrix (i.e. for each factor). The varimax complexity function has a low value if most of the variables in the loadings matrix are close to zero. The rotation therefore aims to create a small number of large loadings (in absolute terms), which can account for most of the common variance of the data set, and otherwise fills the loading matrix with mostly close-to-zero values. This procedure usually results in an interpretable factor structure since the factors are then linked to a small number of variables that have significant loadings, while other variables with near-zero loadings do not have to be considered in explaining the factor. In this paper the varimax rotation is used for initially exploring the factor structure of asset classes in creation of the prior for the Procrustes rotation as described in Section 2.3.

The Procrustes rotation minimizes an objective function, $P(\mathbf{L})$, which is the sum of squared errors between the respective values in the (prior) target matrix and the (posterior) loading matrix:

$$\mathrm{P}(\mathbf{L}) = \sum_{i=1}^{n}\sum_{j=1}^{p}\left(l_{i,j} - t_{i,j}\right)^2 \tag{5}$$

The technique can be interpreted as the optimisation that finds the closest matrix to the target matrix in the Euclidean distance sense. The resulting solution has the same likelihood as both a principal components-type of hierarchical factor solution and the varimax solution, so that mathematically it is just as valid a representation of the data set's common variance. However, it has the great advantage compared to both that it produces the intuitive and easily interpretable global-regional-idiosyncratic structure for the variance decomposition. This structure can in turn be used in policy-relevant applications as shown in the paper.

In this paper orthogonal Procrustes rotation is used, thus the factors resulting from the rotation are uncorrelated with each other. Procrustes rotation also resolves the factor identification problem as the optimisation (apart from limiting cases) leads to a unique solution. The solution to the Procrustes problem is available analytically as shown by Schönemann (1966).

I am not aware of the Procrustes technique's application in economics and finance; however, it has been extensively studied and used in the psychometrics literature. A quick internet search also reveals its use in publications of a wide range of disciplines from analytical chemistry and geophysics to informetrics and zoology.

The Procrustes technique can be used in confirmatory factor analysis settings, where the similarity of two factor structures recovered from different data samples is assessed or where the similarity of a theoretical and an empirical factor structure is tested. In both cases congruence coefficients can be calculated to measure how well the factor structures fit. The technique can also be used in an exploratory setting, when the researcher has a general, a priori concept about the factor structure and wishes to observe what the closest solution to this prior information is that is still consistent with the data set's inherent structure.

This paper uses both concepts. Section 2.3 describes the process of prior selection (confirming the existence of the global component, the necessity of multiple factors and the regionality structure based on varimax rotation) and then takes a confirmatory approach in validating the priors. In particular, factor congruence coefficients are calculated to assess how the Procrustes factor solution of the chosen prior target compares with Procrustes solutions that could be arrived at from other reasonable priors.

Factor congruence measures the similarity of respective columns, j, of the two loadings matrices, $\mathbf{L_A}$ and $\mathbf{L_B}$ by the following formula:

$$Congr_{AB,j} = \frac{\text{diag}\left(L'_{A,j} L_{B,j}\right)}{\sqrt{\text{diag}\left(L'_{A,j}\, L_{A,j}\right) \times \text{diag}\left(L'_{B,j}\, L_{B,j}\right)}} \tag{6}$$

The measure is similar to the ordinary Pearson's correlation coefficient with the difference that column elements are evaluated as deviations from zero as opposed to deviations from the vector mean. Though congruence coefficients are not expected to show identical factor structures of various posteriors, due to the mentioned vagueness of regionality, the coefficients provide a useful means to measure the degree of fit.

As described by McCrae et al. (1996) the use of the Procrustes technique has been subject to criticism following an influential article by Horn (1967) who showed that the technique can capitalize on spurious correlations between random variables to seemingly support a prior theoretical construct. Even though the article discussed the more flexible oblique Procrustes rotation and not the orthogonal version used in this paper, to make sure that the Procrustes solution is not spurious Section 2.3 also reports congruence coefficients between the prior and the posterior and compares them with these measures' random distributions arrived at by running Monte Carlo simulations, i.e. comparing the observed coefficients to values, which a random selection of the priors would result in.

After the confirmatory analysis of the posterior Procrustes solution, Section 3 describes the results in an exploratory factor analysis sense, where the focus lies only on the posterior solution: how weak or strong the factor structures turn out to be; how countries' indicators load on various factors; and what are the most important cross-correlations.

To end the description of the Procrustes factor analytic technique the 'Thurstone regression' methodology used to extract factor score estimates needs to be explained. This is important for the monitoring application developed in Section 4. Factor score estimates are the time series of the estimated latent factors. For the j-th factor, the series are calculated by:

$$\hat{F}_{j,t} = \hat{S}_j\, Z_{i,t} \tag{7}$$

where $\hat{S}_j$ represents a length n vector of score coefficients, which weight the standardised time series, Z_i. This formula can be thought of as the inverse of (1), where factors determine the standardised time series.

Equation (7) also points out the main difference between static and dynamic factor models. In the latter, factor scores at a given point in time are a function of past factor scores and error terms. The score estimation in the static model implies that properties of the original series (e.g. excess kurtosis, volatility clustering) are directly inherited by the factor time series; whereas dynamic factor models usually have to make these features explicit in the specification.

The 'Thurstone regression' calculates score coefficients by maximising the correlation between the factors and the standardised series, which, in the case of orthogonal factors, results in:

$$\hat{\mathbf{S}} = \left(\mathbf{Z}'\mathbf{Z}\right)^{-1}\left(\mathbf{Z}'\mathbf{F}\right) = \text{Cov}\left(\mathbf{Z}\right)^{-1}\mathbf{L} \tag{8}$$

For further details and issues of score estimation refer to Grice (2001).

2.2 DATA SET

For the purposes of this study those financial market time series are considered, which are available for a relatively large number of countries on a daily frequency since at least 2009 and represent quotes of relatively liquid instruments. Based on these criteria time series of CDS spreads, stock market indices, JP Morgan EMBI Global bond spread indices, foreign exchange rates versus the US dollar, and 10-year reference yields of domestic government bond markets are selected for 18-35 countries. (Table A1 of the Appendix contains a detailed listing of the indicators of countries included for each asset class.)

Data are daily changes of last price quotes from Bloomberg in case of all series except for JP Morgan's EMBI Global spreads, which are sourced from Datastream. Percentage changes are used in case of equities and FX rates, while basis point changes are used for CDS spreads, EMBI spreads and domestic bond yields.

The time sample is chosen to begin after early-2009 in order to have a relatively homogenous data set. The financial crisis of 2008-2009 and especially the era before the crisis was characterised by significantly different correlation structures regarding cross-country co-movements (Kocsis and Nagy, 2011). The period between 2009-2011, that of the eurozone sovereign crisis, on the other hand can be regarded as a thematically homogeneous period. Another reason for choosing the time sample to begin in 2009 is the relative better data quality in this period and the larger liquidity in several developed European countries' CDS markets.

The exact beginning and ending dates are adjusted separately for each market so that the key indicators' starting and endpoints are close to each other in levels (see Table A1 for the exact dates of estimation). The rationale behind this choice is that factor analysis operates on standardised variables and therefore neglects the constant term (μ_i in equation (1)), a result of long-term changes in the variable. From a practical viewpoint choosing the sample in this way facilitates analysis as it avoids the constant, which is not attributable to any of the extracted factors. From the theoretical aspect, as well, the data generating process of first differences should not have a significant constant term since this would represent arbitrage opportunities (although smaller constants could be explained on the basis of risk neutral drift and there is a case against arbitrage-free relations in the context of the financial crisis).

2.3 DISCUSSION OF PRIOR SELECTION

Procrustes rotation requires a target loading matrix, a prior. The posterior solution resulting from the Procrustes rotation is necessarily a mathematically adequate representation of the data set's inherent covariance structure as argued before (just like any other orthonormal rotations of the initial loading matrix), though the fit between the prior and the posterior could be better or worse depending on the prior being consistent or inconsistent with the data set's inherent correlation structure. To be prudent it has to be shown that the choice of the prior is at least as good as other logically acceptable alternatives in terms of fit and that these alternatives do not result in entirely different solutions. As a final point, it has to be verified that the chosen priors and the Procrustes solutions are not far from each other: so that the method does not capitalise on chance correlations between variables (see McCrae et al., 1996) and also that the priors are largely consistent with the posterior, so that the resulting factors can be interpreted the same way as the priors.

Therefore the adequacy of the choice of priors is argued through the following steps:

- First, the existence of a strong global factor is verified by investigating correlations with the first principal components of the data sets.
- Second, the criteria of factor number selection are examined to see if it is really the case that more than one factor is needed to represent commonality of the data sets.
- Third, a data-driven exploratory factor analysis rotation method, the varimax rotation, is applied to the initial factor solution to investigate what kind of subgrouping underlies the data sets.
- Fourth, the chosen priors are presented along with alternative (logically sound) priors and their Procrustes solutions are checked to see if the chosen priors are better in terms of fit than alternative priors, and if solutions based on the chosen and alternative priors are close to each other.

- Lastly, the congruence coefficient between the Procrustes solution's loading matrix and the chosen prior is contrasted with similar statistics of solutions based on random priors to verify that the chosen prior's distance from the solution is not significant compared with a random selection of priors.

Table A2 of the Appendix shows the bivariate correlations between original time series and first principal components in case of each data set. In all asset markets except for government domestic bond yields the existence of a global factor underlying the data set is confirmed as the first principal component correlates significantly (and positively) with each country's financial indicator. Thus when the first principal component increases all individual indicators are also expected to increase, which demonstrates a global phenomenon.

The one exception is the market of domestic government bonds, where the existence of a global factor cannot be confirmed. The lack of global co-movement between long-term government yields is probably due to differences in monetary policy across countries. Long-term bond yields are - to a varying extent - linked to short-term money market rates, which are in turn determined by monetary policy. Monetary policy might be less correlated across countries for several reasons, but two primary causes are the differences in expected inflationary and output paths on one hand, and differences in policy reaction functions on the other. A major disparity between countries regarding the policy reaction function is that a deterioration in economic outlook leads to monetary stimulus in one group (e.g. most developed countries), while - due to the ensuing exchange rate depreciation – it instead leads to monetary policy tightening in another group (e.g. most EMEA countries).

Thus, except for government domestic bond yields, the inclusion of a global factor in the prior specification seems appropriate.

Nevertheless, a global factor in itself is not enough to capture co-movements as evidenced by all four factor-number criteria in all five asset classes (see Table A3 of the Appendix). The criteria point to a range of 3-9 necessary factors in the case of CDS spreads; 3-5 factors in case of equity indices; 2-3 factors in case of FX rates; 2-9 factors in case of EMBI Global (FX bond) spreads; and 4-5 factors in case of government bond yields. Note, that in the latter case the lack of a global factor does not mean a lack of commonality in changes of indicators across countries.

Hence multiple factors seem to be determining indicator co-movements. To be able to interpret the factor structure of the data, the commonly used exploratory factor analysis technique, varimax rotation, is carried out in the criteria-implied ranges. Tables A4.1-A4.5 of the Appendix report varimax rotation results for the regional factor numbers eventually chosen. Selection of different factor numbers (within the criteria-implied ranges) produces less interpretable, less clearly segmented factor structures. Though these tables are not included in the paper to save space, they are available from the author on request.

Geographical aspects seem to be material in determining the factor structure of most asset classes, although there are several borderline cases and the concept of geographical regions varies (narrower/wider concept) across different assets.

In the case of CDS spreads Latin American, Asian countries, EMEA and Eurozone countries generally load on separate factors;[1] equity indices separate into European, Asian and American indicators;[2] EMBI Global spreads' factors seem to differentiate between EMEA and Latin American countries though there are relatively high loadings of countries in each group on the other factor signifying a strong global factor. FX rates have a more vague structure, with the euro and EMEA currencies having the highest loading on one factor, emerging Asian countries loading on another, and a group of other countries with no evident geographical content correlating with a third factor. Finally, government domestic bond yields also have a more subtle covariance structure. Asian countries' indicators separate from others, but European countries' yields seem to differentiate based on credit risk: with low risk (developed), medium risk and peripheral countries forming somewhat distinct correlation groups.

Priors are created to be consistent with the findings above. In the case of CDS spreads, equities and EMBI spreads a global factor and four, three, and two regional factors, respectively, are formed. In the target matrices each country's indicators

[1] This classification is supported also by the composite indices of Markit: iTraxx SovX Latin America, Asia-Pacific, CEEMEA and Western Europe. See documentation here.

[2] Such classification is also consistent with composite indices of STOXX: All Europe+Africa, Asia+Asia Pacific and Americas. See documentation here.

receive loadings of $\sqrt{1/3}$ on the global factor and on the regional factor to which the country belongs to geographically. This setting of the loading is consistent with the a priori concept that global and regional factors each explain one third of the indicators' variance ($l^2 = 1/3$) leaving the last third for the idiosyncratic term. Target loadings on other regional factors are set to zero.

The regional structures are more obscure in the FX and government bond markets, therefore – rather than imposing a theoretical classification – a data-driven approach is followed. For FX rates, all currencies receive a $\sqrt{1/3}$ loading for the global and one regional factor as in the above cases, but the regional membership is determined by the maximum loading in the varimax solution. In case of government bond yields there is no global factor. In case of indicators, where the maximum varimax loading is above 0.5 the loading for that factor is set to $\sqrt{2/3}$ and other regional loadings are set to zero. For countries where the maximum loading is below 0.5, i.e. where regional membership is less clear, the factors with the two highest loadings receive $\sqrt{1/3}$ loadings in the target matrix.

To examine the sensitivity of the posterior solution to prior selection, alternative priors are chosen and their Procrustes rotations are created. For CDS spreads, equities and EMBI Global spreads, where geographies are the basis of prior selection, the alternatives are set to be the data-driven varimax loading maximum method outlined above for FX rates and another data-driven prior that downweights the varimax loading matrix by $\sqrt{2/3}$ and augments it with a global factor column of $\sqrt{1/3}$ values. Downweighting is consistent with moving from the varimax setup, where a regional factor is expected to explain half of total variance, to a global plus regional setup, where a regional factor is expected to explain a third of total variance.

In case of FX rates, where already the data-driven varimax loading maximum is chosen as the prior, the first alternative is the downweighted varimax method, while the second alternative is a geography-based segmentation. For government bond yields, where there is no global factor, the varimax solution is the first alternative (without the need to downweight as there is no global factor in this case), whereas the second classification creates a developed country, an EMEA, a Eurozone periphery and an Asian factor prior.

Tables A5.1-A5.5 of the Appendix report the used prior target matrices as well as the alternative priors for each of the asset classes. Tables A6.1-A6.5 report the solutions resulting after the Procustes rotation is applied to the chosen priors.

Table 1 reports factor congruence statistics. A value of 1 indicates identity of factors. Lorenzo-Seva and Berge (2006) argue that values between 0.85-0.94 can be considered to exhibit satisfactory fit, whereas values above this range denote near equivalent factors.

For nearly all factors of each asset class, there is a satisfactory fit between the chosen priors and the posteriors, which means that the factors resulting from the Procrustes rotation can be interpreted the same way as the priors. The exception is the case of government bond yields, where especially the last factor seems inconsistent with the prior; therefore in this case the posterior loadings have to be examined to interpret the factor.

Alternative priors also fit well to their respective Procrustes solutions (columns 2 and 3). Compared with the chosen prior the difference is not significant, therefore it can be argued that, in this respect, the chosen priors are as good as the alternatives.

The last two columns report the fit between the Procrustes solutions based on the chosen and the alternative priors. For CDS spreads, equity indices and EMBI spreads the solutions based on the first alternative, the varimax maximum loadings, priors are identical to those based on the chosen priors, because the geographical classification and the highest varimax loadings coincide in these instances. Apart from these extreme cases congruence coefficients are still high meaning that different priors lead to similar solutions. This is even the case regarding government bond yields, where prior and posterior fit are problematic irrespective of what the priors are: solutions though seem to be more consistent with each other.

Lastly, columns 4 and 5 report percentiles of the fit of priors and posteriors from random prior draws. Random priors are simulated in the following way: For each of the first four asset classes the global factor is not randomised, all assets receive a loading of $\sqrt{1/3}$ as before. One other factor is drawn however at random, which receives a loading of $\sqrt{1/3}$, while other factors receive a loading of 0. Columns are then ordered to best correlate with the chosen prior (to eliminate the effect of factors' re-ordering). For government bond yields the same procedure is performed except that there is no global factor

Table 1
Factor congruence statistics

Factor	PRIOR - POSTERIOR CONGRUENCES					PROCRUSTES CONGRUENCES	
	Chosen Prior	Alternative 1	Alternative 2	Random Prior Distribution Perc 1	Random Prior Distribution Perc 5	Final Solution vs Alternative 1 Solution	Final Solution vs Alternative 2 Solution
				CDS spreads			
GLOBAL	0.987	0.987	0.983	0.988	0.987	1.000	0.997
EMEA	0.938	0.938	0.986	0.714	0.663	1.000	0.996
ASIA	0.928	0.928	0.977	0.706	0.645	1.000	0.941
LATIN AMERICA	0.886	0.886	0.978	0.691	0.629	1.000	0.953
EUROZONE	0.951	0.951	0.977	0.657	0.587	1.000	0.957
				Equity indices			
GLOBAL	0.969	0.969	0.972	0.988	0.984	1.000	0.993
EUROPE	0.964	0.964	0.977	0.760	0.712	1.000	0.989
ASIA	0.866	0.866	0.961	0.739	0.685	1.000	0.899
AMERICA	0.902	0.902	0.974	0.706	0.645	1.000	0.949
				FX rates			
GLOBAL	0.984	0.982	0.999	0.993	0.990	0.994	0.999
EUROPE	0.902	0.985	0.992	0.828	0.781	0.997	0.992
EMERGING ASIA	0.921	0.965	0.924	0.818	0.760	0.922	0.924
OTHER	0.903	0.976	0.863	0.803	0.740	0.975	0.863
				EMBI Global spreads			
GLOBAL	0.981	0.981	0.976	0.984	0.984	1.000	0.997
LATIN AMERICA	0.869	0.869	0.988	0.857	0.816	1.000	0.992
EMEA	0.886	0.886	0.982	0.834	0.790	1.000	0.995
				10-year government bond yields			
DEV'D LOW RISK	0.893	0.993	0.937	0.738	0.681	0.995	1.000
EMEA + EZ PER'Y 1	0.721	0.859	0.222	0.745	0.674	0.990	0.885
ASIA	0.913	1.000	0.881	0.713	0.648	0.978	0.990
EMEA + EZ PER'Y 2	0.350	0.508	0.858	0.663	0.595	0.828	0.789

in this case and that $\sqrt{1/2}$ loading is assigned to the random factor. Procrustes rotation is then executed and congruence coefficients are calculated between the solution and the random prior. For each asset class 10.000 random congruence coefficients are obtained this way and the highest 1 and 5 percentiles are reported. Apart from the global factors (which are not randomised) and the last government bond yield factor, the statistics confirm that the chosen prior is better in fitting the data than 95-99 percent of random prior draws are.

3 General factor analysis results

Bartlett tests and Kaiser-Meyer-Olkin measures demonstrates the data sets' suitability for factor analysis for all asset classes (Table 2). The Bartlett tests reject the null hypothesis in all markets that variance-covariances form an identity matrix (cross-variable independence), thus indicating that correlations between variables are significant. The Kaiser-Meyer-Olkin measures, aggregates of the explained-to-unexplained ratios of variables' variances, are above 0.9 for all markets, which is considered ideal for factor analysis.

Table 2
Adequacy measures for factor analysis

	CDS spreads	Equity indices	10-year yields	EMBI Global spreads	FX rates
Bartlett-test p-value	<0.00005	<0.00005	<0.00005	<0.00005	<0.00005
KMO MSA	0.96	0.97	0.90	0.97	0.95

3.1 THE GLOBAL FACTORS

The previous section confirmed the existence of a global factor in four of the five asset classes analysed. Thus, the prior target matrices have been set up for the Procrustes rotation to include such a factor. The Procrustes solutions (Table A6.1-A6.5) for these asset classes (CDS, equity indices, FX rates, EMBI spreads) extract global factors with significant positive loadings for all countries' financial indicators as expected.

Table 3
Correlations between global factor time series

	CDS spreads	Equity indices	FX rates	EMBI Global spreads
CDS spreads	1.00	−0.61	0.58	0.29
Stock indices		1.00	−0.63	−0.29
FX rates			1.00	0.31
EMBI spreads				1.00

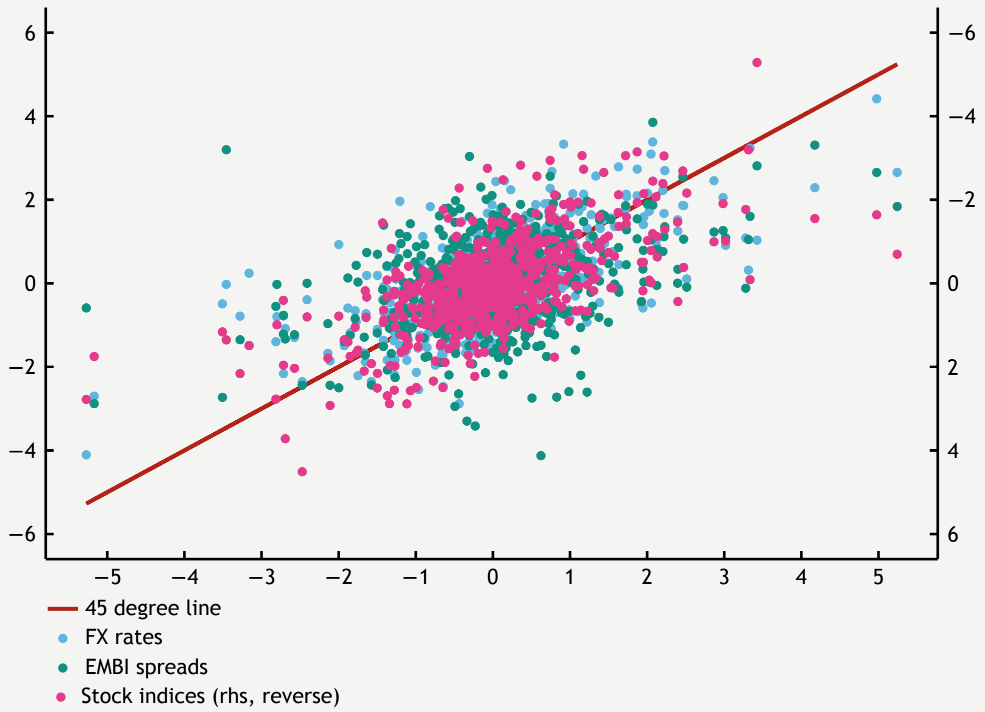
The Thurstone regression method is used to estimate the time series of latent factors, called the factor scores (see Section 2.1). With the time series of global factors created, the correlations across markets can be examined.

Table 3 reveals strong co-movements between three of the four markets. Correlation coefficients of roughly 60 percent between the global components of CDS spreads, equity markets and FX rates indicate that one market's general daily changes explain around 35 percent of the variance in the general movement of other markets. While this is a significant variance share, it also indicates a considerable role for remaining market-specificities across asset classes. Correlations with the EMBI Global spreads' global factor are significantly weaker.

Figure 1 shows the scatter plot between daily changes of the global factors in the equity, FX and CDS markets. A general positive association can be observed between the daily changes of global variables, thus, it is not outliers that influence the correlation statistics. On the other hand extreme movements in CDS spreads in absolute terms are generally associated with

Figure 1
Daily changes of global factors

(standard deviation units)



larger than average movements in other markets as well, although the scales seem to differ from occasion to occasion. These disparities can partly be attributed to the cross-section sample (the list of countries), and partly to market-specificities on the global scale.

Figure 2 displays the time series evolution of global factors in different markets (with the equity market's axis reversed for ease of comparison). Since the onset in May 2009, various markets have displayed considerable volatility, with all asset classes exhibiting favourable tendencies in the second half of 2009, as the threat of the financial crisis receded (credit spreads declined, currencies appreciated, stock indices increased). Early-mid 2010 exhibited turbulence due to Greece and the spread of the crisis to other peripheral countries, but this proved to be smaller in magnitude compared to the financial market stress that returned as of June 2011. At the end of the sample, there has been a global improvement that seems to have affected stock markets relatively more than other asset markets. Besides the general trendlike co-movements of global factors it is again worthy to note that individual spikes on a day-to-day basis have mostly coincided across different markets.

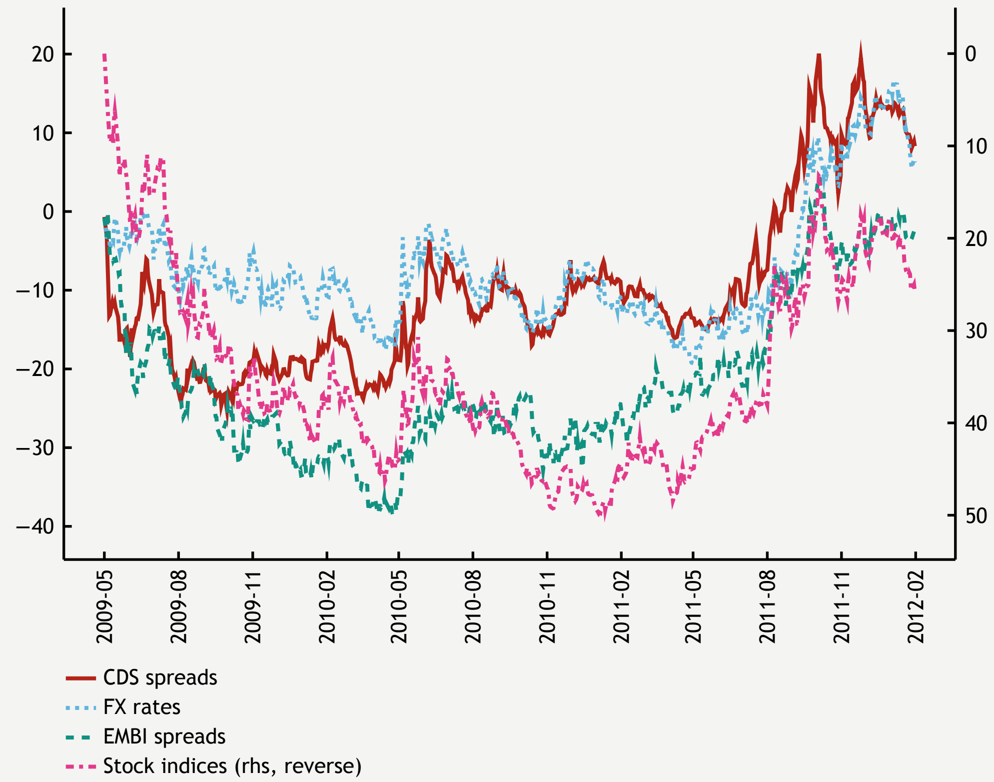
3.2 REGIONAL FACTORS

Section 2.3 discussed the regional aspects of the data sets' factor structure – as pointed out by the varimax solutions – and detailed the selection of the regional priors. Here the final regional factors created through the Procrustes rotations are described.

Solution on the CDS data set (35 countries) corresponds with the global + four regional (EMEA, Asian, Latin American and Eurozone) factors that the prior targets. Most countries exhibit large positive loadings on their respective regional factors and close-to-zero loadings with other factors. Perhaps the Baltic countries can be mentioned to have weaker correlations with the EMEA region; whereas Russia, Turkey, South Africa seem to have mild positive loadings on other factors. Kocsis and Nagy (2011) provides a detailed analysis of the factor solutions for the CDS market for a similar estimation period and also for previous episodes. (Table A6.1 presents the factor structure for the CDS market.)

Figure 2
Cumulated changes of global factors

(standard deviation units)



A relatively similar structure is found to be appropriate for the similar sized (32-country) cross-section of equity indices. The difference lies in having a combined European factor including both Eurozone and emerging European countries. Therefore with equity indices one global and three regional factors are the input for the Procrustes rotation. The common country grouping of Eurozone and EMEA countries does not mean that equity indices have moved on a similar magnitude in the two regions. It only means that the movement patterns were similar. In fact, there were large dissimilarities in the daily volatilities of European indices. Another difference compared with the CDS market is that Asian and American factors each include a developed country, Japan and the US, respectively (Table A6.2 presents the factor structure for the equity market.)

FX rates led to a markedly different factor structure compared to other asset classes. The data-driven varimax solution was used to form a rule-based prior for the Procrustes rotation, which results in a factor structure less on the geographic basis seen in other markets. The solution still separates an emerging Asian bloc (but separates it also from New Zealand and Australia), and one factor has high loadings on European currencies and highest on the EUR/USD exchange rate. Yet there is a hardly interpretable factor with currencies from various geographical regions (South Africa, Mexico, Australia, New Zealand, Canada). (Table A6.3 presents the factor structure for the FX market.)

JP Morgan's EMBI Global spread indices use USD-denominated liquid bonds of emerging markets. Therefore this indicator-type excludes developed countries (hence there is also no Eurozone factor). The factor structure is largely consistent with a geographic segmentation as Latin American countries are separated from the EMEA region. However this separation does not produce such clear factor structure as seen in either the CDS or the equity markets: several countries have relatively large loadings on the other region, while a few countries have low loadings on both regional factors. (Table A6.4 presents the factor structure for EMBI spreads.)

Finally, for 10-year government bond yields reliable data was available for only Asian, European and developed countries. The Latin American region is therefore not represented here. As seen in Section 2.3 setting up the prior has been more problematic in this market than in others. The fit between priors and Procrustes solutions were mixed for the data-driven as well as the geography-based priors. Each result had factors with low congruence coefficients. Somewhat reassuringly, though, different priors seemed to lead to similar Procrustes solutions. Nonetheless, factor results of this market have to be treated with caution. Domestic government bond market factors are thus excluded from calculated aggregates in the applications introduced in Sections 4.2 and 4.3.

In the domestic government bond market the Procrustes solution proposes a relatively obvious Asian factor and multiple, less clearly interpretable subregions for Europe. One of the factors is labelled as a developed country region, because of its high loadings seen for the US, UK and low credit risk eurozone countries. Another factor exhibits higher loadings for medium-risk eurozone countries (France, Belgium, Austria, Italy, Spain) but also has moderate loadings for two CEE countries (Hungary and Poland) and peripheral eurozone countries (Greece, Portugal, Ireland). The last factor is labelled eurozone periphery, although it has only slightly higher loadings for this group of countries as the aforementioned factor (Table A6.5 presents the factor structure for the domestic government bond market.)

4 Applications

Factor analysis with Procrustes rotation can be applied to provide answers to a range of questions regarding the nature of financial markets of any particular country. In this section, addressing some of such relevant questions is presented on the example of Hungarian financial indicators. First, a brief overview is given on which factors explain the variances of daily changes of particular Hungarian markets. Then, an online monitoring application is presented, which shows how shocks of various types have contributed in the past to shaping the Hungarian 5-year CDS spread. Finally, channels of risk propagation between the eurozone periphery and Hungary are examined.

4.1 VARIANCE SHARES OF FACTORS

Equation (3) is used to assess the variance share of different sources of shocks. According to equation (3) the variance share of factor j will be the squared loadings, $l^2_{i,j}$ of country i on the factor.

Table 4
Explained variance shares of factors in various Hungarian markets

	CDS spread					
	Global	EMEA	Asia	Latin America	Eurozone	Idiosyncratic
loadings	0.66	0.46	−0.11	0.04	0.12	
variance share	0.43	0.21	0.01	0.00	0.01	0.33
	Equity (BUX) index					
	Global	Europe	Asia	America		Idiosyncratic
loadings	0.45	0.58	0.13	0.10		
variance share	0.20	0.33	0.02	0.01		0.44
	FX (USD/HUF) rate					
	Global	Europe	Emerging Asia	Other		Idiosyncratic
loadings	0.78	0.47	−0.12	0.15		
variance share	0.62	0.22	0.01	0.02		0.13
	EMBI Global spread					
	Global	Latin America	EMEA			Idiosyncratic
loadings	0.55	0.03	0.25			
variance share	0.30	0.00	0.06			0.63
	10-year government yield					
	Developed and EMEA	Eurozone medium risk	Asia	Eurozone periphery		Idiosyncratic
loadings	−0.03	0.31	−0.26	0.08		
variance share	0.00	0.10	0.07	0.01		0.83

Table 4 presents the variance shares in the case of Hungarian financial indicators. Both similarities and differences are found across markets. In all asset classes the global and the idiosyncratic (Hungarian market-specific) factors together explain most of the variance, while the EMEA/European regional component is less important.

Global impacts are most important in the case of the forint/dollar exchange rate (62%) and the CDS spread (43%), while they are less relevant in the equity and FX bond markets (20% and 30%, respectively). The regional effects are similar across CDS, equity and FX markets explaining around 20-35 percent of the variances, while the less clear-cut regional factors in the domestic government bond market have lower explained variance. Some of the results' variations between markets are a consequence of the different country cross-sections available in various markets, but market-specificities also play a role. For example, in the case of EMBI Global spreads, according to market anecdotes and analysis, the higher variance ratio of the idiosyncratic term may be a result of lower liquidity.

The differences across markets in the explained variances of various components imply differences in domestic policy's room for manoeuvre. The relative large role of global factors in CDS spreads and the FX rate suggests that foreign events, which are outside of Hungarian policy-makers' scope, are more important in determining these indicators. Policy impact may thus be relatively limited. On the other hand, the large unexplained variance of bond market yields and FX bond spreads may indicate a larger role for domestic policies. Though, idiosyncratic terms should be assessed with caution as they may be a result of other country- and market-specific factors besides policy-making.

4.2 ONLINE MONITORING OF COMPONENTS OF THE HUNGARIAN CDS SPREAD

While the overall variance contributions of factors provide important general insights, for day-to-day market monitoring purposes the following application is more useful. By using the time series of factors, the factor score estimates, it is possible to approximate various factors' daily contributions to the evolution of indicators. To see this, equation (1) can be re-written in the following way:

$$X_i = \mu_i + \sigma_i \left(\sum_{j=1}^{p} l_{i,j} F_j + \epsilon_i \right) = \mu_i + \sigma_i \sum_{j=1}^{p} l_{i,j} F_j + \sigma_i \epsilon_i \qquad (9)$$

Factor contributions are given by $\sigma_i \sum_{j=1}^{p} l_{i,j} F_j$; whereas $\sigma_i \epsilon_i$ denotes the idiosyncratic component. Since X_i is in first difference terms, to visualize longer time series of the components, it is useful to plot the cumulated series instead of the changes themselves.

Figure 3 shows the evolution of the three main components of the 5-year Hungarian CDS spread for the period between May 2009 and April 2012. Decreases in any of the components mark a contribution to the improvement in the Hungarian risk premium (lowering of the Hungarian CDS spread), while increases denote a deterioration of the market's risk assessment due to the given latent factor.

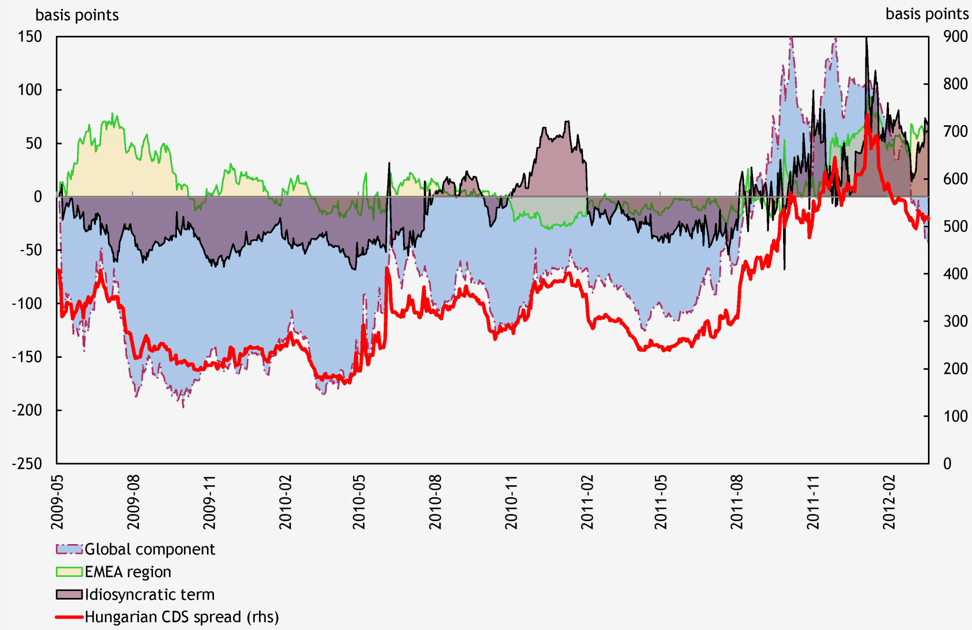
The start of the time series, for example, is characterized by a large decline in the global component of around 200 basis points until early August 2009, which was the prime factor that nearly halved the Hungarian CDS spread in this period. The idiosyncratic term also contributed to the decline to a lesser extent. Later, in spring 2010, the global factor raised the Hungarian CDS premium on the back of Greek debt sustainability worries. The global factor remained volatile in 2010 and early 2011 as the market was deliberating the spread of the crisis to other smaller countries in the periphery. From June 2010 Hungarian domestic policies also played a larger role in shaping the CDS premium. This component caused fluctuations of around 100 basis points in magnitude.

The marked increase in the Hungarian CDS spread since June 2011 reflects dominantly the effect of global factors, as concerns over an immediate Greek default and its potential to cause repercussions either in the eurozone banking sector or in larger sovereign bond markets led to increases of CDS spreads worldwide. Hungarian market-specific issues, e.g. investors' concerns relating to the early mortgage repayment scheme, rating downgrades and the stand-off between the Hungarian government and international institutions also contributed to raising the CDS premium in the winter of 2011-2012. Both global and idiosyncratic factors contributed to the decline of CDS spreads seen in the first quarter of 2012.

4.3 EXTENSION TO MULTIPLE MARKETS

The monitoring application presented above for CDS spreads is also developed for equity indices, EMBI Global spreads, and FX rates. On one hand, this is useful in that it makes online monitoring possible for other Hungarian indicators, but on the

Figure 3
Evolution of the Hungarian CDS premium and its components
(cumulated changes)



other hand it also provides a means to identify factors common to all Hungarian markets. The advantage of extracting the common part of global, regional and idiosyncratic components is that individual markets have various market-specificities, which contaminate inference on the general effects of international and domestic shocks to Hungarian financial markets. Often this general impact is what one is interested in without the peculiarities of specific markets.

Looking at several indicators together makes it possible to strip out the effects that are not common to all markets. To carry this out principal component analysis on related factor scores is an efficient method, since PCA provides those markets with larger weights, which correlate more with others, and a lower weight is assigned to those, which have more of the market-specific features.

Hence extracting the first principal component of global factor score series of the four Hungarian markets provides the general global component; the first principal component of the four markets' EMEA/European regional scores comprises the general EMEA/European regional component; and the first principal component of the four idiosyncratic components constructs the general idiosyncratic term. After principal components are extracted, a scaling is chosen that is characteristic of the Hungarian CDS market. e.g. the general global component is scaled to the Hungarian global CDS factor, the general idiosyncratic component is scaled to the Hungarian CDS spreads' idiosyncratic component.

The general global component is fairly close to the CDS market's global factor series as depicted by Figure A1.1 of the Appendix. The market-specific part of the global CDS factor is thus less important. The general European component is also close in levels to the CDS market's EMEA factor. In contrast to global components' large co-movements, however, regional components of various asset classes exhibit lower correlation, which – beside market-specific features – may be the result of different countries making up regions in different asset classes.

The common part of idiosyncratic shocks can be thought of as the *country-specific* component of Hungarian indicators. First, because this series is constructed from the idiosyncratic series of various Hungarian markets, it is a series that is not common with other countries' indicators, therefore it is Hungary-specific. Second, because it is the common component of idiosyncratic terms of various markets, it is a general, i.e. non-market specific, term. This general idiosyncratic term is exactly what one has in mind, when referring to country-specific risk premium shocks. Figure A1.3 shows that although this country-specific component is different from the original idiosyncratic component of the CDS spread, most marked movements that were observed due to Hungary-specific news does show up in the general country-specific factor, leaving behind a not too interesting market-specific factor of lesser magnitude. Overall, the country-specific component drifted around 50-100 basis points higher than the idiosyncratic CDS term throughout the period. This indicates that the information content of the four asset classes denotes more adverse country-specific spread movements during the sample than what one would infer based on the CDS market alone.

4.4 CHANNELS OF RISK PROPAGATION FROM THE EUROZONE PERIPHERY

The final issue that this study briefly examines is how the eurozone periphery's shocks have affected Hungarian markets. In particular, the focus is on which markets and which channels have been of more or of lesser importance in risk propagation. If a country in the eurozone periphery has an impact on Hungarian markets, this will show up in both the periphery countries' and Hungary's indicators loading significantly on one or more factors. For comparison purposes the link between the Polish and Hungarian indicators are also presented.

As described in Section 2.1 the products of Hungarian and periphery countries' loadings can be analyzed to address the issue. The theoretical +1 value of loading products reflects a perfect positive correlation between the two countries' indicators through the given factor and a value of −1 denotes perfect negative correlation through the factor. Because each country has several factors plus the idiosyncratic term affecting its indicators, loadings will be less than 1 in absolute value, so the product terms will also be closer to zero.

Table 5
Products of Hungarian loadings and loadings of selected countries

	Poland	Spain	Portugal	Ireland	Italy	Greece
			CDS spreads			
GLOBAL	0.436	0.354	0.350	0.326	0.396	
EMEA	0.213	0.047	0.024	−0.002	0.057	
EUROZONE	0.018	0.079	0.077	0.074	0.079	
			Equity indices			
GLOBAL	0.225	0.313	0.278	0.289		
EUROPE	0.383	0.300	0.311	0.298		
			Government yields			
DEVELOPED	0.002	−0.003	0.002	0.003	−0.000	0.003
EMEA + EUROZONE MEDIUM RISK	0.094	0.243	0.082	0.100	0.240	0.081
EUROZONE PERIPHERY	0.007	0.035	0.032	0.032	0.024	0.026

Table 5 displays the results. Correlation channels with eurozone peripheral countries are markedly different across markets, which may be a result of different structure (different regions and different definitions of regions) across markets, as well as a result of other distinct features of asset classes. In terms of CDS spreads it is the global component through which Hungarian and periphery indicators are correlated. The strength of the global component seems to be a general trait of the CDS market as the global factor is the primary correlation channel even with Poland. The loading products between Hungarian and periphery spreads are roughly in line with those between Hungarian and Polish indicators. Since causality is not treated by the method, this could be a consequence of either periphery-specific news affecting Hungarian markets or both the periphery and Hungary reacting similarly to third-country global news shocks (theoretically there is a third option of Hungary affecting the periphery, which however is not realistic during this sample). In the CDS market EMEA and Eurozone regional factors have been weak channels of co-movement. This is reassuring, since it suggests that Hungarian indicators were not directly impacted by the periphery through regional proximity. To phrase another way, similar beta Asian or Latin American CDS spreads were affected to a comparable extent.

Equity indices have displayed a different picture. While the global factor was much less important in Hungary's case, the loading on the European factor was significantly larger, resulting in relatively greater loading products with peripheral countries through this factor – similar in magnitude as the global channel. The Hungarian and eurozone equity indices have exhibited larger total correlations than CDS indicators.

In case of the government domestic bond market, correlations between Hungarian and other country yields have generally been low. The developed and eurozone periphery channels have been negligible in explaining the Hungarian variable. Only the 'EMEA + Eurozone medium risk' factor presented some moderate loading products, notably with Spain and Italy, pointing out less significant correlation channels.

One notable shortcoming of the method used here to assess correlation channels is that these loading products are derived from a time-invariant factor structure of indicators for the full three-year period. They are, as a result, incapable of accounting for shifts in the correlation structure, which may however be a crucial point in better understanding risk propagation from crisis countries. A dynamic analysis would require a different methodology, which lies out of this paper's scope and is left for future research.

5 Conclusions

This paper uses factor analysis with Procrustes rotation to analyse financial time series of a large cross-section of countries in both developed and emerging markets. Indicators are examined for five asset classes: CDS spreads account for credit derivatives, equity indices for stock markets, FX rates versus the USD for the currency market, EMBI Global spreads for the FX bond market, and 10-year government reference yields for domestic bond markets. The method allows a segmentation of indicators into global, regional and idiosyncratic components, which is not possible via similar methods, such as PCA or standard factor analysis.

A segmentation of indicators points to the importance of a global component in most markets, which supports a general finding of the literature. The extracted global components of nearly all markets show significant correlation with each other in line with the risk-on/risk-off dichotomy in financial markets observed since the crisis. An interesting exception is the asset class of domestic government bonds, where disparities regarding monetary policy reactions may lead to yields behaving differently in international comparison – weakening the case for global co-movements.

In addition to the global factor, factor analysis points to the importance of further country groups in all of the markets studied. The finding of Kocsis and Nagy (2011) that country groups are formed mainly on a regional basis in CDS markets is supported for most other asset classes. Regional groups mainly follow a geographical pattern.

An online application is developed based on factor analysis results, which provides a method for the daily monitoring of market developments of any particular country's indicator. The application identifies global, regional and idiosyncratic components of the selected indicator's daily movements. General risk premium shocks of global, regional and country-specific origins, cleaned of market-specific noise, can also be extracted by using the information content of multiple asset classes.

Factor analysis can also be used to gauge, which channels – global or regional – have been relatively more important in correlations between countries. In the Hungarian example, factor analysis points to differences across asset classes in how eurozone periphery shocks' have propagated. While the global factor has been important in both CDS and equity markets, in the latter market the direct regional link has also been noteworthy. There has not been material evidence of correlation between domestic bond markets of Hungary and the eurozone periphery. Nevertheless it has to be emphasised that these results are general to the relatively long estimation sample and may conceal recent developments in the factor structure. It is left for future research to develop the model further into one that is also capable of incorporating the dynamics of factor structures.

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Appendix A Additional tables and figures

Table A1
Estimation sample periods and country regional grouping

ASSET CLASS		
CDS spreads	Estimation Period	1 May 2009 - 31 Aug 2011
	GLOBAL	35 countries
	EMEA	Hungary, Poland, Czech Republic, Slovakia, Romania, Croatia, Bulgaria, Lithuania, Estonia, Ukraine, Russia, Turkey, South Africa, Kazakhstan
	EUROZONE	Austria, France, Belgium, Netherlands, Spain, Portugal, Ireland, Italy
	LATIN AMERICA	Mexico, Brazil, Argentina, Peru, Venezuela, Chile, Colombia
	ASIA	China, Thailand, Malaysia, Indonesia, Vietnam, South Korea
equity indices	Estimation Period	13 Aug 2009 - 31 Jan 2012
	GLOBAL	32 countries
	EUROPE	Hungary, Poland, Czech Republic, Romania, Russia, Turkey, South Africa, Israel, Ireland, Portugal, Spain, Austria, Netherlands, Sweden, Germany, France, United Kingdom, Switzerland
	ASIA	India, Thailand, China, Indonesia, Hong Kong, Philippines, Australia, New Zealand, Japan
	AMERICA	Mexico, Brazil, Argentina, Chile, United States
FX rates	Estimation Period	7 July 2009 - 8 Sept 2011
	GLOBAL	18 countries
	EUROPE	Hungary, Poland, Czech Republic, Romania, Croatia, Eurozone, United Kingdom
	EMERGING ASIA	Malaysia, Indonesia, South Korea, Philippines
	OTHER	Russia, Turkey, South Africa, Mexico, Australia, New Zealand, Canada
EMBI Global spreads	Estimation Period	1 July 2009 - 4 Aug 2011
	GLOBAL	25 countries
	EMEA	Hungary, Poland, Bulgaria, Serbia, Ukraine, Russia, Turkey, South Africa, Kazakhstan, Lebanon, Iraq, Ghana, Gabon
	LATIN AMERICA	Mexico, Brazil, Argentina, Chile, Peru, Colombia, Panama, Venezuela, Uruguay, Dominican Republic, Jamaica, El Salvador
10-year reference yields	Estimation Period	14 July 2009 - 31 Jan 2012
		26 countries
	DEVELOPED LOW RISK	United Kingdom, United States, Norway, Switzerland, Germany, Finland, Netherlands, Sweden, Slovakia, France, Austria
	EUROZONE MEDIUM RISK + CEE	Belgium, Spain, Italy, Hungary, Poland, Czech Republic, South Africa
	EUROZONE PERIPHERY	Spain, Italy, Portugal, Greece, Ireland
	ASIA	Japan, Australia, Hong Kong, South Korea, Taiwan

Table A2
Correlations with first principal components

CDS SPREADS	
Hungary	0.790
Poland	0.818
Czech Rep	0.810
Slovakia	0.708
Romania	0.826
Croatia	0.828
Bulgaria	0.846
Lithuania	0.602
Estonia	0.568
Ukraine	0.454
Russia	0.899
Turkey	0.879
South Africa	0.878
Kazakhstan	0.774
China	0.697
Thailand	0.672
Malaysia	0.680
Indonesia	0.700
Vietnam	0.610
South Korea	0.751
Mexico	0.735
Brazil	0.765
Argentina	0.554
Peru	0.704
Venezuela	0.552
Chile	0.496
Colombia	0.786
Spain	0.593
Portugal	0.551
Ireland	0.513
Italy	0.662
Austria	0.709
France	0.583
Belgium	0.589
Netherlands	0.672

EQUITY INDICES	
Hungary	0.723
Poland	0.818
Czech Rep	0.745
Romania	0.618
Russia	0.783
Turkey	0.634
South Africa	0.803
Israel	0.632
Mexico	0.657
Brazil	0.647
Argentina	0.699
Chile	0.647
India	0.575
Thailand	0.470
China	0.309
Indonesia	0.511
Hong Kong	0.577
Philippines	0.213
Australia	0.537
New Zealand	0.345
Ireland	0.821
Portugal	0.812
Spain	0.836
Austria	0.866
Netherlands	0.930
Sweden	0.875
Germany	0.898
France	0.929
UK	0.900
Switzerland	0.857
Japan	0.398
United States	0.722

FX RATES VS USD	
Hungary	0.903
Poland	0.923
Czech Rep	0.876
Romania	0.866
Croatia	0.837
Russia	0.707
Turkey	0.800
South Africa	0.791
Mexico	0.741
Malaysia	0.421
Indonesia	0.385
South Korea	0.515
Philippines	0.388
Australia	0.851
New Zealand	0.811
Eurozone	0.865
UK	0.687
Canada	0.760

EMBI GLOBAL SPREADS	
Hungary	0.587
Poland	0.546
Bulgaria	0.746
Serbia	0.794
Ukraine	0.570
Russia	0.924
Turkey	0.908
South Africa	0.877
Kazakhstan	0.770
Lebanon	0.763
Iraq	0.812
Ghana	0.750
Gabon	0.800
Mexico	0.846
Brazil	0.905
Argentina	0.770
Chile	0.489
Peru	0.851
Colombia	0.852
Panama	0.898
Venezuela	0.659
Uruguay	0.886
Domin. Rep.	0.626
Jamaica	0.526
El Salvador	0.867

10-YEAR GOV'T REFERENCE YIELDS	
Hungary	−0.106
Poland	−0.090
Czech Rep	0.267
South Africa	0.039
UK	0.814
United States	0.613
Norway	0.594
Switzerland	0.769
Germany	0.931
Finland	0.934
Netherlands	0.929
Sweden	0.823
Slovakia	0.537
France	0.783
Austria	0.803
Belgium	0.390
Spain	0.049
Italy	−0.010
Portugal	−0.090
Greece	−0.153
Ireland	−0.121
Japan	0.285
Australia	0.312
Hong Kong	0.343
South Korea	0.145
Taiwan	0.285

Table A3
Number of factors proposed by various criteria for different asset classes and the number of factors chosen in the final Procrustes priors

	Minimum eigenvalue of 1	Cumulated explained variance 60%	Minimum average partial	Scree plot	**Chosen factor number**
CDS spreads	5	3	6	6	**5: global + 4 regional**
Equity indices	3	3	3	4	**4: global + 3 regional**
FX rates vs USD	3	2	3	4	**4: global + 3 regional**
EMBI Global spreads	3	2	3	5	**3: global + 2 regional**
10-year gov't yields	5	5	4	7	**4: 4 regional**

Table A4.1
Factor structure (loadings matrix after Varimax rotation) — CDS spreads

	EMEA	ASIA	LATIN AMERICA	EUROZONE
Hungary	0.670	0.129	0.288	0.352
Poland	0.654	0.224	0.304	0.355
Czech Republic	0.675	0.272	0.291	0.257
Slovakia	0.651	0.213	0.195	0.198
Romania	0.780	0.201	0.237	0.296
Croatia	0.756	0.203	0.291	0.304
Bulgaria	0.743	0.259	0.301	0.283
Lithuania	0.534	0.267	0.152	0.179
Estonia	0.470	0.223	0.179	0.098
Ukraine	0.437	0.146	0.204	0.108
Russia	0.666	0.403	0.409	0.266
Turkey	0.650	0.351	0.430	0.316
South Africa	0.677	0.386	0.370	0.268
Kazakhstan	0.616	0.389	0.338	0.275
China	0.237	0.798	0.255	0.136
Thailand	0.225	0.716	0.167	0.208
Malaysia	0.256	0.810	0.164	0.132
Indonesia	0.320	0.770	0.200	0.088
Vietnam	0.246	0.635	0.167	0.146
South Korea	0.277	0.836	0.255	0.153
Mexico	0.309	0.200	0.871	0.168
Brazil	0.310	0.192	0.881	0.200
Argentina	0.322	0.247	0.519	0.166
Peru	0.278	0.170	0.773	0.158
Venezuela	0.239	0.218	0.458	0.146
Chile	0.230	0.162	0.396	0.107
Colombia	0.335	0.226	0.868	0.178
Spain	0.231	0.129	0.110	0.801
Portugal	0.177	0.128	0.136	0.791
Ireland	0.128	0.102	0.085	0.771
Italy	0.276	0.185	0.111	0.823
Austria	0.405	0.131	0.208	0.580
France	0.209	0.103	0.200	0.669
Belgium	0.202	0.074	0.143	0.793
Netherlands	0.282	0.221	0.200	0.633

Table A4.2
Factor structure (loadings matrix after Varimax rotation) — Equity indices

	EUROPE	ASIA	AMERICA
Hungary	0.599	0.282	0.202
Poland	0.675	0.319	0.253
Czech Republic	0.610	0.406	0.104
Romania	0.461	0.460	0.047
Russia	0.578	0.420	0.271
Turkey	0.539	0.230	0.161
South Africa	0.627	0.374	0.278
Israel	0.528	0.205	0.220
Mexico	0.399	0.087	0.734
Brazil	0.367	0.105	0.749
Argentina	0.457	0.130	0.678
Chile	0.410	0.258	0.474
India	0.325	0.502	0.205
Thailand	0.216	0.534	0.144
China	0.082	0.462	0.128
Indonesia	0.224	0.645	0.122
Hong Kong	0.221	0.795	0.172
Philippines	0.011	0.509	−0.032
Australia	0.219	0.778	0.099
New Zealand	0.173	0.561	−0.093
Ireland	0.762	0.222	0.241
Portugal	0.768	0.184	0.226
Spain	0.852	0.110	0.237
Austria	0.776	0.290	0.247
Netherlands	0.900	0.215	0.294
Sweden	0.803	0.217	0.319
Germany	0.879	0.158	0.314
France	0.922	0.186	0.280
United Kingdom	0.836	0.235	0.315
Switzerland	0.799	0.223	0.281
Japan	0.136	0.675	0.033
United States	0.549	0.010	0.684

Table A4.3
Factor structure (loadings matrix after Varimax rotation) — FX rates versus the USD

	EUROPE	EMERGING ASIA	OTHER
Hungary	0.720	0.174	0.539
Poland	0.683	0.183	0.597
Czech Republic	0.805	0.118	0.436
Romania	0.858	0.166	0.361
Croatia	0.908	0.116	0.287
Russia	0.434	0.392	0.400
Turkey	0.400	0.216	0.679
South Africa	0.354	0.232	0.686
Mexico	0.263	0.114	0.747
Malaysia	0.052	0.865	0.120
Indonesia	0.037	0.713	0.071
South Korea	0.143	0.689	0.230
Philippines	0.126	0.522	0.151
Australia	0.409	0.302	0.727
New Zealand	0.421	0.264	0.659
Eurozone	0.933	0.100	0.314
United Kingdom	0.528	0.122	0.420
Canada	0.336	0.173	0.730

Table A4.4
Factor structure (loadings matrix after Varimax rotation) — EMBI Global spreads

	LATIN AMERICA	EMEA
Hungary	0.292	0.502
Poland	0.248	0.490
Bulgaria	0.350	0.700
Serbia	0.401	0.712
Ukraine	0.254	0.539
Russia	0.592	0.724
Turkey	0.682	0.611
South Africa	0.554	0.689
Kazakhstan	0.353	0.736
Lebanon	0.486	0.574
Iraq	0.454	0.687
Ghana	0.320	0.743
Gabon	0.351	0.775
Mexico	0.849	0.340
Brazil	0.882	0.396
Argentina	0.627	0.440
Chile	0.401	0.248
Peru	0.860	0.330
Colombia	0.853	0.344
Panama	0.835	0.427
Venezuela	0.422	0.471
Uruguay	0.776	0.463
Dominican Republic	0.351	0.499
Jamaica	0.420	0.290
El Salvador	0.732	0.468

Table A4.5
Factor structure (loadings matrix after Varimax rotation) — 10-year government yields

	DEVELOPED LOW RISK	EUROZONE PERIPHERY	ASIA	EUROZONE MEDIUM RISK
Hungary	−0.047	0.249	−0.256	0.205
Poland	−0.093	0.255	−0.041	0.166
Czech Republic	0.221	0.080	0.047	0.158
South Africa	0.052	0.177	0.004	−0.012
United Kingdom	0.777	−0.055	0.219	−0.046
United States	0.605	−0.002	0.032	−0.067
Norway	0.488	−0.150	0.354	−0.075
Switzerland	0.674	−0.088	0.278	0.038
Germany	0.962	−0.119	0.119	−0.004
Finland	0.963	−0.017	0.069	0.156
Netherlands	0.954	−0.023	0.089	0.139
Sweden	0.747	−0.151	0.340	−0.070
Slovakia	0.525	0.043	−0.034	0.113
France	0.693	0.068	0.077	0.586
Austria	0.733	0.080	0.032	0.565
Belgium	0.311	0.449	−0.015	0.652
Spain	0.011	0.818	0.046	0.338
Italy	−0.081	0.720	0.076	0.388
Portugal	−0.032	0.453	−0.074	−0.044
Greece	−0.053	0.390	−0.217	0.007
Ireland	−0.064	0.493	−0.080	−0.007
Japan	0.109	−0.005	0.550	0.017
Australia	0.082	−0.112	0.763	0.005
Hong Kong	0.121	−0.080	0.756	−0.002
South Korea	0.032	−0.072	0.356	−0.009
Taiwan	0.132	0.034	0.472	0.047

Table A5.1
Factor structure (prior loadings matrices) — CDS spreads

	PRIOR USED (GEOGRAPHY, MARKIT ITRAXX)					ALTERNATIVE 1: VARIMAX LOADING MAXIMUM					ALTERNATIVE 2: VARIMAX DOWNWEIGHTED				
	GLOBAL	EMEA	ASIA	LATIN AMERICA	EUROZONE	GLOBAL	EMEA	ASIA	LATIN AMERICA	EUROZONE	GLOBAL	EMEA	ASIA	LATIN AMERICA	EUROZONE
Hungary	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.547	0.106	0.235	0.288
Poland	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.534	0.183	0.248	0.290
Czech Republic	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.552	0.222	0.237	0.210
Slovakia	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.532	0.174	0.159	0.162
Romania	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.637	0.164	0.193	0.242
Croatia	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.617	0.166	0.238	0.248
Bulgaria	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.606	0.211	0.245	0.231
Lithuania	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.436	0.218	0.124	0.146
Estonia	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.384	0.182	0.146	0.080
Ukraine	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.357	0.120	0.167	0.088
Russia	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.544	0.329	0.334	0.217
Turkey	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.531	0.287	0.351	0.258
South Africa	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.553	0.315	0.302	0.219
Kazakhstan	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.503	0.317	0.276	0.224
China	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.194	0.652	0.208	0.111
Thailand	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.184	0.584	0.136	0.170
Malaysia	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.209	0.662	0.134	0.108
Indonesia	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.262	0.629	0.163	0.071
Vietnam	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.201	0.519	0.137	0.120
South Korea	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.226	0.683	0.208	0.125
Mexico	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.252	0.163	0.711	0.137
Brazil	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.253	0.157	0.719	0.163
Argentina	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.263	0.202	0.424	0.135
Peru	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.227	0.139	0.631	0.129
Venezuela	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.195	0.178	0.374	0.119
Chile	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.187	0.132	0.323	0.088
Colombia	0.577	0.000	0.000	0.577	0.000	0.577	0.000	0.000	0.577	0.000	0.577	0.274	0.185	0.709	0.146
Spain	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.189	0.105	0.090	0.654
Portugal	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.144	0.105	0.111	0.646
Ireland	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.104	0.083	0.070	0.630
Italy	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.226	0.151	0.091	0.672
Austria	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.331	0.107	0.169	0.474
France	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.171	0.084	0.163	0.546
Belgium	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.165	0.060	0.116	0.647
Netherlands	0.577	0.000	0.000	0.000	0.577	0.577	0.000	0.000	0.000	0.577	0.577	0.230	0.180	0.163	0.517

Table A5.2
Factor structure (prior loadings matrices) — Equity indices

	PRIOR USED (GEOGRPAHY, NASDAQ STOXX)				ALTERNATIVE 1: VARIMAX LOADING MAXIMUM				ALTERNATIVE 2: VARIMAX DOWNWEIGHTED			
	GLOBAL	EUROPE	ASIA	AMERICA	GLOBAL	EUROPE	ASIA	AMERICA	GLOBAL	EUROPE	ASIA	AMERICA
Hungary	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.489	0.230	0.165
Poland	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.551	0.260	0.207
Czech Republic	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.498	0.332	0.085
Romania	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.376	0.375	0.039
Russia	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.472	0.343	0.221
Turkey	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.440	0.188	0.131
South Africa	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.512	0.305	0.227
Israel	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.431	0.167	0.179
Mexico	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.326	0.071	0.599
Brazil	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.299	0.086	0.612
Argentina	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.374	0.107	0.554
Chile	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.334	0.211	0.387
India	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.265	0.410	0.168
Thailand	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.176	0.436	0.117
China	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.067	0.377	0.105
Indonesia	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.183	0.527	0.100
Hong Kong	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.180	0.649	0.141
Philippines	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.009	0.415	−0.026
Australia	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.179	0.635	0.081
New Zealand	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.141	0.458	−0.076
Ireland	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.622	0.181	0.197
Portugal	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.627	0.150	0.185
Spain	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.695	0.090	0.193
Austria	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.634	0.236	0.202
Netherlands	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.735	0.175	0.240
Sweden	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.656	0.177	0.260
Germany	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.718	0.129	0.256
France	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.753	0.152	0.229
United Kingdom	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.682	0.192	0.257
Switzerland	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.652	0.182	0.229
Japan	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.111	0.551	0.027
United States	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.449	0.008	0.559

Table A5.3
Factor structure (prior loadings matrices) — FX rates versus the USD

	PRIOR USED (VARIMAX LOADING MAXIMUM)				ALTERNATIVE 1: VARIMAX DOWNWEIGHTED				ALTERNATIVE 2: GEOGRAPHIES			
	GLOBAL	EUROPE	EMERGING ASIA	OTHER	GLOBAL	EUROPE	EMERGING ASIA	OTHER	GLOBAL	EUROPE	ASIA PACIFIC	AMERICA
Hungary	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000
Poland	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000
Czech Republic	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000
Romania	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000
Croatia	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000
Russia	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000
Turkey	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.577	0.000	0.000
South Africa	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.577	0.000	0.000
Mexico	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577
Malaysia	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000
Indonesia	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000
South Korea	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000
Philippines	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000	0.577	0.000
Australia	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.577	0.000
New Zealand	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.577	0.000
Eurozone	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000
United Kingdom	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000
Canada	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577	0.577	0.000	0.000	0.577

Table A5.4
Factor structure (prior loadings matrices) — EMBI Global spreads

	PRIOR USED (GEOGRAPHIES)			ALTERNATIVE 1: VARIMAX LOADING MAXIMUM			ALTERNATIVE 2: VARIMAX DOWNWEIGHTED		
	GLOBAL	LATIN AMERICA	EMEA	GLOBAL	LATIN AMERICA	EMEA	GLOBAL	LATIN AMERICA	EMEA
Hungary	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.239	0.410
Poland	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.203	0.400
Bulgaria	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.286	0.572
Serbia	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.328	0.582
Ukraine	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.207	0.440
Russia	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.484	0.591
Turkey	0.577	0.000	0.577	0.577	0.577	0.000	0.577	0.557	0.499
South Africa	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.453	0.563
Kazakhstan	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.288	0.601
Lebanon	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.397	0.468
Iraq	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.370	0.561
Ghana	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.261	0.607
Gabon	0.577	0.000	0.577	0.577	0.000	0.577	0.577	0.286	0.633
Mexico	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.693	0.278
Brazil	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.720	0.324
Argentina	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.512	0.360
Chile	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.327	0.202
Peru	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.702	0.270
Colombia	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.696	0.281
Panama	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.682	0.348
Venezuela	0.577	0.577	0.000	0.577	0.000	0.577	0.577	0.344	0.385
Uruguay	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.633	0.378
Dominican Republic	0.577	0.577	0.000	0.577	0.000	0.577	0.577	0.287	0.407
Jamaica	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.343	0.237
El Salvador	0.577	0.577	0.000	0.577	0.577	0.000	0.577	0.598	0.382

Table A5.5
Factor structure (prior loadings matrices) — 10-year government yields

	PRIOR USED (VARIMAX LOADING MAXIMUM)				ALTERNATIVE 1: VARIMAX				ALTERNATIVE 2: GEOGRAPHIES			
	DEVELOPED LOW RISK	EMEA + EUROZONE MEDIUM RISK I	ASIA	EMEA + EUROZONE MEDIUM RISK II	DEVELOPED LOW RISK	EUROZONE MEDIUM RISK I	ASIA	EUROZONE MEDIUM RISK II	DEVELOPED CORE	EMEA	ASIA	PIIGS
Hungary	0.000	0.577	0.000	0.577	−0.047	0.249	−0.256	0.205	0.000	0.577	0.000	0.000
Poland	0.000	0.577	0.000	0.577	−0.093	0.255	−0.041	0.166	0.000	0.577	0.000	0.000
Czech Republic	0.577	0.000	0.000	0.577	0.221	0.080	0.047	0.158	0.000	0.577	0.000	0.000
South Africa	0.577	0.577	0.000	0.000	0.052	0.177	0.004	−0.012	0.000	0.577	0.000	0.000
United Kingdom	0.816	0.000	0.000	0.000	0.777	−0.055	0.219	−0.046	0.577	0.000	0.000	0.000
United States	0.816	0.000	0.000	0.000	0.605	−0.002	0.032	−0.067	0.577	0.000	0.000	0.000
Norway	0.577	0.000	0.577	0.000	0.488	−0.150	0.354	−0.075	0.577	0.000	0.000	0.000
Switzerland	0.816	0.000	0.000	0.000	0.674	−0.088	0.278	0.038	0.577	0.000	0.000	0.000
Germany	0.816	0.000	0.000	0.000	0.962	−0.119	0.119	−0.004	0.577	0.000	0.000	0.000
Finland	0.816	0.000	0.000	0.000	0.963	−0.017	0.069	0.156	0.577	0.000	0.000	0.000
Netherlands	0.816	0.000	0.000	0.000	0.954	−0.023	0.089	0.139	0.577	0.000	0.000	0.000
Sweden	0.816	0.000	0.000	0.000	0.747	−0.151	0.340	−0.070	0.577	0.000	0.000	0.000
Slovakia	0.816	0.000	0.000	0.000	0.525	0.043	−0.034	0.113	0.000	0.577	0.000	0.000
France	0.816	0.000	0.000	0.000	0.693	0.068	0.077	0.586	0.577	0.000	0.000	0.000
Austria	0.816	0.000	0.000	0.000	0.733	0.080	0.032	0.565	0.577	0.000	0.000	0.000
Belgium	0.000	0.000	0.000	0.816	0.311	0.449	−0.015	0.652	0.577	0.000	0.000	0.000
Spain	0.000	0.816	0.000	0.000	0.011	0.818	0.046	0.338	0.000	0.000	0.000	0.577
Italy	0.000	0.816	0.000	0.000	−0.081	0.720	0.076	0.388	0.000	0.000	0.000	0.577
Portugal	0.577	0.577	0.000	0.000	−0.032	0.453	−0.074	−0.044	0.000	0.000	0.000	0.577
Greece	0.000	0.577	0.000	0.577	−0.053	0.390	−0.217	0.007	0.000	0.000	0.000	0.577
Ireland	0.000	0.577	0.000	0.577	−0.064	0.493	−0.080	−0.007	0.000	0.000	0.000	0.577
Japan	0.000	0.000	0.816	0.000	0.109	−0.005	0.550	0.017	0.000	0.000	0.577	0.000
Australia	0.000	0.000	0.816	0.000	0.082	−0.112	0.763	0.005	0.000	0.000	0.577	0.000
Hong Kong	0.000	0.000	0.816	0.000	0.121	−0.080	0.756	−0.002	0.000	0.000	0.577	0.000
South Korea	0.577	0.000	0.577	0.000	0.032	−0.072	0.356	−0.009	0.000	0.000	0.577	0.000
Taiwan	0.577	0.000	0.577	0.000	0.132	0.034	0.472	0.047	0.000	0.000	0.577	0.000

Table A6.1
Factor structure (loadings matrix after Procrustes rotation) — CDS spreads

	GLOBAL	EMEA	ASIA	LATIN AMERICA	EUROZONE
Hungary	0.657	0.457	−0.109	0.045	0.122
Poland	0.664	0.466	0.003	0.084	0.144
Czech Republic	0.650	0.479	0.053	0.073	0.050
Slovakia	0.541	0.483	0.030	0.013	0.027
Romania	0.779	0.494	−0.141	−0.122	−0.037
Croatia	0.758	0.486	−0.103	−0.026	0.006
Bulgaria	0.787	0.469	−0.066	−0.037	−0.035
Lithuania	0.549	0.324	0.053	−0.069	−0.031
Estonia	0.496	0.270	0.015	−0.039	−0.107
Ukraine	0.355	0.362	0.039	0.102	0.011
Russia	0.656	0.588	0.236	0.258	0.113
Turkey	0.654	0.574	0.186	0.284	0.169
South Africa	0.635	0.602	0.225	0.224	0.123
Kazakhstan	0.636	0.501	0.210	0.172	0.110
China	0.678	0.045	0.566	0.017	−0.105
Thailand	0.585	0.087	0.531	−0.013	0.022
Malaysia	0.620	0.095	0.608	−0.037	−0.074
Indonesia	0.617	0.161	0.569	0.003	−0.113
Vietnam	0.517	0.132	0.478	0.016	−0.010
South Korea	0.678	0.112	0.621	0.045	−0.063
Mexico	0.703	0.127	−0.038	0.636	−0.068
Brazil	0.721	0.123	−0.052	0.641	−0.042
Argentina	0.528	0.207	0.087	0.367	0.012
Peru	0.634	0.108	−0.047	0.558	−0.057
Venezuela	0.474	0.113	0.061	0.306	−0.006
Chile	0.393	0.131	0.034	0.272	−0.017
Colombia	0.721	0.154	−0.012	0.634	−0.056
Spain	0.539	0.104	−0.021	−0.037	0.652
Portugal	0.533	0.053	−0.025	−0.016	0.633
Ireland	0.496	−0.005	−0.052	−0.071	0.609
Italy	0.603	0.125	0.008	−0.063	0.647
Austria	0.620	0.204	−0.086	−0.015	0.364
France	0.577	0.020	−0.101	−0.012	0.461
Belgium	0.550	0.047	−0.099	−0.031	0.618
Netherlands	0.598	0.119	0.032	0.010	0.443

Table A6.2
Factor structure (loadings matrix after Procrustes rotation) — Equity indices

	GLOBAL	EUROPE	ASIA	AMERICA
Hungary	0.448	0.576	0.128	0.104
Poland	0.503	0.664	0.152	0.154
Czech Republic	0.455	0.615	0.259	0.005
Romania	0.415	0.432	0.321	−0.048
Russia	0.522	0.548	0.255	0.168
Turkey	0.386	0.515	0.091	0.077
South Africa	0.584	0.508	0.169	0.132
Israel	0.441	0.427	0.038	0.104
Mexico	0.588	0.184	−0.116	0.558
Brazil	0.569	0.176	−0.086	0.587
Argentina	0.640	0.197	−0.103	0.478
Chile	0.546	0.241	0.066	0.316
India	0.462	0.246	0.342	0.085
Thailand	0.416	0.128	0.388	0.030
China	0.352	−0.040	0.335	0.009
Indonesia	0.476	0.113	0.479	−0.017
Hong Kong	0.601	0.040	0.589	−0.016
Philippines	0.222	−0.012	0.450	−0.089
Australia	0.620	−0.033	0.577	−0.115
New Zealand	0.363	0.039	0.438	−0.213
Ireland	0.646	0.517	−0.044	0.042
Portugal	0.620	0.540	−0.079	0.025
Spain	0.700	0.521	−0.207	−0.018
Austria	0.661	0.564	0.028	0.051
Netherlands	0.796	0.536	−0.128	0.024
Sweden	0.709	0.522	−0.073	0.099
Germany	0.769	0.521	−0.176	0.051
France	0.822	0.521	−0.183	−0.021
United Kingdom	0.763	0.504	−0.086	0.066
Switzerland	0.721	0.485	−0.079	0.044
Japan	0.504	−0.094	0.507	−0.150
United States	0.650	0.260	−0.237	0.472

Table A6.3
Factor structure (loadings matrix after Procrustes rotation) — FX rates versus the USD

	GLOBAL	EUROPE	EMERGING ASIA	OTHER
Hungary	0.784	0.470	−0.116	0.154
Poland	0.831	0.410	−0.142	0.177
Czech Republic	0.681	0.607	−0.100	0.136
Romania	0.658	0.672	−0.024	0.094
Croatia	0.560	0.771	−0.008	0.105
Russia	0.619	0.250	0.185	0.142
Turkey	0.752	0.161	−0.090	0.287
South Africa	0.683	0.160	−0.022	0.371
Mexico	0.650	0.073	−0.151	0.404
Malaysia	0.507	−0.121	0.701	−0.029
Indonesia	0.420	−0.115	0.571	−0.072
South Korea	0.505	−0.013	0.533	0.091
Philippines	0.429	−0.026	0.365	−0.025
Australia	0.622	0.271	0.151	0.679
New Zealand	0.570	0.304	0.127	0.589
Eurozone	0.589	0.791	−0.038	0.105
United Kingdom	0.509	0.396	−0.032	0.226
Canada	0.636	0.170	−0.051	0.478

Table A6.4
Factor structure (loadings matrix after Procrustes rotation) — EMBI Global spreads

	GLOBAL	LATIN AMERICA	EMEA
Hungary	0.550	0.026	0.253
Poland	0.562	−0.048	0.212
Bulgaria	0.557	0.151	0.534
Serbia	0.664	0.127	0.461
Ukraine	0.372	0.147	0.461
Russia	0.658	0.382	0.571
Turkey	0.715	0.421	0.390
South Africa	0.724	0.266	0.436
Kazakhstan	0.522	0.193	0.622
Lebanon	0.700	0.167	0.277
Iraq	0.667	0.187	0.443
Ghana	0.599	0.090	0.525
Gabon	0.643	0.100	0.537
Mexico	0.612	0.662	0.186
Brazil	0.685	0.654	0.204
Argentina	0.493	0.503	0.352
Chile	0.431	0.209	0.066
Peru	0.675	0.614	0.119
Colombia	0.595	0.685	0.209
Panama	0.796	0.506	0.119
Venezuela	0.404	0.320	0.401
Uruguay	0.835	0.403	0.109
Dominican Republic	0.552	0.103	0.271
Jamaica	0.497	0.185	0.069
El Salvador	0.829	0.351	0.105

Table A6.5
Factor structure (loadings matrix after Procrustes rotation) — 10-year government yields

	DEVELOPED	EMEA + EUROZONE MEDIUM RISK	ASIA	EUROZONE PERIPHERY
Hungary	−0.035	0.312	−0.257	0.085
Poland	−0.063	0.303	−0.036	0.080
Czech Republic	0.253	0.135	0.012	−0.003
South Africa	0.044	0.097	0.014	0.150
United Kingdom	0.768	−0.189	0.149	0.100
United States	0.573	−0.149	−0.013	0.144
Norway	0.500	−0.220	0.305	−0.022
Switzerland	0.695	−0.129	0.203	−0.002
Germany	0.945	−0.233	0.024	0.071
Finland	0.975	−0.050	−0.039	0.056
Netherlands	0.965	−0.064	−0.016	0.058
Sweden	0.750	−0.259	0.267	0.022
Slovakia	0.527	0.025	−0.091	0.061
France	0.811	0.369	−0.057	−0.194
Austria	0.839	0.353	−0.101	−0.159
Belgium	0.436	0.724	−0.095	−0.003
Spain	0.073	0.781	0.058	0.409
Italy	0.001	0.771	0.082	0.284
Portugal	−0.061	0.262	−0.033	0.374
Greece	−0.085	0.258	−0.183	0.307
Ireland	−0.085	0.321	−0.038	0.376
Japan	0.174	0.012	0.529	−0.060
Australia	0.173	−0.054	0.736	−0.163
Hong Kong	0.208	−0.045	0.729	−0.127
South Korea	0.073	−0.046	0.344	−0.085
Taiwan	0.194	0.053	0.450	−0.035

Figure A1.1
Global factors of various markets and their first principal component

(scaled to Hungarian CDS spreads' global term, basis points)

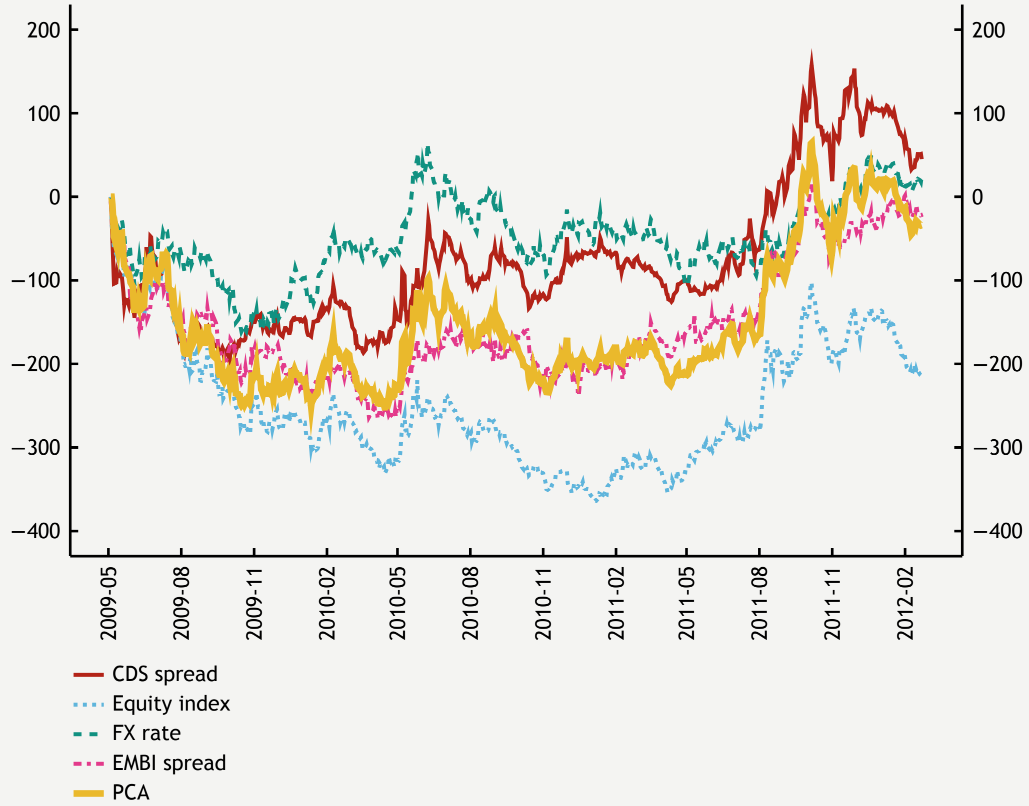


Figure A1.2
EMEA factors of various markets and their first principal component

(scaled to Hungarian CDS spreads' EMEA term, basis points)

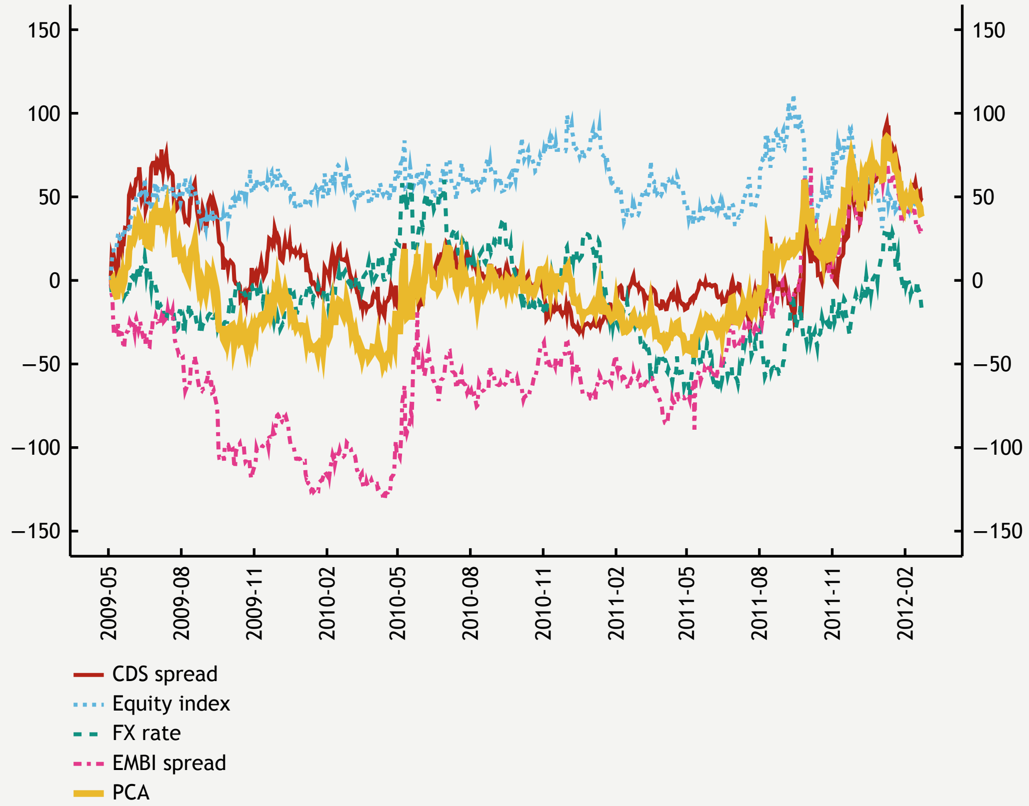
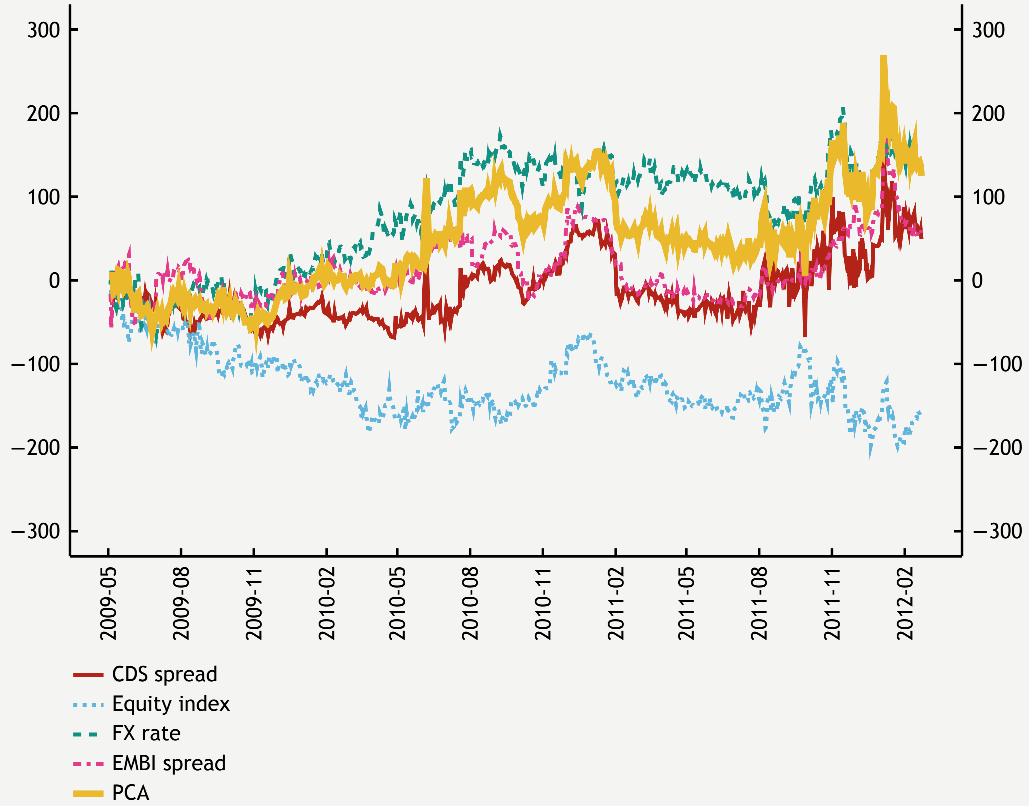


Figure A1.3
Idiosyncratic components of various markets and their first principal component

(scaled to Hungarian CDS spreads' idiosyncratic term, basis points)



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