



BANK OF ENGLAND

# Working Paper No. 430

## Identifying risks in emerging market sovereign and corporate bond spreads

Gabriele Zinna

July 2011

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## Identifying risks in emerging market sovereign and corporate bond spreads

Gabriele Zinna<sup>(1)</sup>

### Abstract

This study investigates the systematic risk factors driving emerging market (EM) credit risk by jointly modelling sovereign and corporate credit spreads at a global level. We use a multi-regional Bayesian panel VAR model, with time-varying betas and multivariate stochastic volatility. This model allows us to decompose credit spreads and to build indicators of EM risks. We find that indices of EM sovereign and corporate credit spreads differ because of their specific reactions to global risk factors. Following the failure of Lehman Brothers, EM sovereign spreads ‘decoupled’ from the US corporate market. In contrast, EM corporate bond spreads widened in response to higher US corporate default risk. We also find that the response of sovereign bond spreads to the VIX was short-lived. However, both EM sovereign and corporate bond spreads widened in flight-to-liquidity episodes, as proxied by the OIS-Treasury spread. Overall, the model is capable of generating other interesting results about the comovement of sovereign and corporate spreads.

**Key words:** Bayesian econometrics, factor models, emerging markets and credit spreads.

**JEL classification:** F31, F34.

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## Summary

Monitoring emerging markets' (EMs) credit risk is of paramount importance, not only for emerging market economies (EMEs), but also for developed countries. In particular, the evolution of risks embedded in EM securities determines the riskiness of international portfolios. Underdiversified portfolios may expose international investors to severe losses, trigger sudden capital flow reversals, and raise financial stability concerns. Adverse events originated in EMEs can spill over to developed countries. But there may also be 'second round' effects, whereby a crisis that originates in developed countries and is transmitted to EMEs worsens as it then feeds back to developed countries.

As EMEs have become more financially integrated, the EM asset class has become more important for the stability of global financial markets. Consequently, an increasing number of studies have focused on the EM asset class, and our understanding of sovereign EM credit risk has improved significantly. For example, some studies have documented a strong dependence of EM sovereign spreads on global risk factors, highlighting the urgency for EME governments to implement policies to insulate their economies from external shocks. However, in recent years, corporate bonds have increased to become an important member of the EM asset class. For instance, EM corporate issuance in 2007 matched that of the US high-yield sector. The rise of the corporate market brought with it new challenges for EM authorities. And, yet, the joint nature of sovereign and corporate risks remains largely unexplored.

We aim to shed light on the different behaviour of these two markets by jointly modelling indices of EM sovereign and corporate bonds. This not only allows us to emphasise the comovement of sovereign and corporate bonds but also to highlight their differences. In addition, instead of focusing on a particular region, we take a global perspective, whereby we jointly model regional indices of bond spreads for Latin America, Europe, Asia and the Middle East. But using so many bond indices comes at the cost of having too many parameters. As a result, we turn this original system of equations (a vector autoregression) into a more parsimonious model where the spreads depend on a small number of observable risk factors. This allows us to use time-varying responses of the spreads to changes in the risk factors; a feature of the model which enables us to monitor EM credit risk over the crisis. Moreover, time-varying coefficients can accommodate varying degrees of EM integration. In addition, we allow the volatility to change over time in



order to account for the increased size of financial shocks during the recent market turmoil.

Our model is also a useful tool for building indicators of EM credit risk, as it informs us of changing risks across a number of dimensions. For example, these indicators are able to capture variations of credit spreads which are common across spreads ('common' indicator); variations which are regional specific ('regional' indicators); variations which are specific to the sovereign or corporate market ('variable' specific indicators); and variations due to global risks ('global risk' indicators). However, *a priori* a number of model specifications can look plausible. But, alternative model specifications reveal different information on the nature of systemic risks in EM bonds. To this end, we test for the model which best matches the data.

Our main result is that the behaviour of sovereign and corporate spreads differs because of their specific reactions to global risk factors (VIX, US corporate default risk, and overnight index swap (OIS) -Treasury spread). In the aftermath of Lehman Brothers' default, EM corporate bonds were severely hit by spillovers from US corporate default risk. But the VIX and the OIS-Treasury spread, which proxy for global risk aversion and demand for liquid securities respectively, also contributed to widen corporate spreads. By contrast, sovereign spreads 'decoupled' from the US corporate bond market, as they narrowed in response to higher US corporate default risk. That said, the narrowing in sovereign spreads was largely attributable to a higher demand for liquid securities, whereas the effect of heightened risk aversion quickly reverted. In this way, our credit risk indicators highlight the differing responses of sovereign and corporate bonds as the crisis spread from advanced economies to EMEs.

Overall, we find that the financial turmoil spread to all EMs, as the common component of EM credit risk increased sharply around October 2008. But we also find that corporates were more affected than sovereigns, and the most affected region was emerging Europe.

## 1 Introduction

Monitoring emerging markets' (EMs) credit risk is of paramount importance, not only for emerging market economies (EMEs), but also for developed countries. In particular, the evolution of risks embedded in EM securities determines the riskiness of international portfolios. Underdiversified portfolios may expose international investors to severe losses, trigger sudden capital flow reversals, and raise financial stability concerns. Adverse events originated in EMEs can spill over to developed countries. But there may also be 'second-round' effects, whereby a crisis that originates in developed countries is transmitted to EMEs and then feeds back to developed countries.

As EMEs have become more financially integrated, the EM asset class has become more important for the stability of global financial markets. Consequently, an increasing number of studies have focused on the EM asset class (Longstaff *et al* (2010), among others),<sup>1</sup> and our understanding of sovereign EM credit risk has improved significantly. For example, the international finance literature has extensively documented a strong dependence of EM sovereign spreads on global risk factors, highlighting the urgency for EME governments to implement policies to insulate their economies from external shocks. However, in recent years, corporate bonds have increased to become an important member of the EM asset class. For instance, EM corporate issuance in 2007 matched that of the US high-yield sector. The rise of the corporate market brought with it new challenges for EM authorities. And, yet, the joint nature of sovereign and corporate risks remains largely unexplored.

In this study we aim to contribute to fill this gap by investigating not only the behaviour of portfolios of EM sovereign bonds, but also of corporates. The recent crisis provides a valuable sample to assess the response of the EM asset class as a whole to EM ('pull') and global ('push') factors, as well as the specific reactions of sovereign and corporate bonds. In particular, we address the question whether indices of EM sovereign and corporate bonds are exposed to the same systemic risk factors, and whether their sensitivities to global risk factors differ. For example, their risks may differ only because of market-specific responses to global risk factors (VIX, US corporate default risk, and flight to liquidity). But in order to answer to this question we also need to control for regional differences in credit risk.

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<sup>1</sup>Eichengreen and Mody (2000), Zhang (2003), Maier and Vasishtha (2008) and Pan and Singleton (2008).

As the credit crunch hit developed markets in the summer of 2007, the EM asset class proved resilient to the financial turmoil. This response to the crisis was in stark contrast with past episodes when EMs were rapidly and severely affected by adverse global financial developments. However, as the crisis developed, and intensified with the Lehman Brothers' default, the financial turmoil transmitted to a number of EMs. As of mid-October 2008 the three-month outflow from EM bond and equity funds reached \$29.5 billion, the highest level since 1995 (Financial Times (2008c)). A wave of deleveraging from global banks in advanced economies is partly responsible for the rise of EM credit spreads (Cetorelli and Goldberg (2009)). But the crisis did not spread equally across regions, and sovereign and corporate securities displayed different behaviours.

This sequence of events demonstrates the need for our model to be sufficiently accurate to capture these complex dynamics. For instance, it is of paramount importance to look both at the cross-sectional and time-series dimension of EM bond spreads. To this end, in this study we jointly model EM sovereign and corporate bond spreads at a global level. We employ the multi-country panel VAR proposed by Canova and Ciccarelli (2008). Precisely, we estimate this model on daily regional indices of sovereign and corporate credit spreads, over the period from January 2004 to February 2009, in four regions: Latin America (LatAm hereafter), Europe, Asia and Middle East (Mideast hereafter).

This model allows us to emphasise structural time-variation, maintaining complex dynamics and interdependencies across regions and markets. The estimation is Bayesian, and the otherwise overparameterised VAR is transformed into a parsimonious model, with a small number of loadings on certain linear combinations of right hand side variables (factors). Interestingly, this factorisation conveys a clear economic interpretation to the systematic correlation structure, and implicitly decomposes credit spread changes into few credit indices. Ultimately, a basic specification may consist of common, variable, regional and global factors. These indicators inform on the evolution of EM credit risk, trading off the relative importance of each component over time.

In order to explore the correlation structure over cyclical fluctuations, and during episodes of financial turmoil, the coefficients (factor loadings) are time-varying. This is a crucial feature, because EM credit spreads have shifted radically since the outset of the crisis. And this episode seems to have changed the nature of EM credit risk, and its exposure to global risks.

Furthermore, several papers, among which Bekaert and Harvey (1995), point to the importance of

time-varying factor loadings to accommodate for various degrees of market integration. Besides, daily financial data exhibit changing volatility over time. On top of this, the financial turmoil has intensified the size of the shocks. We model multivariate stochastic volatility as in Cogley and Sargent (2005), in order to capture changing cross-variance patterns of EM credit spread changes. Finally, to select the best model across a set of competing models, we employ a Reversible Jump Markov Chain Monte Carlo (RJMCMC) algorithm similarly to Primiceri (2005).

The literature on EM corporate spreads has typically relied on the concept of the ‘sovereign ceiling’, meaning that no firm is more creditworthy than its government. According to Durbin and Ng (2005) the data support the idea of the ‘sovereign ceilings’, with only few exceptions. Differently, Dittmar and Yuan (2008) shed light on the impact of the issuance of sovereign bonds on corporate securities. They find that sovereign bonds enhance the liquidity of the corporate market, reducing adverse selection costs, and the information flows from the sovereign to the corporate market.

Our study contributes to this literature, though without assuming the sovereign ceiling hypothesis. Instead it takes an international perspective to model EM sovereign and corporate bond spreads. We assess comovements in sovereign and corporate spreads, and their respective vulnerability to global factors. Our framework also relates to Bekaert, Harvey, and Ng (2005) in that risk parameters are time-varying, and regional and US factors determine returns on EM securities. Finally we follow Pesaran, Schuermann, and Treutler (2005) in that we also look at credit risk from a global perspective.

We find that indices of sovereign and corporate EM spreads differ because of their idiosyncratic responses to global risks. And these sovereign and corporate-specific sensitivities to global risks account for the different behaviour of the sovereign and corporate bond spreads. In other words, within the set of competing models, the RJMCMC selects the model with a common EM factor, four regional factors, and three global factors. But crucially the global factors load differently on sovereign and corporate spreads.

We also find that the financial turmoil affected corporate spreads more than sovereigns spreads. In the aftermath of Lehman Brothers’ default, EM corporate bonds were severely hit by spillovers from US corporate default risk. But the VIX and the OIS-Treasury spread, which proxy for global risk aversion and flight-to-liquid securities respectively, also contributed to

widen corporate spreads. By contrast, sovereign spreads ‘decoupled’ from the US corporate bond market, as they narrowed in response to higher US corporate default risk. That said, the narrowing in sovereign spreads was largely attributable to a flight-to-liquidity phenomenon, whereas the effect of heightened risk aversion quickly reverted. In summary, our credit risk indicators highlight the differing responses of sovereign and corporate bonds as the crisis spread from advanced economies to EMEs.

Moreover, the common EM indicator suggests a high comovement among sovereign and corporate regional spreads. This indicator accounted for a great part of the compression of the spreads, over the first part of the sample, and slightly rebounded in two episodes, as of July and December 2007. This finding is consistent with the subdued response of EMEs to the start of the credit crunch. However, EMEs caught up with developed economies shortly after Lehman Brothers’ default, when our common EM indicator markedly jumped. Even if the crisis transmitted to all EMs, the regional indicators highlight regional differences. In particular, Asia was the first region hit by the crisis, though, as the crisis intensified, the European indicator reaches values far above all the other regions. Finally, stochastic volatility is a key feature of the data, increasing tenfold during the crisis period.

In addition to estimating the importance of our credit indicators over time we attempt to ascertain what they reflect. This exercise is helpful, for these indicators result from combining the estimated time-varying betas with the observable factors. Interestingly, we find that our indicators correlate with measures of systemic risk such as exchange rates volatilities, commodity prices, and US interest rates and stock market returns.

The remainder of the paper is organised as follows. Section 2 introduces the model and relates it to the existing literature. Section 3 provides a formal description of the benchmark model with multivariate stochastic volatility. Section 4 presents the data and refers to the Bayesian estimation method, whereas the details of the MCMC algorithm are left to the appendix. Section 4 also deals with Bayesian model selection. Section 5 presents the estimates of the time-varying loadings and volatilities. In Section 6 we build credit indicators, and comment on the results. Finally, Section 7 concludes.

## 2 A gentle introduction to the model

This section relates our model to the existing literature on EM sovereign and corporate spreads and then introduces a simplified version of our model.<sup>2</sup> The academic literature on EM corporate bonds is scarce, so that our understanding of this market is limited. In contrast, some of the international finance literature has investigated the relation between EM corporate to sovereign bond spreads at a country level.

In particular, this literature has often relied on the idea of the ‘sovereign ceiling’ (Durbin and Ng (2005)), which means that firms cannot receive a better rating than their government, or that corporate yield spreads pay a firm risk premium over the government spread. In other words, the government’s cost of capital rewards the investor for the country risk to which it is exposed, whereas the corporate’s cost of capital compensates the investor not only for the country risk but also for the idiosyncratic risk of the firm. This is the case for two reasons. First, the government and the corporates operate in the same environment, and are exposed to the same macroeconomic risks. Thus, adverse episodes, such as a currency devaluation or an economic downturn, hit both the government and the corporate. Second, even if only the government is the target of a negative shock, the government is likely to pass the consequences to the private sector (‘transfer risk’). The government, facing a deterioration of its repayment capacity, has the power to tax firms, impose currency controls, or seize firms’ assets (Durbin and Ng (2005)). Any of these actions by the government ends up enhancing the default risk of the corporate sector.

This theory of the ‘sovereign ceiling’ translates to the modelling of sovereign and corporate bond prices. Here we look at the existing literature, and Dittmar and Yuan (2008) in particular. The (log) price of a sovereign bond,  $P_{S,t}$ , depends on few (unobserved) systematic factors,  $F_t$ , which proxy for the risk of the country at hand. The (log) price of a corporate bond,  $P_{C,t}$ , is exposed to the same systematic factors of its government, but also displays an idiosyncratic risk specific to the company,  $v_{C,t}$ . A discrete version of their model<sup>3</sup> in first differences is:

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<sup>2</sup>For a moment we abstract from our multi-country setting, and from the fact that we use indices instead of single name bonds.

<sup>3</sup>Originally, Duffie, Pedersen and Singleton (2003) used a continuous time version of this model to describe the behaviour of the (log) price of Russian bonds. Here, we refer to this discrete version in first differences, because it facilitates the mapping between bond returns, and credit spread changes.

$$\Delta \ln P_{S,t} = \alpha_S + \beta'_S F_t \quad (1)$$

$$\Delta \ln P_{C,t} = \alpha_C + \beta'_C F_t + v_{C,t}. \quad (2)$$

What follows aims to reconcile this model, widely used in the literature, with our model. We first note that we depart from (1) and (2) because we use indices of bonds instead of single-name bonds, and this directly affects the modelling of corporate bonds. In particular, a sufficiently large portfolio of corporate securities with linearly independent factor loadings, by replicating the factors, spans the same systemic risk faced by the government (Dittmar and Yuan (2008)). In short, a well-diversified portfolio (or index) of corporate bonds is free of idiosyncratic risk, and should only depend on systematic risk. So if  $P_{C,t}$  is a well-diversified portfolio then the impact of the idiosyncratic shocks ( $v_{C,t}$ ) vanishes.<sup>4</sup> However, in our model we still allow the corporate and sovereign indices' exposures to systematic risk to differ. A time-invariant version of our model, which for the moment abandons its regional dimension, is

$$Y_{S,t} = \beta F_t + \beta_S F_{S,t} \quad (3)$$

$$Y_{C,t} = \beta F_t + \beta_C F_{C,t}, \quad (4)$$

where  $Y_{S,t}$  and  $Y_{C,t}$  are the spread changes of sovereign and corporate indices.<sup>5</sup> And  $F_t$ ,  $F_{S,t}$  and  $F_{C,t}$  are the common (EM), sovereign and corporate factors, respectively. In our model the risk factors are (observed) linear combinations of lagged dependent variables.<sup>6</sup> Moreover, because the loading on the systematic factor ( $\beta$ ) is common to sovereign and corporate spreads,  $\beta_S F_{S,t}$  and  $\beta_C F_{C,t}$  accommodate for differences between sovereign and corporate spreads, which in Dittmar and Yuan are guaranteed by ( $\beta_S$ ) and ( $\beta_C$ ).

Our benchmark model extends the simplified model ((3)-(4)) under several dimensions. First, we use a multi-regional model, modelling the interdependencies between sovereign and corporate

<sup>4</sup>This study considers regional indices, which consist of single name corporate bonds of several countries in the region at hand. Because of this international composition, in principle these regional indices should benefit a higher degree of diversification than country portfolios of corporate bonds.

<sup>5</sup>Elton *et al* (2001) show that a change in the spread is equal to minus the excess return on the zero-coupon bond, given an adjustment for the maturity. Here, we rely on this equality and define the problem in changes in yield spreads instead of returns.

<sup>6</sup>In this set-up we have that  $F_{R,t} = Y_{S,t-1} + Y_{C,t-1}$ ,  $F_{S,t} = Y_{S,t-1}$ , and  $F_{C,t} = Y_{C,t-1}$ .

spreads, within the same region, and across regions. The type of linkages is a modelling choice, as is the outcome of the factor structure imposed.<sup>7</sup> Second, we use time-varying factor loadings to allow for the presence of changing regional and sectorial integration.<sup>8</sup> Third, we model stochastic volatility as in Cogley and Sargent (2005), among others. This modelling is sensible to the ordering of the variables, as emerges from Section 3.1. We address this issue exploiting the fact that information flows from the sovereign to the corporate market. In other words, the innovations in the sovereign bond yield spreads influence the volatility of yield spreads on corporate bonds (Dittmar and Yuan (2008)). To this end, we order the regional sovereign index before the respective corporate index.

A common exercise in international finance consists of investigating whether the issuance of sovereign bonds helps complete the market (Dittmar and Yuan, (2008)). We instead address the problem from another perspective, and ask whether different risk factors drive regional sovereign and corporate bonds. In concrete this is done by including, or not, an EM ‘variable’ factor which is market specific (sovereign or corporate). But, we also recognise that sovereign and corporate bond spreads may differ because they have specific exposures to exogenous global events. For instance, episodes of flight to liquidity may affect corporate securities more than sovereign. Similarly, reversals of global risk aversion, or phases of repricing of risk by international investors, could particularly affect the corporate market, which feature higher information asymmetries. If this is true we would expect a model with sovereign and corporate betas on the exogenous variables to perform better.

The next section introduces formally our model. It presents a benchmark model which consists of a global, four regional, two ‘variable’ factors (sovereign and corporate), and three exogenous variables. Under this factorisation the ‘variable’ factors account for market-specific sources of risk. However, this is only one among several modelling choices available to model sovereign and corporate credit risk. Hence, each model, characterised by a unique combination of factor and factor loadings, displays a specific composition of risks. In particular, what varies across models is the presence of the variable factor, and/or the factor loadings on the exogenous variables, among other things.<sup>9</sup>

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<sup>7</sup>Observe that the factor structure implicitly determines these interdependencies. The benchmark model assumes that the loading on the emerging market factor describes the dependence between sovereign and corporate spreads of two regions.

<sup>8</sup>Bekaert and Harvey (1995, 1997), Ng (2000), and Bekaert, Harvey and Ng (2005), among others, use a time-varying beta framework. However, differently from our model, most of these studies refer to the stock market, in a CAPM setting, and, often link the betas time-variability to the trade linkages across countries.

<sup>9</sup>The set of models compared with the RJMCMC also includes models that account for a perfect specification.



### 3 Model set-up

This section outlines the multi-country Bayesian panel VAR developed in Canova and Ciccarelli (2008), and in Canova, Ciccarelli and Ortega (2007). This model accounts for time-varying parameters, unit (or regional) specific dynamics, and cross-unit interdependencies. More important, by imposing a factorisation on the coefficients, the number of parameters to be estimated considerably reduces, and the original VAR model takes the form of a factor model with observable factors. The remaining of this section explains the six steps to set up the model in the factor form.

*Step 1:* Let us start with the following VAR specification

$$y_{it} = D_{it}(L)Y_{t-1} + C_{it}(L)W_{t-1} + e_{it} \quad (5)$$

where  $i = 1, \dots, N$  denotes the region,  $t = 1, \dots, T$  the time, and  $y_{it}$  is a  $G \times 1$  vector, containing the sovereign and corporate spreads, for each region  $i$ .  $Y_t = (y'_{1t}, y'_{2t}, \dots, y'_{Nt})'$  is a vector of dimension  $GN \times 1$ , which stacks the  $y_{it}$  vectors.  $D_{it,j}$  are  $G \times GN$ , and  $C_{it,j}$  are  $G \times q$  matrices for each  $j$ .  $W_{t-1}$  is a  $q \times 1$  vector of common exogenous variables, eg  $q = 3$  since in our case the exogenous variables proxy for global risk aversion, US corporate credit risk and liquidity. And,  $e_{it}$  is a  $G \times 1$  vector of disturbances. If we define  $p$  and  $r$  as the number of lags for the endogenous and exogenous variables respectively, each equation has  $k = GNp + qr$  coefficients. Finally, by stacking the  $N$  regional blocks, as in equation (5), we obtain the multi-country VAR.

*Step 2:* We now move from the canonical VAR representation to the seemingly unrelated regression (SUR) representation. Let  $\delta_{it} = (\delta_{it}^1, \dots, \delta_{it}^G)'$  be a  $Gk \times 1$  vector where  $\delta_{it}^g$  stacks the  $g$ -th rows of the matrices  $D_{it}(L)$  and  $C_{it}(L)$ . Similarly, stacking the  $\delta_{it}$  vectors, for  $i = 1, \dots, N$ , we get a  $GNk \times 1$  vector  $\delta_t = (\delta'_{1t}, \dots, \delta'_{Nt})'$ . Moreover, if  $X_t = I_{NG} \otimes \mathbf{X}'_t$ , where  $\mathbf{X}'_t = (Y'_{t-1}, Y'_{t-2}, \dots, Y'_{t-p}, W'_t, \dots, W'_{t-l})$ , we get the following SUR representation

$$Y_t = X_t \delta_t + E_t \quad E_t \sim N(0, \Omega) \quad (6)$$

*Step 3:* But the number of parameters to be estimated each period  $t$  is far too large. Thus, we look for a more parsimonious representation, which eventually has an intuitive economic

interpretation. To this end, we impose a flexible structure on the coefficients.  $\delta_t$  is decomposed into few  $F$  factors  $\theta_{ft}$ , as

$$\delta_t = \sum_f^F \Xi_f \theta_{ft} + u_t \quad u_t \sim N(0, \Omega \otimes V) \text{ and } V = \sigma^2 I \quad (7)$$

and  $\Xi_f$  are matrices of 0s and 1s, conformable to the factor structure. The factor structure is flexible, specific to the problem at hand, and, eventually, to the sample. For example, we may consider a specification that encompasses one common,  $N$  regional,  $G$  variable, and  $q$  exogenous factors. Accordingly, each  $\delta_t^{i,g}$  coefficient is factorised as

$$\delta_t^{i,g} = \Xi_1 \theta_{1t} + \Xi_2 \theta_{2t}^i + \Xi_3 \theta_{3t}^g + \Xi_4 \theta_{4t}^w + u_t^{i,g} \quad (8)$$

where  $\theta_{1t}$  is a scalar capturing movements common across regions and variables spreads,  $\theta_{2t}^i$  is a  $N \times 1$  vector capturing movements common across the spreads of region  $i$ ,  $\theta_{3t}^g$  is a  $G \times 1$  vector capturing movements common across spreads of variable  $g$ , and  $\theta_{4t}^w$  is a  $q \times 1$  vector of factors loading on  $q$  exogenous variables. To provide an intuition on how to set up the  $\Xi_f$  matrices, let us consider a simplifying model with  $N = 2$  regions,  $G = 2$  endogenous variables, and  $q = 1$  exogenous variable. Moreover,  $p = 1$  and  $r = 1$ , ie we only consider one lag. Then the  $\Xi_f$  matrices are

$$\Xi_1 = \begin{bmatrix} i_0 \\ i_0 \\ i_0 \\ i_0 \end{bmatrix}_{NGkx1} \quad \Xi_2 = \begin{bmatrix} i_1 & 0 \\ i_1 & 0 \\ 0 & i_2 \\ 0 & i_2 \end{bmatrix}_{NGkxN} \quad \Xi_3 = \begin{bmatrix} i_3 & 0 \\ 0 & i_4 \\ i_3 & 0 \\ 0 & i_4 \end{bmatrix}_{NGkxG} \quad \Xi_4 = \begin{bmatrix} i_5 \\ i_5 \\ i_5 \\ i_5 \end{bmatrix}_{NGkx1}$$

where  $i_0 = (1 \ 1 \ 1 \ 1 \ 0)'$ ,  $i_1 = (1 \ 1 \ 0 \ 0 \ 0)'$ ,  $i_2 = (0 \ 0 \ 1 \ 1 \ 0)'$ ,  $i_3 = (1 \ 0 \ 1 \ 0 \ 0)'$ ,  $i_4 = (0 \ 1 \ 0 \ 1 \ 0)'$ ,  $i_5 = (0 \ 0 \ 0 \ 0 \ 1)'$ .

The above factor structure may not be complete, therefore  $u_t^{i,g}$  accounts for unmodelled dynamics of the coefficient  $\delta_t^{i,g}$ , such as lag specific, time specific or idiosyncratic effects. That said, this factorisation substantially reduces the number of parameters to be estimated each time  $t$ .<sup>10</sup>

<sup>10</sup>For example, assuming a factorisation as the one in equation (4), in a model with four regions (LatAm, Europe, Asia, and Mideast), two variables (sovereign and corporate), and three exogenous variables (VIX, CREDIT, and FL) the number of parameters shrinks from 88 to 10 for each time  $t$ .

*Step 4:* Hence, by replacing (8) into (6), it follows that

$$Y_t = (X_t \Xi_1) \theta_{1t} + (X_t \Xi_2) \theta_{2t}^i + (X_t \Xi_3) \theta_{3t}^g + (X_t \Xi_4) \theta_{4t}^w + (X_t u_t + E_t) \quad (9)$$

where  $X_t \Xi_1$ ,  $X_t \Xi_2$ ,  $X_t \Xi_3$ ,  $X_t \Xi_4$  are the common,  $N$  regional,  $G$  variable, and  $q$  exogenous factors, respectively, at time  $t$ . It is worth noting the following. First, the new regressors, or factors, are linear combinations of the original regressors, and equally weight the information in all variables. Second, the factors are observable and do not need to be estimated. Third, as we increase the number of lags  $p$ , the factors become moving average of order  $p$ , emphasising low frequency movements. Fourth, the common, regional, and variable factors are correlated by construction, since these factors are built as linear combinations of  $Y_{t-1}$ . However, as the dimensionality of  $N$  and  $G$  increases the factors become independent.

*Step 5:* To close the model we need to specify the law of motion of the coefficients.

$$\delta_t = \Xi \theta + u_t \quad u_t \sim N(0, \Omega \otimes V) \quad (10)$$

$$\theta_t = \theta_{t-1} + \eta_t \quad \eta_t \sim N(0, B) \quad (11)$$

where  $\Xi = [\Xi_1, \Xi_2, \Xi_3, \Xi_4]$  and  $\theta_t = [\theta'_{1t}, \theta'_{2t}, \theta'_{3t}, \theta'_{4t}]'$ . The vector  $u_t$  has zero mean and covariance matrix  $\Omega \otimes V$ , where  $V$  has the spherical form  $\sigma^2 I$ ,  $\sigma^2$  is a scalar, and  $I$  has dimension  $k \times k$ . Similarly to Canova, Ciccarelli and Ortega (2007) the coefficients follow a random walk. The covariance matrix  $B$  features homoschedastic errors, though alternative specifications, which account for heteroschedastic errors, may be considered. It is crucial that the  $B$  matrix is block diagonal,  $B = \text{diag}(B_1, B_2, B_3, B_4)$ , this helps the identification of the factors (Canova and Ciccarelli (2008)).

*Step 6:* Finally, the model has the following convenient state-space representation

$$Y_t = (X_t \Xi) \theta_t + \varsigma_t \quad \varsigma_t \sim N(0, \sigma_t \Omega) \quad (12)$$

$$\theta_t = \theta_{t-1} + \eta_t \quad \eta_t \sim N(0, B)$$

where  $\sigma_t = (1 + \sigma^2 X_t' X_t)$ . The errors  $\varsigma_t = X_t u_t + E_t$  consist of two sources of uncertainty: the errors governing the precision of the coefficients factorisation ( $u_t$ ), and the errors of the original VAR representation ( $E_t$ ).

### 3.1 Making the $\Omega$ stochastic

*Step 7:* This section introduces stochastic volatility. We add an extra source of heteroskedasticity, so that the unobservable shocks  $\varsigma_t$  have covariance matrix  $\sigma_t \Omega_t$ . The new state space takes the form

$$\begin{aligned} Y_t &= (X_t \Xi) \theta_t + \varsigma_t & \varsigma_t &\sim N(0, \sigma_t \Omega_t) \\ \theta_t &= \theta_{t-1} + \eta_t & \eta_t &\sim N(0, B) \end{aligned} \tag{13}$$

Following the literature on multivariate stochastic volatility models, Cogley and Sargent (2005) among others, we decompose the covariance matrix  $\Omega_t$  such as

$$\Omega_t = A^{-1} H_t A^{-1'} \tag{14}$$

where  $H_t$  is the diagonal matrix

$$H_t = \begin{pmatrix} h_{1,t} & 0 & \cdots & 0 \\ 0 & h_{2,t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & h_{NG,t} \end{pmatrix} \tag{15}$$

The  $h$  elements on the diagonal of  $H$  are independent univariate stochastic volatilities. We assume that each element of  $h_i$  evolves (independently) according to the following geometric random walk

$$\ln h_{it} = \ln h_{it-1} + \sigma_{SV,i} \epsilon_{it} \tag{16}$$

Under this specification, the volatility innovations  $\epsilon_{it}$  are mutually independent, and the associated free parameter  $\sigma_{SV,i}^2$  determines the variance of  $\Delta \ln h_{it}$ . Modelling the variances (or

standard deviations) as driftless random walks ensures that the standard deviation of the shocks takes non-negative values at every point in time, and together with the factorisation of equation (14), guarantees that  $\Omega_t$  is positive definite. These assumptions are common in the context of time-varying VAR (Cogley and Sargent (2005) and Primiceri (2005) among others).<sup>11</sup>

$A$  is the time-invariant lower triangular matrix with 1s on the main diagonal

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{1,1} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{NG,1} & \alpha_{NG,2} & \cdots & 1 \end{pmatrix} \quad (17)$$

The non-zero and non-one elements of the  $A$  matrix drive the correlation in the measurement innovations. Using a constant  $A$  matrix, we implicitly assume that an innovation to the  $i$ -th variable has a time-invariant effect on the  $j$ -th variable, and only the  $h_{it}$  processes determine the (stochastic) time variation of the covariances. Alternative specifications, as in Primiceri (2005) among others, allow for time-varying  $\alpha_{i,j}$ . That said, the high dimensionality of this factor model suggests the use of a more parsimonious representation.

The  $A$  matrix orthogonalises the  $\tilde{\zeta}_t$  disturbances, where  $\tilde{\zeta}_t$  is defined as  $\zeta_t \cdot (\sigma_t)^{-0.5}$ , such as

$$A\tilde{\zeta}_t = \hat{\zeta}_t \quad (18)$$

And the  $\hat{\zeta}_t$  disturbances are zero-mean with variance-covariance matrix  $\Omega_t$ . This operation consists of a rotation of the disturbances, and it has the unappealing consequence that the order of the variables matters for the estimate of the VAR innovation variance. Namely,  $y_{1,t}$  has one source of volatility,  $y_{2,t}$  has one more source of volatility, and so on. This implies that the  $i$ -th row of  $\Omega_t$  is a linear combination of  $h_{1,t} \dots h_{i,t}$  variances.

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<sup>11</sup>It is worth noting that a random walk process has the undesirable feature of hitting any upper or lower bound with probability one. However, this assumption should be innocuous over a limited period of time (Primiceri (2005)). The model could be easily extended to incorporate a more general autoregressive behaviour, though this would increase the number of parameters in the estimation procedure. Thus, the geometric assumption has the advantage of reducing the dimensionality of the model, and it still captures permanent shifts in the volatility.

## 4 The data

The fastest growing segments of the EM asset class are local currency bonds for sovereigns, whereas foreign currency for corporates. Over the past years, sovereigns have reduced their foreign currency debt, issuing local currency instruments. However, the corporate sector has kept borrowing in foreign currency, eg the case of Russia, among others. That said, the stock of externally issued foreign currency bonds still exceeds the outright holdings of local instruments by a factor of four. And EM corporate issuance in 2007 (\$150 billion) matched the US high-yield issuance (\$147 billion). In 2008, the EM corporate issuance is forecast to slow down to \$117 billion (JP Morgan Securities (2008)). Moreover, the number of stressed and distressed EM issuers, trading at spreads greater than 700 and 1,000 basis points respectively, rose to 142 in August 2008 compared to only 5 in August 2007 (Financial Times (2008a)).

The data of this study consist of daily indices of EM sovereign and corporate spreads compiled by JP Morgan, the EM Bond Index Global Diversified (EMBI) and the Corporate EM Bond Index Broad Diversified (CEMBI), respectively. These indices track US dollar-denominated debt issued by EM sovereign and corporate entities, which satisfy a minimum standard of liquidity, and with average maturity of three to five years. The EMBI is widely used in international finance as a measure of sovereign credit risk, while CEMBI is a more recent (starting in January 2002) liquid global benchmark for US dollar corporate bonds, and it has sub-indices by region, sector and country. Because our underlying model has a multi-regional setting, we use the regional sub-indices of EMBI and CEMBI. Namely the study considers the following regions: Asia (\$32 billion, \$33 billion), Europe (\$37 billion, \$8 billion), LatAm (\$67 billion, \$18 billion) and Mideast (\$7 billion, \$16 billion).<sup>12</sup> The sample spans the period from 2 January 2004 to 19 February 2009.<sup>13</sup>

Relying on a general theoretical framework, as in Duffie and Singleton (1999) and Longstaff *et al* (2010) among others, credit spreads can be decomposed (approximately) as  $\lambda_Q L_Q + l$ . Here,  $\lambda_Q L_Q$  is the expected risk neutral loss, where  $\lambda_Q$  and  $L_Q$  are the risk neutral intensity and loss given default, respectively. Risk premia maps risk neutral expected losses into actual (objective) ones (see Duffee (1999) and Driessen (2005) among others). And  $l$  compensates the investors for

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<sup>12</sup>In the parenthesis we denote the market capitalisation as of November 2008 for EMBI and CEMBI, respectively.

<sup>13</sup>The pre-sample from 18 September 2003 is used to estimate a time-invariant version of the model to initialise the priors. 18 September 2003 is the first date that the OIS data is available.

illiquidity. In light of this framework, correlation between EM spreads and global factors may arise from any of these components. Thus, we use as exogenous factors, variables that proxy for global volatility (risk aversion), US corporate default risk and liquidity risks.

First, we use the implied volatility of S&P 500, VIX, as a measure of global volatility risk, which proxies investors' aversion to global 'event risk' in credit markets. Structural models predict that volatility changes increase the probability of default, and thus the credit spreads. Consistently, US corporate spreads and VIX are strongly correlated (Collin-Dufresne *et al* (2001), and Schaefer and Strebulaev (2004)). VIX also comoves with spreads on sovereign entities (Pan and Singleton (2008)). Second, CREDIT, defined as high yield (HY) minus investment-grade (IG) Merrill Lynch US corporate, features US corporate default risk. As US corporate default risk deteriorates, risk premia embedded in sovereign default swap increase (Zhang (2003)). Third, the spread between overnight index swap (OIS) and three-month Treasury yields (FL) is a measure of flight to liquidity (Caballero, Fahri and Gourinchas (2008)). As credit risk rises in financial markets, liquidity dries up, and a flight to liquid assets materialises. During these episodes investors demand an higher liquidity premium to hold illiquid assets, such as EM securities. It follows that their spreads widen, despite their relatively low default risk (Dungey *et al* (2004)).

## 5 Econometric methodology

### 5.1 Bayesian inference

The estimation of the model is Bayesian in nature, precisely a Markov Chain Monte Carlo (MCMC) is used to evaluate the posterior distribution. MCMC methods facilitate the estimation of complex models, where exact analytical solutions of the densities, or numerical integration methods may be unfeasible. In particular, a Gibbs sampler, which belongs to the family of MCMC methods, decomposes the original (intractable) estimation problem into independent plain vanilla ones, sampling iteratively from the conditional densities of the parameter blocks. To this end, Bayesian methods are particularly suitable for those models made difficult by non-linearities and the high dimensionality of the parameter space, where classical maximum likelihood methods strive to yield a robust estimate of the parameters. Moreover, by using Bayesian techniques we implicitly account for the uncertainty surrounding the estimates, either of the factors or the hyperparameters, and the model.

The details of the estimation are left to the appendix, here we sketch the basic algorithm. Let  $Y^T = [y'_1, \dots, y'_T]'$ ,  $\theta^T = [\theta'_1, \dots, \theta'_T]'$  and

$$H^T = \begin{bmatrix} h_{1,1} & h_{1,2} & \cdots & h_{1,NG} \\ h_{2,1} & h_{2,2} & \cdots & h_{2,NG} \\ \vdots & \vdots & \vdots & \vdots \\ h_{T,1} & h_{T,2} & \cdots & h_{T,NG} \end{bmatrix} \quad (19)$$

denote the history of the data, the time-varying loadings, and the time-varying stochastic volatilities, respectively. And let  $\sigma_{SV}$  collect the standard deviations of the log-volatility innovations. We stack the lower diagonal elements of the  $A$  matrix in a vector  $\alpha$ , such that  $\alpha = [\alpha_{2,1}, \alpha_{3,1}, \alpha_{3,2}, \dots, \alpha_{NG,NG-1}]$ . The posterior density

$$\pi(\sigma, B, \sigma_{SV}, H^T, \alpha, \theta^T | Y^T) \quad (20)$$

updates our prior beliefs about the free parameters with the information contained in the history of the data. Conditioning on all the other hyperparameters, factors, and data, the joint posterior (20) breaks down into four blocks of parameters,  $\sigma, B, \sigma_{SV}, \alpha$ , and two sets of latent factors,  $H^T$  and  $\theta^T$ , the volatilities and the betas, respectively. By repeatedly simulating from the known conditional distribution of each block in turn, the Gibbs sampler yields samples of draws, which approximate the target densities.

The first two steps of the Gibbs sampler consists of drawing the factor precision  $\sigma$ , and the variance-covariance matrix  $B$  of the factor loadings disturbances. Conditional on the data, initial values for the factor loadings ( $\theta^T$ ), the time-varying volatilities ( $H^T$ ), and the vector of covariances ( $\alpha$ ), we draw the precision parameter  $\sigma$ . Since the conditional posterior is non-standard, this step requires a Metropolis algorithm within the Gibbs sampler as in Canova and Ciccarelli (2008).<sup>14</sup> Given the knowledge of the factor loadings, and under their independence, each block of  $B$  is drawn from the respective inverse Wishart distribution. Next, the Gibbs sampler focuses on the drifting variances parameters,  $\sigma_{SV}, \alpha$ , and states  $H^T$ . This step uses a multivariate version of the Jacquier, Polson and Rossi (1994) stochastic volatility algorithm following Cogley and Sargent (2005). It is worth recalling that reduce form residuals of our model have an additional source of error stemming from the factorisation we imposed on

<sup>14</sup>This Metropolis step is similar in spirit to that of Canova and Ciccarelli (2008), though the likelihood function is modified to account for the presence of stochastic volatilities, see appendix.

the factor loadings. Thus, before applying the stochastic volatility algorithm, the residuals  $\varsigma_t$  are divided by  $(\sigma_t)^{.5}$ . The standard innovations of the drifting volatilities are mutually independent and the posterior has an inverse gamma distribution, conditional on the realisation of the respective volatility. The covariance parameters,  $\alpha$ , have normal posteriors as in Cogley and Sargent (2005), conditional on the stochastic volatilities, and the factorisation precision sigma  $\sigma$ . As for the stochastic volatility, we apply the date-by-date blocking scheme of Jacquier, Polson and Rossi (1994) to each element of the VAR residuals, once the latter have been cleaned from the impact of  $\sigma$ , and then orthogonalised. Finally, conditional on the new draw of all the other parameters, and the data, we simulate a sample of the unobservable factor loadings, using a simulation smoother (Carter and Kohn (1994), among others).

The above procedure outlines a single draw from the posterior distribution. We must repeat this cycle until the chain converges. To this end, we perform 100,000 replications, of which the first 50,000 are ‘burned’ to insure convergence of the chain to the ergodic distribution, and we save 1 every 50 draws of the last 50,000 replications of the Markov chain.<sup>15</sup> This yields a sample of 1,000 draws, and estimates are computed as medians of this sample. Convergence of the algorithm is standard given the structure of the model (Canova and Ciccarelli (2008)). Results are provided in the appendix.

## 5.2 Model selection

So far the exposition focused on a model with a specific structure, namely with a global, regional, and variable specific factors, and eventually with a number of exogenous variables. Although we may have a strong prior on this particular model set-up, alternative specifications are as much likely and economically sound. So we let the data select the best model, as the model yielding the highest marginal likelihood. The remaining of this section deals with Bayesian model comparison, and introduces the RJMCMC method used in this study.

A key statistics for Bayesian model selection is the marginal likelihood. Let us define the marginal likelihood for  $Y^T$  in model  $M_m$  as

$$\ell(Y^T|M_m) = \int F(Y^T|\varphi_m, M_m)\pi(\varphi_m|M_m)d\varphi_m \quad (21)$$

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<sup>15</sup>Observe that saving 1 over 50 iterations, we economise on the storage space and benefit from independent draws, though we may increase the variance of the estimates (Cogley and Sargent (2005)).

where  $\varphi_m$  collects the unknown parameters of model  $M_m$ ,  $F(Y^T|\varphi_m, M_m)$  denotes the density of the data under  $M_m$ , and  $\pi(\varphi_m|M_m)$  is the prior density of  $\varphi_m$ . This formula tells us that by integrating out the parameters  $\varphi_m$ , we can then infer on the model applying Bayes' theorem. However, marginal data densities can be evaluated analytically only in a few cases so that it often needs to be approximated numerically. Several numerical methods have been proposed: the harmonic mean estimator (Newton and Raftery (1994)), the Gelfand and Dey estimator (Gelfand and Dey (1994)), and the candidate estimator (Chib (1995)), among others. Then, once an estimate of the marginal likelihood is obtained, the resulting Bayes factor,  $B_{mm'} = \ell(Y^T|M_m)/\ell(Y^T|M_{m'})$ , is used for pairwise model comparison. In particular, this ratio rewards the model with the better one step ahead prediction performance, while penalising it for the higher number of parameters.

As the complexity and the dimensionality of the model increase, these numerical techniques may not be feasible, or may be subject to numerical problems.<sup>16</sup> To address this problem, Carlin and Chib (1995) introduced, and later on Dellaportas, Forster and Ntzoufras (2002) extended, the RJMCMC. This method consists of, first, specifying a set of proposal distributions and jumping rules, and then exploring proper posterior probabilities for the set of competing models (the RJMCMC algorithm is described in the appendix). Differently from other methods, the RJMCMC well adapts to the context of uncertainty about static and dynamic factor structures (see Lopes and West (2000), Justiniano (2004), and Primiceri (2005)).<sup>17</sup> Moreover, the RJMCMC allows us to compare a set of models, not only pairwise as it is the case using the Bayes factor. The RJMCMC is rather simple to implement, considering the high dimensionality of our problem.

Once equipped with a selection criterion, we move on to defining the set of competing models. The type of models may (roughly) differ across three dimensions. First, the factorisation we impose can be exact or not. Second, the factor loadings can be common across all the units, or can show common patterns across the variable or regional dimensions. For example, sovereign and corporate spreads may display a different response to the exogenous variables. Third,

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<sup>16</sup>Geweke (1999) has introduced a correction of the harmonic mean estimator to address numerical instability problems. That said, the dimensionality of our model is such that this method is not easily implemented. Precisely we should invert a matrix that is (approximately)  $(TxNG+TxNG) \times (TxNG+TxNG)$ .

<sup>17</sup>The RJMCMC takes into account the fact that once we move across models with different structures, the dimension and, consequently, the interpretations of the parameters changes. Moreover, the theory behind the RJMCMC insures that we achieve convergence in a very general framework. In particular, the choice of the jumping rule determines computationally efficient and theoretically effective methods (Lopes and West (2000)).

competing models can differ for the number of factors. This is a common issue across the factor model literature as the factors are often assumed to be unobserved. And it remains a key issue also in our case where the factors are observed. But we can have two models with equal number of factors, which are qualitatively different. Table A summarises the set of models considered.

## 6 Model estimates

Our first result is that the model M7 prevailed over the set of competing models. M7 has an exact factorisation with a global factor, four regional factors, and three exogenous factors. More importantly, the loadings on the exogenous US variables are sovereign and corporate specific. In light of this result, the sovereign and corporate market heterogeneous responses to global risks account for the different behaviour of these two markets over the sample at hand. In other words, once we control for an EM factor, common to both sovereign and corporate bond spreads, for regional differences and heterogeneous responses to global risks, there is no EM factor specific to the corporate market. This result is consistent with the fact that, because the corporate indices are sufficiently diversified, corporate and sovereign bonds are exposed to the same EM risk factors. However, their sensitivity to global risk factors differs. In particular, we have used the RJMCMC method to select the best model as in Primiceri (2005), see the appendix for a detailed description of the method. Next we present the estimated factor loadings and stochastic volatilities which refer to M7.

### 6.1 Systematic - factor loadings ( $\theta_t$ )

This section deals with interpreting the estimated factor loadings, or coefficients,  $\theta_t$ .<sup>18</sup> As for the *common* factor loading, if  $\theta_{1t}$  is significantly different from zero we can conclude that EM credit risk tends to comove. However, a positive (negative) factor does not tell us that credit risk is rising (falling) across EMs. It holds the following. First, if  $\theta_{1t}$  is large relative to the regional coefficients  $\theta_{2t}$ , then the spread changes of Asia, Europe, LatAm, and Mideast tend to comove. Second, if  $\theta_{1t}$  is zero, and the  $\theta_{2t}$  are fairly big, the regional spreads feature an idiosyncratic behaviour, eg in a two-regions world,  $y_t^A$  and  $x_t^A$ , the sovereign and corporate spreads of region A, respectively, may drift apart from  $y_t^B$  and  $x_t^B$ .

The estimate of the global coefficient (Figure 1) is significantly different from zero most of the

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<sup>18</sup>The model has been estimated on credit spread changes, and the data have been standardised.

times. This fact suggests a strong comovement across regional sovereign and corporate spreads. The coefficient  $\theta_{1t}$  is rather volatile, most likely because of the high volatility of the common factor. The common loading displays a cyclical behaviour, though it is more pronounced during the second half of the sample. Before May 2006 (approximately) the loading shows an erratic behaviour, being often not different from zero, except for few events, eg the marked trough in November 2005. In the second part of the sample, the coefficient trends upward between May and October 2006, and during the first two quarters of 2008. Conversely, it drifts downward after the start of the credit crunch (June 2007) for about two quarters. Interestingly, over the end of the sample this comovement vanishes, and the confidence intervals widen likely due to higher uncertainty.

The *regional* factor loading  $\theta_{2t}^i$  accounts for the idiosyncratic behaviour of region  $i$ , and counterbalances an eventual overshooting provoked by the common factor. For example, if bond spreads increase in Asia, Europe, and LatAm, while decreasing in Mideast, we would expect  $\theta_{1t}$  to be different from zero. However,  $\theta_{1t}$  would yield positive bond spreads in Mideast as well. To correct for this fact, the  $\theta_{2t}$  on Mideast must be sufficiently high, in absolute value, to push the spreads down in the region. That said, the following considerations hold. First, if  $\theta_{2t}^i$  is statistically different from zero, then we may conclude region  $i$  features an idiosyncratic behaviour. Second, only looking at the sign of the coefficient we cannot conclude whether credit risk is increasing or decreasing relative to the other regions. Third, a negative sign of the region coefficient induces mean reversion in the spread, ie a positive (negative) change in the spreads today predicts a negative (positive) change in the spreads tomorrow. In contrast, a significant positive coefficient suggests ongoing either bad or good times in the region (momentum).

Figure 2 presents the estimated regional loadings for LatAm, Europe, Asia, and Mideast. At a first glance, the volatility of the loadings differs across the regions. The loading on Mideast is rather persistent, and rapidly drops, and raises again, as the credit crunch spreads to EMs (about August 2007). By contrast, the loadings on the remaining regions are more volatile. The coefficient on LatAm is skewed upward, but it becomes significantly negative in the last quarter of 2008. During the same episode, the European coefficient turns positive, and the loading on the common factor is not significantly different from zero. This is a clear example of low comovement, where LatAm and Europe display (opposite) idiosyncratic risks. It is less clear for Asia and Mideast, where sovereign and corporate bonds may perform differently. Finally, the loading on Asia is rather volatile for most of the sample, but it shows a series of marked lows and

highs over the first months of the credit crunch.

The  $G \times 1$  vectors  $\theta_{3t}^g, \theta_{4t}^g, \theta_{5t}^g$  capture the impact of the exogenous variables, VIX, CREDIT, and FL, at time  $t-1$  on EM sovereign ( $\theta_{it}^1$ ) and corporate ( $\theta_{it}^2$ ) spreads at time  $t$  (Figure 3). Because the  $\theta_{it}^1$  differ from  $\theta_{it}^2$ , for any  $i$ , sovereign and corporate spreads display an heterogeneous exposure to the variables of the US market. This implies that exogenous factors are responsible for the evolution of sovereign and corporate credit risk. The interpretation of the coefficients,  $\theta_{3t}$ , is straightforward. For instance, a one standard deviation change of VIX in  $t-1$  determines  $\theta_{3t}^1$  ( $\theta_{3t}^2$ ) standard deviations change of all the sovereign (corporate) spreads at time  $t$ .

Over the first half of the sample, the VIX factor loading on sovereign spreads was rarely different from zero, and the confidence intervals were rather large. There were negative loadings in a few episodes, this fact may suggest that sovereign securities benefited from increased risk aversion in developed markets. After two episodes where sovereign spreads were highly sensitive to changes in risk aversion, the coefficient trended downward for a consistently long period. This trend abruptly ended with the start of the credit crunch, when a rise in risk aversion by two standard deviations raised sovereign spreads by more than one standard deviation. Sovereign spreads remained sensitive to VIX as the crisis developed, though with less intensity. The evolution of the loading of VIX on corporates resembled the one on sovereign, though with lower magnitude. A few episodes also revealed a strong impact of VIX on corporate credit risk. As the crisis started global risk aversion widened corporate spreads but to a lower extent than the sovereign. Interestingly,  $\theta_{3t}^2$  reaches its all-time high after Summer 2008, when the crisis worsens with the default of Lehman Brothers.

As for the impact of CREDIT on sovereign spreads, the coefficient shows marked swings. In two episodes during the first phase of the credit crunch, US corporate default risk markedly spilled over to sovereign credit spreads, namely about January 2007. But as the crises evolved it became more a crisis of confidence and liquidity, and the loading on credit became not significant. Towards the end of the sample the coefficient drifts downward, though the confidence intervals also widen considerably. Moving to the corporate market, the coefficient of CREDIT displays less time-variability, and tends to be confined to negative values, though hardly significant, with the exception of a spike in June 2005. This happens a few months after the automobile crisis in the United States. And the coefficient takes its highest values during the same episodes of the sovereign, and of similar magnitude. Overall, the volatility of the factor loadings suggest that the

impact of CREDIT is more persistent on EM corporate bonds than sovereign.

FL shifted from stable low values to volatile high levels over the second half of the sample. This was consistent with the fact that during the crisis market participants withdrew from interbank lending, so that the market stopped functioning, and the spread of OIS-Treasury spread widened. So we should attach more importance to changes of the loadings  $\theta_{5t}^g$  which take place during the crisis. By contrast large swings in  $\theta_{5t}^g$  over the first part of the sample, though pronounced, are of less importance. Otherwise we might end up overlooking the episode of May 2007 when the drops in  $\theta_{5t}^g$  were large, but the spread was still low. With the start of the crisis both the sovereign and corporate loadings are back to positive values, and the confidence intervals narrow. Toward the end of the sample, the uncertainty raised as the confidence intervals were extremely large.

## 6.2 *Non-systematic - stochastic volatility ( $h_t$ )*

Next the analysis focuses on the evolution of the estimated  $\Omega_t$ , and discusses several issues related to using stochastic volatility. Figure 4 presents the posterior means of the square root of the diagonal elements of  $\Omega_t$ , ie the standard deviation of the innovations. The estimates support the intuition that time-varying volatility is a key feature of the data. In light of this finding, the volatilities skyrocket about the Lehman Brothers' default, being roughly ten times higher than in normal times. In particular, Asia corporate witnesses the highest values of the volatility. Moreover, the increase in volatility during the start of the credit crunch is far lower than the one that realises as the crisis transmits from advanced economies to EMs, at the end of the third quarter of 2008. That said, each plot displays a peculiar evolution. For example, Europe corporates' volatility experiences a trend as the crisis begins, a jump as the crisis worsens, and then stays above the pre-crisis levels towards the end of the sample.

The results presented on the innovations volatilities refers to the ordering LatAm, Europe, Asia and Mideast, with the sovereign preceding the respective corporate. As documented in Section 3.1, decomposing the covariance matrix as in equation (14), the estimates of VAR innovations are sensible to the ordering of the variables (see Cogley and Sargent (2005)). However, because our study is at a daily frequency, the impact of the ordering of the variable should be negligible. By contrast, it may be more problematic in macro study which are at a lower frequency. Furthermore, in our case economics does not help us choose a particular ordering; we only know that the information flows from the sovereign to the corporate market (see Section 2).

Accordingly, we order the sovereign index before the respective regional corporate index.<sup>19</sup> In sum, while an ordering of the variables that slightly changes the drift of  $\theta$  may exist, this is highly unlikely to alter any of the results of this study.

There is evidence of time-varying volatility in the real interest rates faced by EMEs (Fernández-Villaverde *et al* (2009)). But there are also a number of other reasons which justify the use of stochastic volatility. First, a common critique to time-varying parameters VAR with constant volatility is that the misspecified volatility may exaggerate the time-variability of the parameters (Sims (2001) and Stock (2001)). Second, the daily frequency of the data suggests the use of stochastic volatility, conversely at this frequency regime switch models are likely to perform poorly.<sup>20</sup> Third, stochastic volatility efficiently takes care of outliers, which would otherwise confuse these episodes for changes in  $\theta$ . In our case, changes in the composition of the index generate jumps which carry no economic content.

Abstracting from the factor structure, the outcome of the RJMCMC suggests that the specification with stochastic volatility, and precise factorisation, ie  $\sigma = 0$ , is preferable over an alternative specification with  $\sigma \neq 0$ .<sup>21</sup> This result raises the following considerations. By using no stochastic volatility, and assuming that the factorisation is not precise, we implicitly introduce heteroskedasticity. Precisely, as in Canova and Ciccarelli (2008), the sum of the regressors at time  $t - 1$  determines the variance at time  $t$ ,  $\sigma_t$ . This specification should work properly in the presence of common shocks, as in the case of a global financial crisis. On the contrary, it suffers in the presence of a unit specific shock, understating the variance of this unit, while overstating the one of the other units. This happens because  $\sigma_t$  determines a parallel shift of the covariance matrix. So, this specification may lack a sufficient degree of flexibility. More fundamentally, stochastic volatility allows for another source of random error.

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<sup>19</sup>As emerges from the above considerations, the theory does not suggest how to order the variables, especially across regions. The ordering may be sample specific, and remains an empirical question. In light of this consideration, the ordering could be the result of a model selection, across models only differing for the order of the variables. The RJMCMC may be easily used to find the best ordering, though the number of possible orderings exponentially increases with the number of dependent variables. Thus, it is paramount to restrict the number of competing models, ie orderings, in base of any previous knowledge.

<sup>20</sup>See Cogley and Sargent (2005) for a discussion of the advantages and disadvantages of stochastic volatility versus regime switch methods.

<sup>21</sup>To some extend, this results is consistent with Canova and Ciccarelli (2008), where they find that the model performs better in a fully homoskedastic version, with  $\sigma = 0$ .

## 7 (Credit risk) indicators

This section deals with decomposing credit spreads and building indicators of credit risk. Factor loadings are informative about the intensity and time-variation of comovements of credit spread changes. But they are *per se* uninformative about credit risk, eg whether it is rising or falling. So only by building credit indicators can we monitor the evolution of credit risk over time and capture the contribution of the different sources of risk.

Credit risk indicators simply combine the time-varying coefficients with the corresponding observed factors, eg the EM common factor,  $X_t \Xi_1$ , times the loading on the common factor,  $\theta_{1t}$ , yields the EM indicator,  $EMEI_t$ . This decomposition is already embedded in (8), whereby each spread change consists of the sum of several indicators. For example we may decompose the predicted  $\hat{y}_{g,t}^i$ , eg the change in the  $g$  variable spread of region  $i$ , into the sum of the common indicator,  $EMEI_t$ , the regional indicator,  $REGI_t^i$ , and the  $g$  exogenous indicators,  $EXGI_t^g$ .

The top plots of Figure 5 present the risk indicators over the full sample period. It emerges that the volatility, and the magnitude of the indicators, intensify during the credit crunch, and in particular in the last quarter of 2008, following the Lehman Brothers' default. The bottom plots facilitate the analysis of the results, showing the cumulative sum of the indicators. These plots emphasise the trending behaviour of the different risks, though maintaining the same information content of the original volatile indicators.

Visual inspection of the plots suggests the following considerations. First, the common EM indicator trended downward over the first part of the sample, which ends with the start of the credit crunch. And the magnitude of this common compression of the spreads overwhelmed the impact of any other factor. Second, during the crisis there is an evident 'decoupling' and subsequent 'recoupling' of EM spreads with the United States (IMF (2009a)). Our common indicator kept narrowing after the first phase of the crisis, and jumped upward in the last quarter of 2008, with the default of Lehman Brothers. Third, the Asian indicator stayed positive during (almost) the whole sample. However, the crisis hit Europe more than the other regions, and at the end of the sample the European and Asian indicators were about the same. Fourth, during the pre-crisis period a well-functioning interbank market, ie a low FL, contributed to narrow EM corporate spreads more than sovereign. While FL increased and contributed to widen EM spreads as the market liquidity dried up (about October 2008). The sovereign and corporate FL indicators

were similar. On the contrary, as the crisis developed and worsened, EM sovereign and corporate credit spreads displayed a different reaction to deteriorating global risk aversion (VIX) and US corporate default risk (CREDIT).

### **7.1 Credit risk indicators over the crisis**

Figure 6 focuses on the crisis period. The EM indicator slightly increased at the outset of the credit crunch (late July 2007), and except for a blip in December 2007, EM (common) credit risk continued to fall. In July 2008, there was a first signal that EM assets were not immune to the crisis. The catch-up materialised shortly after the Lehman Brothers' default. The sharp increase of the common EM indicator stopped in late October, about the time the IMF approved a credit plan for Hungary, and the FED announced the introduction of a new swap facility for Brazil, Korea, Mexico and Singapore.

By the fourth quarter of 2008 the global financial stress spread to all EMs, though we find that the intensity and timing of the contagion differed across regions. The European indicator jumped upward, and reached values far above all the other regional indicators.<sup>22</sup> That said, Asia was the first region to be affected by the crisis, since its indicator stayed above all the others during the first phase of the crisis.<sup>23</sup>

We now look at the global indicators. Among these indicators, the FL indicator was responsible for the largest increase of sovereign credit spreads. Interestingly, the corporate FL indicator showed a similar pattern to the sovereign. But as far as corporates were concerned, FL played a limited role relative to CREDIT, and, to a lesser extent, also to VIX. This result emphasises the crucial role played by the interbank market in the recent crisis in explaining the transmission of the crisis to EMs. More in general, our results seem consistent with the following sequence of events. Lehman Brothers' default induced market participants to withdraw from interbank lending, due to raising liquidity and counterparty concerns. So the FL indicator reached high values. Global banks deleveraged, taking money out from parent banks in EMEs, to meet internal capital needs. This process severely damaged banks and corporates in EMEs, and their assets

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<sup>22</sup>During this crisis, financial links, and the bank lending channel in specific, brought the crisis to emerging markets. Severe losses hit advanced economies' lenders, forcing them to deleverage and to withdraw credit from emerging markets. This transmission channel may explain why Europe is the country that suffered the most. In particular, in Eastern Europe bank liabilities exceeded 50% of its GDP (IMF (2009a)).

<sup>23</sup>This finding is consistent with what is written in the *World Economic Outlook* (IMF (2009a) page 147), 'Signs of crisis first appeared in Asia and multiplied quickly across all other regions.'

became highly illiquid. And cross-over investors hedged their exposures to banks and corporates in the more liquid sovereign market.<sup>24</sup> Thus, the crisis spreads from advanced economies markets, to both corporate and sovereign EM securities. In sum, the hedging behaviour of international investors can partly explain the similar response of sovereign and corporate spreads to the FL indicator.

Our VIX indicator hints that global risk aversion spilled over to sovereign spreads in October 2008. Moreover, the CREDIT indicator pushed down the component of the spread due to US corporate default risk, eventually compensating for the higher contribution of global risk premia to the sovereign spreads. The drop of the sovereign CREDIT indicator differentiated sovereign from corporate securities. In light of these results, the crisis in the sovereign market appeared to be mostly linked to the heightened global risk aversion, and to a flight-to-liquidity episode.<sup>25</sup> In contrast, all three indicators (CREDIT, VIX and FL) pointed towards higher EM corporate spreads. That said, the impact of deteriorating US corporate default risk prevailed for EM corporates. This suggests that corporate spreads in EMs widened mainly because of higher default probabilities in the United States, and to a lesser extent because of higher global risk and liquidity premia.<sup>26</sup>

## 7.2 Explaining credit indicators

This section explores the information content of our credit indicators, by analysing the simple contemporaneous correlations between the indicators and several variables. The set of variables includes changes in short and long US Treasury yields, and their difference (the slope), US stock market returns, measures of exchange rate volatility, and other measures as commodity prices and proxies of EM credit risk. This analysis is conducted at a monthly frequency, and we move from our daily indicators to monthly ones, simply aggregating over the original daily indicators for each month. Furthermore, instead of using the indicator for region  $i$ ,  $REGI_t^i$ , we use a modified version,  $REG-GI_t^i$ , which consists of  $EMEI_t$  plus  $REGI_t^i$ . Recall that the regional indicator,  $REGI_t^i$ , displays the relative performance of region  $i$ , adjusting the  $EMEI_t$  accordingly.

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<sup>24</sup>As noted in Section 5, sovereign securities only consists of systematic risk, providing an imperfect hedge to corporate and bank securities. That said, international investors reduce the cost of the hedge benefiting from the higher liquidity of sovereign securities.

<sup>25</sup>'Many countries should not be trading as high as they are on a fundamental basis. They are widening like all credit products globally', (Financial Times (2008b)). To some extent our results strengthen, but refine, this conclusion, stressing the fact that sovereign spreads narrow as the US corporate default probability increases.

<sup>26</sup>These results fully agree with the following statement 'On corporate debt, analysts are more cautious. An increasing number of bonds are trading a distressed levels, more than 1000 basis points over US Treasuries, implying a much greater risk of default', (Financial Times (2008b)).

This implies that  $REGI_t^i$  may point to the opposite direction of the regional spreads.<sup>27</sup> Overall, Table E presents the correlations for the full sample from January 2004 to February 2009.

Positive changes in the three-month Treasury yields are associated with lower EM credit risk,  $EMEI_t$ , and Latin America and Asia display the highest correlation in absolute value, minus 33% and 31%, respectively. The ten-year Treasury yield does not correlate with  $EMEI_t$ , since it correlates with positive and negative signs with regional indicators. The information of long-term Treasury yields is controversial, as both risk premia and expected short-term interest rates may account for long-term yields, and these components seem to point towards different phases of the business cycle. The slope of the US term structure, ten-year minus three-month Treasury yields, positively correlates with the common and regional indicators. Recessions are characterised by upward-sloping term structures (Ang, Piazzesi and Wei (2006)), and the slope of the yield curve also features bond risk premia (Ilmanen (1995)). As the shape of the US term structure flattens, the US economy faces better times, and a strong US demand benefits exporting EM countries. Accordingly, the risk premia international investors ask to invest in EM assets decrease. Furthermore, returns on the stock markets are negatively correlated to the indicators. This result confirms the importance of the state of the US economy, because returns on the stock market proxy for the state of the economy (Collin-Dufresne *et al* (2001)). The stock market return is also a simple, and model-free proxy for the equity risk premium (Longstaff *et al* (2010)).

Exchange rate market pressures represent a common source of stress in EMEs (IMF (2009a)). To this end, we use the realized volatility of the US dollar effective exchange rate. This measure (USD-RV) is highly positively correlated with the common and regional indicators. Then, we move to four regional measures of exchange rate realised volatility (EM-RV) to investigate their relation with the respective regional indicators, and to an EM measure to explain the common indicator.<sup>28</sup> Interestingly, the correlations between EM-RV and the indicators range from 62% for the Mideast indicator to 87% for the Asian one, and the correlation with the Latin America indicator reaches 84%. Overall, foreign exchange market volatility strongly correlates with EM credit risk. Consistently, the risk of currency depreciation may have exacerbated the burden of external corporate indebtedness, raising the number of defaults, and consequently widening EM

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<sup>27</sup>For example,  $EMEI_t$  may increase by five standard deviations, whereas  $REGI_t^i$ , ie the Latin America indicator, may drop by two. This fact implies increasing credit spreads in Latin America by two standard deviations. On the contrary, by only looking at  $REGI_t^i$ , we may erroneously think that credit spreads are decreasing.

<sup>28</sup>To construct regional measures of exchange rate realised volatility we compute an average across the country measures. And to compute the emerging market measure we average over the regional measures. Bakshi, Carr and Wu (2008) have used a similar methodology of averaging across country variables to explain a global risk premium.

spreads. Moreover, we find that oil and commodity price changes have a correlation with the indicators of about -50%. This result suggests that high commodity prices benefit emerging countries. In general, higher commodity prices increase the probability exporters pay back their external debt, reducing the probability of default, and the premium charged on the international capital markets (Hilscher and Nosbusch (2010)). Finally, our indicators, except for Mideast, have a strong correlation with a neat measure of EM credit risk as spread changes of the EM credit default index (CDX.EM).

## 8 Conclusion

Motivated by the alternating fortunes that the EM asset class has experienced over recent years, and by the sharp rise of the corporate bond market in EMEs, the aim of this study is twofold. First, it sheds light on the nature of (systemic) risks embedded in EM corporate bond indices. To this end, we jointly model sovereign and corporate bond spreads to focus on their common and market-specific risks. Second, this study provides an analytical framework to jointly model, and consequently monitor, sovereign and corporate EM credit risks along different dimensions.

We use the Bayesian multicountry panel VAR of Canova and Ciccarelli (2008), which accounts for structural time-variation and complex interdependencies. The coefficients (factor loadings) are time-varying, whereas the factors are observed. But we also extend this model for the presence of multivariate stochastic volatility, as in Cogley and Sargent (2005). We apply this model to daily credit spread changes of sovereign and corporate regional indices compiled by JP Morgan, EMBI Global Diversified and the CEMBI Broad Diversified, respectively, for the following regions: LatAm, Europe, Asia and Mideast. Moreover, we employ a RJMCMC algorithm similarly to Primiceri (2005) to select the best model across a set of competing models. This exercise reveals information about the nature of comovement in EM bond spreads.

Our main result is that global risk factors (VIX, US corporate default risk, and a measure of flight to liquidity) impacted sovereign and corporate spreads differently. Precisely, we find that the ‘winning’ model consists of a common emerging market factor, four regional factors and three global factors. More importantly, sovereign and corporate bond spreads display market-specific loadings on the global risk factors. And these market-specific loadings account for the idiosyncratic behaviour of sovereign and corporate credit risk.

We show that following Lehman Brothers' default corporates were severely affected by spillovers from US corporate default risk. But also global risk aversion, proxied by the VIX, and the OIS-Treasury spread contributed to widen corporate spreads. By contrast, sovereign spreads 'decoupled' from US corporate default risk, instead they were mainly affected by a flight-to-liquidity episode. Heightened risk aversion also contributed to widen sovereign spreads, but this effect quickly reverted.

Moreover, we find that the financial turmoil spread to all EMs, as the common component of EM credit risk jumped. But we also find that corporates were hit more than sovereigns, and the most affected region was emerging Europe. Finally, our credit indicators correlate with foreign exchange rate volatility and with other measures of systemic risk.

## Appendix: Inference

### Priors

This section shows the prior distributions. Under the assumption of block independence between the hyperparameters and initial states, the product of the marginal priors yields the joint prior, as follows

$$p(\sigma^2, B_f, h_{10}, \dots, h_{NG,0}, \sigma_{SV,1}^2, \dots, \sigma_{SV,NG}^2, \alpha) = p(\sigma^2) \cdot \prod_f p(B_f) \cdot \prod_i (p(\ln h_{i0}) \cdot p(\sigma_{SV,i}^2)) \cdot p(\alpha) \quad (\text{A-1})$$

Let us denote  $IG()$  as the inverse gamma,  $IW()$  as the inverse Wishart, and  $N()$  as the normal distribution, then we have

$$\begin{aligned} p(\sigma^2) &= IG\left(\frac{\bar{\sigma}_{OLS}^2}{2}, \frac{1}{2}\right) \\ p(B_f) &= IW\left(\left(Q_0^f\right)^{-1}, z_f\right) \\ p(\sigma_{SV,i}^2) &= IG\left(\frac{S_0}{2}, \frac{\nu_0}{2}\right) \\ p(\ln h_{i0}) &= N(\ln \bar{h}_{OLS,i}, 100) \\ p(\alpha) &= N(0, 10000 \cdot I_{NG}) \end{aligned} \quad (\text{A-2})$$

To calibrate some of the priors hyperparameters, we estimate a time invariant version of the model over a trial sample (71 observations, from 19 September 2003 to 31 December 2003). For example,  $\bar{\sigma}_{OLS}^2$  is the average of the estimated variances of  $NG$  AR(p) models, as in Canova, Ciccarelli and Ortega (2007). Following Cogley and Sargent (2005), the prior for  $h_{i0}$  is log-normal, where the mean is calibrated to the OLS point estimate of the residual variance of equation  $i$  of the time-invariant version of the model. A variance of 10 is rather big on the log scale. As in Cogley and Sargent (2005), the parameters governing the prior of  $\alpha$  are set with zero mean, and a big diagonal variance-covariance matrix. As for the prior on  $\sigma_{SV,i}^2$ , ie the variance of the  $i$  stochastic volatility, we set  $S_0 = 0.01 \cdot \nu_0$  and  $\nu_0 = 5$  as in Kim, Shepard and Chib (1998). Overall, the priors on the stochastic volatility states and hyperparameters are set rather arbitrarily,

though the variances are such that these priors are proper but weakly informative, thus giving the data the opportunity to speak.

Setting a prior that allows a sufficient time-variability of the coefficients  $\theta^T$  is crucial. Canova and Ciccarelli (2008) use an inverse gamma and set an arbitrary large variance. Here, we use an inverse Wishart prior with parameters  $Q_0^f = k_B \cdot \text{var}(\bar{\theta}_{OLS,f}) \cdot z_f$ , where  $z_f = T_{IVAR}$  and  $k_B = 0.01$ . This choice of parameters responds to the following motivations. Using the inverse Wishart parameterisation the scale matrix has the interpretation of the sum of squared residuals. Therefore, the scale matrix over the degree of freedom,  $\frac{Q_f}{z_f}$ , is interpretable as a variance-covariance matrix. Accordingly, we calibrate the scale matrix to the variance-covariance matrix of the OLS estimates of the parameters,  $\text{var}(\bar{\theta}_{OLS})$ , times the size of the trial sample,  $T_{IVAR}$ . The factors loadings needs to be independent to be identified (Canova and Ciccarelli (2008)). To this end,  $Q_f$  refers to the  $f$  block of the scale matrix  $\text{var}(\bar{\theta}_{OLS}) \cdot T_{IVAR}$ .

The choice of the degree of freedoms,  $z_f$ , determines the weight the prior has on the posterior estimate. First, an inverse Wishart prior is proper when the degrees of freedom exceed the dimension of the scale matrix. Second, Primiceri (2005) shows that the conditional posterior mean of the coefficient amount of time variation is a weighted average

$$E(B_f|\theta^T) = \frac{z_f}{z_f+T} \left( \frac{Q_f}{z_f} \right) + \frac{T}{z_f+T} (B_f^*)$$

where  $B_f^*$  is the maximum likelihood estimate of the  $B_f$  var-cov matrix, and  $\frac{z_f}{z_f+T}$  is the weight of the prior over the posterior estimate. This means that we attach a weight of less than 5% to the prior. Finally, multiplying the scale matrix by  $k_B$ , as in Cogley and Sargent (2005) and Primiceri (2005), we implicitly assume that time variation accounts for only 1% of the standard deviation of the time-invariant coefficients.

### ***Gibbs sampler algorithm***

By combining the priors with likelihood of the model we obtain the joint posterior. The likelihood of the reparameterised SUR takes the form

$$L(\theta, \Upsilon|Y) \propto \prod_t |\Upsilon_t|^{-1/2} \exp \left[ -1/2 \sum_t (Y_t - X_t \Xi \theta_t)' \Upsilon_t^{-1} (Y_t - X_t \Xi \theta_t) \right] \quad (\mathbf{A-3})$$

where  $\Upsilon_t = (1 + \sigma^2 \mathbf{X}'_t \mathbf{X}_t) \Omega_t \equiv \sigma_t \Omega_t$ . Observe that if  $\Omega_t$  was not heteroskedastic, equation **(A-3)**, was exactly as the likelihood in Canova and Ciccarelli (2008).

The rest of this section lays out the Gibbs sampler to numerically simulate a sample from the joint posterior distribution  $\pi(\sigma, B, \sigma_{SV}, H^T, \alpha, \theta^T | Y^T)$ . Overall, conditionally sampling from simple

blocks of the joint posterior density consists of six steps, of which four for the hyperparameters,  $\sigma$ ,  $B$ ,  $\sigma_{SV}$ ,  $\alpha$ , and two for the latent volatilities and loadings,  $H^T$  and  $\theta^T$ , respectively.

*Step i: Factorisation precision ( $\sigma$ )*

The conditional posterior of  $\sigma^2$  is not known in close form,

$$\pi(\sigma|H^T, \alpha, \theta^T, Y^T) \propto L(Y^T|\psi) \cdot \pi(\sigma^2) \quad (\mathbf{A-4})$$

thus we require a Metropolis step within the Gibbs sampler. This step consists of drawing a candidate  $(\sigma^2)'$  from a proposal density, ie a normal density. To this end, let us define  $(\sigma^2)' = (\sigma^2)^o + v$ , where  $v$  is normally distributed with zero mean and variance  $c^2$ . Let us define  $\psi_{-\sigma^2}$  as all the free parameters but  $\sigma^2$ , we accept the candidate draw  $(\sigma^2)'$  with probability

$$a = \min \left\{ \frac{L(Y^T|\psi_{-\sigma^2}, (\sigma^2)') \cdot p((\sigma^2)')}{L(Y^T|\psi_{-\sigma^2}, (\sigma^2)^o) \cdot p((\sigma^2)^o)}, 1 \right\} \quad (\mathbf{A-5})$$

We set the  $c$  parameter such that the acceptance ratio falls in the range 15%-30% (Koop (2003)).

*Step ii: Innovation variance for VAR parameters ( $B$ )*

We now focus on drawing the variance-covariance matrix  $B$  of the coefficients' innovations  $\eta_t$ . Conditional on a realisation of the  $\theta^T$ , the  $\eta_t$  are observable. Moreover, conditional on  $H^T$  and  $\alpha$  the knowledge of  $\sigma_{SV}$  is redundant, and, since  $\eta_t$  is independent of the other shocks of the model  $u_t$  and  $\varsigma_t$ , also  $\sigma$ ,  $H^T$  and  $\alpha$  are redundant to draw  $B$ .

Under the assumption of independence of the factors, we draw separately the blocks of  $B$ . Given an inverse Wishart prior for  $B_f$  and a normal likelihood, the posterior of  $B_f$  has itself an inverse Wishart distribution:

$$\pi(B_f|\theta^T, Y^T) = IW \left( \left( Q_1^f \right)^{-1}, z_1^f \right) \quad (\mathbf{A-6})$$

with scale and degree-of-freedom parameters

$$Q_1^f = Q_0^f + \sum_{t=1}^T (\theta_t^f - \theta_{t-1}^f) (\theta_t^f - \theta_{t-1}^f)'$$

$$z_1^f = z_0^f + T$$

*Step iii: Standard deviation of volatility innovation ( $\sigma_{SV}$ )*

The full conditional posterior of  $\sigma_{SV}$ ,  $\pi(\sigma_{SV} | \sigma, B, H^T, \alpha, \theta^T, Y^T)$ , includes conditioning variables that turn out to be redundant. The argument goes (approximately) as in Cogley and Sargent (2005). The  $B$  matrix contains information about  $\theta^T$ , but conditional on  $\theta^T$ ,  $B$  does not provide useful information to estimate  $\sigma_{SV}$ . Further,  $\theta^T$  determines both  $\varsigma_t$  and  $\eta_t$ , though these disturbances are independent of  $\sigma_{SV}$ . Observe that  $\sigma$  and  $\alpha$ , the latter orthogonalises the  $\Omega_t$  matrix, carry information about  $H_t$ . That said, by direct observation of  $H^T$  both the information of  $\sigma$  and  $\alpha$  are irrelevant to infer  $\sigma_{SV}$ . The knowledge of  $H^T$  determines the time series of scale errors  $\sigma_{SV,i}\epsilon_i$ , for  $i = 1, 2, 3, \dots, NG$ . By equation (15), the stochastic volatilities are  $NG$  univariate mutually independent, this fact simplifies the problem, ie we work with the full conditional density equation by equation. Let  $\sigma_{SV,-i}$  denote all the  $\sigma_{SV}$  but  $\sigma_{SV,i}$ , the density for  $\sigma_{SV,i}$  is

$$\pi(\sigma_{SV,i} | \sigma_{SV,-i}, H^T, Y^T) = \pi(\sigma_{SV,i} | h_i^T, Y^T) \quad (\mathbf{A-7})$$

The scaled errors  $\sigma_{SV,i}\epsilon_i$  are *iid* normally distributed with zero mean, and standard deviation  $\sigma_{SV,i}$ . Using an inverse gamma prior the posterior is still inverse gamma, as follows

$$\pi(\sigma_{SV,i} | h_i^T, Y^T) = IG\left(\frac{S_1}{2}, \frac{\nu_1}{2}\right) \quad (\mathbf{A-8})$$

with scale and shape parameter

$$S_1 = S_0 + \sum_{t=1}^T (\Delta \ln h_{it})^2$$

$$\nu_1 = \nu_0 + T$$

*Step iv: Stochastic volatilities ( $H^T$ )*

This step deals with sampling from the univariate posterior density of the stochastic volatility  $h_i^T$ , the algorithm of Jacquier, Polson and Rossi (1994) is repeated for each  $h_i^T$  due to mutually independent stochastic volatilities. However, the errors of the SUR model  $\varsigma_t$ , once the factor structure on the coefficients has been imposed, are normal with mean zero and variance  $\sigma_t \Omega_t$ . To

this end, both the factorisation precision, and the variance-covariance matrix of the original VAR, contribute to the variance of  $\varsigma_t$ . That said, the stochastic volatility only refers to the  $\Omega_t$  matrix. It follows that to implement the stochastic volatility algorithm we must clean the residuals  $\varsigma_t$  from the effect of the factorisation precision to work directly with  $\Omega_t$ . This leads to standardise the residuals  $\varsigma_t$  by the square-root of  $\sigma_t$ , thus let define  $\widehat{\varsigma}_t$  as  $\varsigma_t \cdot (\sigma_t)^{-0.5}$ .

Let us work with a generic equation  $i$ , and repeat the same argument for each of the remaining (NG-1) equations. Exploiting the Markovian structure of the stochastic density, the univariate posterior of  $h_{i,t}$  simplifies as

$$\pi(h_{i,t} | h_{-t,i}, \widetilde{\varsigma}_i^T, \sigma_{SV,i}) = \pi(h_{i,t} | h_{t+1,i}, h_{t-1,i}, \widetilde{\varsigma}_i^T, \sigma_{SV,i}) \quad (\text{A-9})$$

where  $h_{-t,i}$  denotes the  $h_i$  at any time but  $t$ , and  $\widetilde{\varsigma}_t$  are the orthogonalised residuals,  $\widetilde{\varsigma}_t = A^{-1}\widehat{\varsigma}_t$ . This density takes an unusual form, which stems from the product of the normal form for the conditional sampling density,  $\pi(\widetilde{\varsigma}_{i,t} | h_{i,t})$ , and the log-normal form for the volatility equations,  $\pi(h_{i,t+1} | h_{i,t})$  and  $\pi(h_{i,t} | h_{i,t-1})$ .

$$\pi(h_{i,t} | h_{t+1,i}, h_{t-1,i}, \widetilde{\varsigma}_i^T, \sigma_{SV,i}) \propto h_{i,t}^{-1.5} \exp\left(-\frac{\widetilde{\varsigma}_{i,t}^2}{2h_{i,t}}\right) \exp\left(-\frac{-(\ln h_{i,t} - \mu_{i,t})}{2\sigma_{h,i}^2}\right) \quad (\text{A-10})$$

where for the random walk case,  $\mu_{i,t} = (\ln h_{i,t+1} + \ln h_{i,t-1})/2$  and  $\sigma_{h,i} = (\sigma_{SV,i}^2)/2$ . To draw from this density, we use an accept/reject sampling method. As in Cogley and Sargent (2005), we sample  $h_{i,t}$  from a log-normal proposal density, of the same form of the prior, namely

$$q(h_{i,t}) \propto h_{i,t}^{-1} \exp\left(-\frac{-(\ln h_{i,t} - \mu_{i,t})}{2\sigma_{h,i}^2}\right) \quad (\text{A-11})$$

And the probability of accepting the  $d - th$  draw reduces to the ratio of the likelihoods of  $h_{i,t}^d$  and  $h_{i,t}^{d-1}$ , respectively. The acceptance ratio is

$$a = \min \left\{ \frac{(h_{i,t}^d)^{-0.5} \exp(-\frac{\widetilde{\varsigma}_{i,t}^2}{2h_{i,t}^d})}{(h_{i,t}^{d-1})^{-0.5} \exp(-\frac{\widetilde{\varsigma}_{i,t}^2}{2h_{i,t}^{d-1}})}, 1 \right\} \quad (\text{A-12})$$

and, we retain  $h_{i,t}^{d-1}$  when we reject the proposal  $h_{i,t}^d$ . Observe that we need to implement a Metropolis step date to date, for each  $i$ .

*Step v: Covariance parameters ( $\alpha$ )*

This step deals with sampling constant covariance parameters conditional on the data and the other parameters. In particular, given  $Y^T$ , and the realisations of  $\sigma$  and  $\theta^T$ ,

$$A\tilde{\zeta}_t = \hat{\zeta}_t \quad (\mathbf{A-13})$$

where  $\hat{\zeta}_t$  is a vector of orthogonalised residual  $\tilde{\zeta}_t$  (note that the latter have already been standardised by  $\sigma_t$ ) with error variance  $H_t$ . Following again Cogley and Sargent (2005), the system above takes the form of NG unrelated equations, where the first equation

$$\tilde{\zeta}_{1,t} = \hat{\zeta}_{1,t} \quad (\mathbf{A-14})$$

is an identity. Next, the remaining NG-1 equations take the form of transformed equations. For example the second and third equations are

$$\begin{aligned} h_{2,t}^{-.5}\tilde{\zeta}_{2,t} &= \alpha_{2,1}(-h_{2,t}^{-.5}\tilde{\zeta}_{1,t}) + (h_{2,t}^{-.5}\hat{\zeta}_{1,t}) \\ h_{3,t}^{-.5}\tilde{\zeta}_{3,t} &= \alpha_{3,1}(-h_{3,t}^{-.5}\tilde{\zeta}_{1,t}) + \alpha_{3,2}(-h_{3,t}^{-.5}\tilde{\zeta}_{2,t}) + (h_{3,t}^{-.5}\hat{\zeta}_{2,t}) \end{aligned} \quad (\mathbf{A-15})$$

and, the same logic applies to for  $i = 4, \dots, NG$ . The usual argument applies, conditional on the data,  $\sigma$ ,  $\theta^T$  and  $H^T$ , the realisations of  $B$  and  $\sigma_{SV}$  are irrelevant to sample the covariance parameters. However, observe that, because the standardised residuals are independent, to sample any covariance on the  $i$ -th row of  $A$ , the realisations of  $h_j^T$  for  $j \neq i$  are irrelevant. To sum up, the covariance parameters are simply the coefficients of NG unrelated Gaussian and linear regression models. Hence, given a normal prior for the regression coefficients in each equation

$$\pi(\alpha_i) = N(\alpha_{i,0}, V_{i,0}), \quad i = 2, 3, \dots, NG$$

the posterior is normal,

$$\pi(\alpha_i | Y^T, \theta^T, h_i^T, \sigma) = N(\alpha_{i,1}, V_{i,1}), \quad i = 2, 3, \dots, NG \quad (\mathbf{A-16})$$

where

$$\begin{aligned} V_{i,1} &= (V_{i0}^{-1} + Z_i' Z_i)^{-1} \\ \alpha_{i,1} &= V_{i,1}(V_{i0}^{-1} \alpha_{i,1} + Z_i' z_i) \end{aligned}$$

and the  $Z_i$  and  $z_i$  are the right and left-hand variables of equation  $i$ , respectively.

*Step vi: Factor loadings ( $\theta^T$ )*

The model is linear, and has a conditional Gaussian state-space representation. Conditional on  $\alpha$  and  $H_t$ , we can compute  $\Omega_t$ , and given a realisation of  $\sigma$ , we recover the full variance-covariance matrix of the measurement equation  $\Upsilon_t$ .<sup>29</sup> Conditional on  $B$ , and  $\Upsilon^T$ , defined as the entire sequence of  $\Upsilon_t$ , the joint posterior density of  $\theta^T$  is

$$\pi(\theta^T | \Upsilon^T, B, Y^T) = \pi(\theta_T | \Upsilon^T, B, Y^T) \prod_{t=1}^{T-1} \pi(\theta_t | \theta_{t+1}, \Upsilon_t, B, Y^t) \quad (\mathbf{A-17})$$

The conditional posterior of  $\theta^T$  can be obtained with a run of the Kalman filter and a simulation smoother as in Carter and Kohn (1994), or Chib and Greenberg (1995) among others. Given  $\theta_{0|0}$  and  $R_{0|0}$  the Kalman filter forward recursion are

$$\begin{aligned} K_t &= R_{t|t-1} (\Xi X_t) ((\Xi X_t)' R_{t|t-1} (\Xi X_t) + \Upsilon_t)^{-1} \\ \theta_{t|t} &= \theta_{t-1|t-1} + K_t (Y_t - (\Xi X_t)' \theta_{t-1|t-1}) \\ R_{t|t-1} &= R_{t-1|t-1} + B \\ R_{t|t} &= R_{t|t-1} - K_t (\Xi X_t)' R_{t|t-1} \end{aligned} \quad (\mathbf{A-18})$$

<sup>29</sup>In general,  $\Upsilon_t$  displays two sources of heteroskedasticity, one due to the factor structure imposed, and the second due to the time-varying volatilities of the original VAR representation. Note that if the factor structure imposed on the coefficients is perfect,  $\Upsilon_t = \sigma_t \Omega_t$  and we (approximately) go back to a standard state space with stochastic volatility as in Cogley and Sargent (2005) among others. On the contrary, if  $\Omega$  is homoskedastic,  $\Upsilon_t = \sigma_t \Omega$ , the posterior of  $\theta^T$  is specified as in Canova and Ciccarelli (2008).

where  $\theta_{t|t} \equiv E(\theta_t | \Upsilon^T, B, Y^t)$ ,  $P_{t|t-1} \equiv Var(\theta_t | \Upsilon^T, B, Y^{t-1})$ , and  $P_{t|t} \equiv Var(\theta_t | \Upsilon^T, B, Y^{t-1})$  are the mean and, respectively, the predicted and smoothed variance-covariance matrices.

The last forward recursion delivers  $\pi(\theta_T | \Upsilon^T, B, Y^T) = N(\theta_{T|T}, R_{T|T})$ , the first term of the joint posterior ((A-17)). The simulation smoother provides the updated estimates of the conditional means and variances,  $\theta_{t|t+1} \equiv E(\theta_t | \theta_{t+1}, \Upsilon^T, B, Y^t)$  and  $P_{t|t} \equiv Var(\theta_t | \theta_{t+1}, \Upsilon^T, B, Y^t)$ , respectively. Precisely,

$$\begin{aligned}\theta_{t|t+1} &= \theta_{t|t} + R_{t|t} R_{t+1|t}^{-1} (\theta_{t+1}^d - \theta_{t|t}) \\ R_{t|t+1} &= R_{t|t} - R_{t|t} R_{t+1|t}^{-1} R_{t|t}\end{aligned}\tag{A-19}$$

fully determine the remaining densities of equation (A-17),

$$\pi(\theta_t | \theta_{t+1}, \Upsilon_t, B, Y^t) = N(\theta_{t|t+1}, R_{t|t+1})\tag{A-20}$$

To obtain an entire sample of  $\theta^T$ , the simulation smoother works as follows. First, draw  $\theta_T^d$ , then compute  $R_{T-1|T}$  and  $\theta_{T-1|T}$ , using  $\theta_T^d$ . Second, draw  $\theta_{T-1}^d$  from  $N(\theta_{T-1|T}, R_{T-1|T})$  and so forth. Finally, draw  $\theta_1^d$  from  $N(\theta_{1|2}, R_{1|2})$ .

### ***Reversible jump Monte Carlo Markov Chain (RJCMC)***

The RJCMC selects the best model out of M competing models. Model specifications vary because of the number of factors, the type of factors and factor loadings, and the precision of the factorisation (Table A summarises all the combinations considered). Let define  $\Theta_m$  as a collection of unknown parameters and latent factors of model  $m$ , as

$$\Theta_m = \{\sigma^{2,m}, B^m, \theta_1^m, \dots, \theta_T^m, \log h_1^m, \dots, \log h_T^m, \alpha^m\}\tag{A-21}$$

The RJCMC addresses the problem of simulating the joint posterior probability distribution of the couple  $(\Theta_m, m)$ , by drawing from a proposal density  $q_P(\Theta_m, m)$ . By the Bayes theorem this density is decomposed as the product of  $J(m)$  and  $q(\Theta_m | m)$ . This implies two steps, a model  $m$  is drawn, and conditional on  $m$  a sample  $\Theta_m$  is simulated. That said, the bulk of the RJCMC hinges upon a Metropolis step. As usual the chain shifts to a new proposal couple  $(\Theta_{m'}, m')$ , or remains at the old one  $(\Theta_m, m)$ , according to an acceptance/rejection ratio  $a$ . Among other

things, the way the acceptance ratio is computed is peculiar. What follows describes step by step the RJMCMC algorithms, and it closely follows Primiceri (2005), with the appropriate changes due to the underlying model.

*Step 0:* the RJMCMC requires a set of proposal densities. The matrix  $J(m)$ , with prespecified transition probabilities, determines the migration across models. Precisely, in our case the migration matrix is such that there is equal probability of migrating to any of the other models from each model, and zeros on the main diagonal. As for drawing the parameters conditional on the models, we use the following distributions

$$q(\sigma^{2,m}|m) = IG(\overline{3\sigma^{2,m}}, 5) \quad (\text{A-22})$$

$$q(B^m|m) = IW(100 \cdot \overline{B^m}, 100)$$

$$q(\theta_t^m|m) = N(\overline{\theta_t^m}, 2 \cdot \overline{var(\theta_t^m)})$$

$$q(\log h_t^m|m) = N(\overline{\log h_t^m}, 2 \cdot \overline{var(\log h_t^m)}) \quad (\text{A-23})$$

$$q(\alpha^m|m) = N(\overline{\alpha^m}, \overline{var(\alpha^m)})$$

To calibrate these densities, a preliminary estimate is necessary for every model.<sup>30</sup> The variables denoted with the upper bar are the outcome of the preliminary estimate for model  $m$ . Precisely,  $\overline{\sigma^{2,m}}$ ,  $\overline{\theta_t^m}$ ,  $\overline{\log h_t^m}$ , and  $\overline{\alpha^m}$  are posterior means, whereas  $\overline{var(\theta_t^m)}$ ,  $\overline{var(\log h_t^m)}$  and  $\overline{var(\alpha^m)}$  are posterior variances. Observe we need to simulate the proposal  $q(\sigma^{2,m}|m)$  only for those models with no perfect factorisation.

*Step 1:* Initialise the algorithm by selecting a starting model  $m$ , and draw a sample  $\Theta_m$  from  $q(\Theta_m|m)$ .

*Step 2:* Draw a new couple  $(\Theta_{m'}, m')$ . First, draw a candidate model,  $m'$ , from the proposal distribution  $J(m)$ . Second, given  $m'$ , draw the parameters  $\Theta_{m'}$ .

*Step 3:* Compute the acceptance probability as

$$a = \min \left\{ \frac{L(Y^T|\Theta_{m'}, m') \cdot \pi(\Theta_{m'}) \cdot p(m')}{L(Y^T|\Theta_m, m) \cdot \pi(\Theta_m) \cdot p(m)} \frac{q(\Theta_m|m) \cdot J(m' \rightarrow m)}{q(\Theta_{m'}|m') \cdot J(m \rightarrow m')}, 1 \right\} \quad (\text{A-24})$$

<sup>30</sup>Primiceri (2005) performs 2,000 iterations, of which the first 500 are discarded. In this paper, the proposal densities are centred to a complete estimate of the model.

Here, for each value  $j$ ,  $L(Y^T|\Theta_j, j)$  is the likelihood function,  $\pi(\Theta_j)$  is the prior on the parameters,  $p(j)$  is the prior on the model, and  $J(m' \rightarrow m)$  the transition probability from model  $j'$  to model  $j$ . Thus, accept the jump to the new couple  $(\Theta_{m'}, m')$  with probability  $a$ , otherwise keep the old couple  $(\Theta_m, m)$ .

*Step 4:* Go back to 2. And iterate over the steps 2-3 until convergence.

### ***Convergence diagnostics***

This appendix deals with the convergence of the Markov chain Monte Carlo algorithm. Recall, we performed 100,000 replications of which the first  $S_0 = 50,000$  are burned, and we retain 1 every 50 draws of the last  $S_1 = 50,000$  replications of the Markov chain. To explore whether the chain has converged we consider two diagnostics, the numerical standard error (NSE), and the convergence diagnostic (CD) of Geweke (1992). The NSE is a widely used measure of the approximation error, furthermore a good estimate of NSE has to compensate for the correlation in the draws (Koop (2003)). The second diagnostic, CD, relies on the idea that an estimate of the parameter based on the first half of the draws must be essentially the same to an estimate based on the last half. If this was not the case, then either the number of replications is too small, or the effect of the starting value has not vanished. Namely, CD is computed as

$$CD = \frac{\hat{\beta}_{S_A} - \hat{\beta}_{S_C}}{\frac{\hat{\sigma}_{S_A}}{\sqrt{S_A}} + \frac{\hat{\sigma}_{S_C}}{\sqrt{S_C}}} \quad (\text{A-25})$$

where  $\hat{\beta}_{S_A}$  and  $\hat{\beta}_{S_C}$  are the posterior estimates of the parameter  $\beta$  over  $S_A$  and  $S_B$ , the first 10% of draws the last 40% of the draws, respectively.<sup>31</sup> And  $\frac{\hat{\sigma}_{S_A}}{\sqrt{S_A}}$  and  $\frac{\hat{\sigma}_{S_C}}{\sqrt{S_C}}$  are the numerical standard errors. CD is distributed as a standard normal, thus values of CD less than 1.96, in absolute value, support the convergence of the Markov chain Monte Carlo. Table B, C and D present the posterior results, and the convergence diagnostics, for the standard deviations of the stochastic volatilities, the Cholesky parameters, and the variances of the time-varying factor loadings.<sup>32</sup> And the convergence diagnostic support convergence of the chain. Finally, Figure 7 provides the CD for the stochastic volatilities, and the evidence is in favour of convergence, a part for few states, which mainly correspond to outliers in the data.

<sup>31</sup>Following Koop (2003), the middle set of 50% of the draws is dropped to have the first and second set of draws to be independent.

<sup>32</sup>To compute the NSE and CD I use the codes of James P LeSage.

**Table A: Model comparison**

	EM Fac	Reg. Fac.	Var. Fac.	Exg. Fac.		Fac Prec.
				C	V	$\sigma = 0$
<b>M1</b>	×	×	×	×		×
<b>M2</b>	×	×	×		×	×
<b>M3</b>	×	×	×	×		
<b>M4</b>	×	×	×		×	
<b>M5</b>	×	×		×		×
<b>M6</b>	×	×		×		
<b>M7</b>	×	×			×	×
<b>M8</b>	×	×			×	

Notes: This table summarises the features of several competing models (M1-M8), these models are compared by means of the RJMCMC, see appendix for a description of the method. These models differ for the specification of the factor structure, and of the loadings on the factors. The first row denotes the factors, the emerging market factor (EM Fac), the regional factor (Reg. Fac.), the variable factor (Var. Fac.), the exogenous factor (Exg. Fac.), and the last column (Fac. Prec.) indicates whether the factorisation is precise or not. The second row describes the factor loading structure, whether the loading is common to all the units (C), or variable specific (V). Finally, the ticker × selects the appropriate combination.

**Table B: Posterior results for  $\sigma_{SV,i}$** 

	mean	st. dev	NSE	CD
$\sigma_{SV,1}$	0.254	0.028	0.0009	1.28
$\sigma_{SV,2}$	0.462	0.047	0.0015	0.24
$\sigma_{SV,3}$	0.246	0.027	0.0009	0.74
$\sigma_{SV,4}$	0.311	0.039	0.0012	0.48
$\sigma_{SV,5}$	0.240	0.029	0.0009	0.42
$\sigma_{SV,6}$	0.383	0.044	0.0014	0.30
$\sigma_{SV,7}$	0.790	0.066	0.0021	1.32
$\sigma_{SV,8}$	0.437	0.046	0.0015	0.07

Notes: This table presents the posterior mean, the standard deviation (st. dev.), the numerical standard error (NSE), and the absolute value of the convergence diagnostic (CD), as in Geweke (1992), for the standard deviations of the stochastic volatility innovations ( $\sigma_{SV,i}$ ).

**Table C: Posterior results for A**

	mean	st. dev.	NSE	CD		mean	st. dev.	NSE	CD
$\alpha(2, 1)$	-0.582	0.032	0.0010	1.13	$\alpha(6, 5)$	-0.281	0.029	0.0009	0.28
$\alpha(3, 1)$	-0.550	0.028	0.0009	0.75	$\alpha(7, 1)$	0.053	0.029	0.0009	0.46
$\alpha(3, 2)$	-0.175	0.017	0.0005	0.74	$\alpha(7, 2)$	-0.231	0.031	0.0010	0.35
$\alpha(4, 1)$	-0.002	0.015	0.0005	0.13	$\alpha(7, 3)$	-0.098	0.038	0.0012	0.70
$\alpha(4, 2)$	-0.150	0.021	0.0007	0.26	$\alpha(7, 4)$	-0.088	0.040	0.0013	0.10
$\alpha(4, 3)$	-0.389	0.022	0.0007	0.82	$\alpha(7, 5)$	-0.265	0.034	0.0011	0.54
$\alpha(5, 1)$	-0.181	0.029	0.0009	-0.12	$\alpha(7, 6)$	-0.118	0.015	0.0005	0.80
$\alpha(5, 2)$	-0.126	0.021	0.0007	0.37	$\alpha(8, 1)$	0.005	0.013	0.0004	0.72
$\alpha(5, 3)$	-0.313	0.038	0.0012	0.71	$\alpha(8, 2)$	-0.108	0.018	0.0006	0.96
$\alpha(5, 4)$	-0.218	0.035	0.0011	0.09	$\alpha(8, 3)$	-0.011	0.035	0.0011	0.26
$\alpha(6, 1)$	0.019	0.016	0.0005	0.07	$\alpha(8, 4)$	-0.268	0.043	0.0014	0.48
$\alpha(6, 2)$	-0.154	0.026	0.0008	0.87	$\alpha(8, 5)$	-0.029	0.027	0.0008	0.50
$\alpha(6, 3)$	-0.097	0.043	0.0014	1.15	$\alpha(8, 6)$	-0.184	0.018	0.0006	0.55
$\alpha(6, 4)$	-0.389	0.054	0.0017	0.32	$\alpha(8, 7)$	-0.002	0.010	0.0003	0.96

Notes: This table presents the posterior mean, the standard deviation (st. dev.), the numerical standard error (NSE), and the absolute value of the convergence diagnostic (CD), as in Geweke (1992), for the Cholesky parameters of matrix A, recall that  $\Omega_t = A^{-1}H_tA^{-1'}$ .

**Table D: Posterior results for B**

	mean (%)	st. dev (%)	NSE (%)	CD
$\text{var}(\theta_1)$	0.21	0.03	0.0009	0.73
$\text{var}(\theta_2^1)$	0.42	0.06	0.0018	0.16
$\text{var}(\theta_2^2)$	0.30	0.04	0.0013	0.32
$\text{var}(\theta_2^3)$	0.40	0.04	0.0012	0.68
$\text{var}(\theta_2^4)$	0.13	0.02	0.0005	0.82
$\text{var}(\theta_3^1)$	1.29	0.18	0.0057	1.57
$\text{var}(\theta_3^2)$	0.78	0.09	0.0028	0.05
$\text{var}(\theta_4^1)$	0.92	0.15	0.0048	1.10
$\text{var}(\theta_4^2)$	0.48	0.08	0.0024	0.62
$\text{var}(\theta_5^1)$	1.55	0.18	0.0057	1.05
$\text{var}(\theta_5^2)$	1.01	0.09	0.0029	0.46

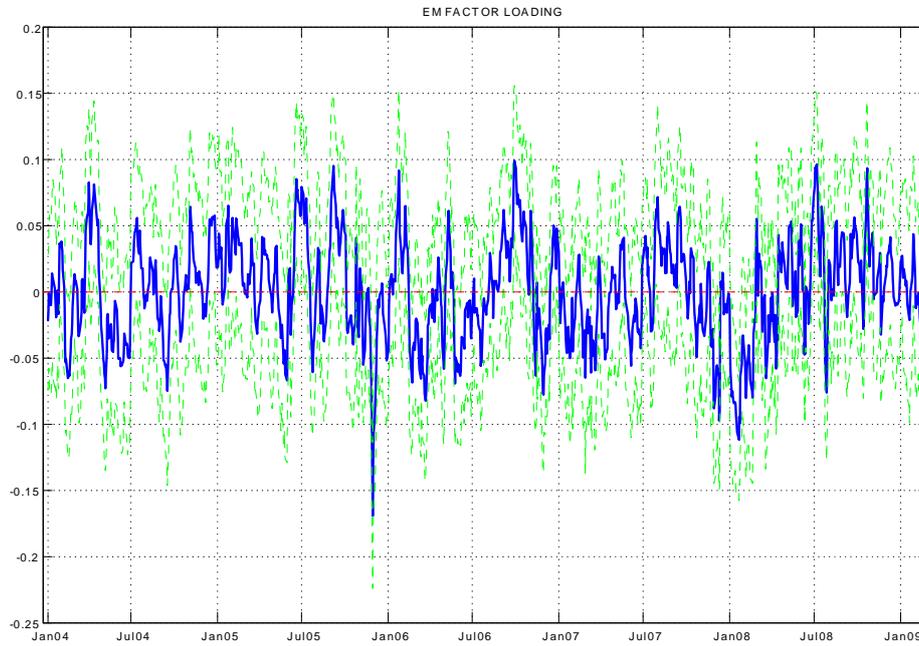
Notes: This table presents the posterior mean, the standard deviation (st. dev.), the numerical standard error (NSE), and the absolute value of the convergence diagnostic (CD), as in Geweke (1992), for variances of the factor loadings innovations, ie the main diagonal of the matrix B. Recall that,  $\theta_1$  is the common emerging market loading, and  $\theta_2^i$  is the country loading of the regions LatAm, Europe, Asia, and Mideast, for  $i=1 \dots 4$ , respectively.  $\theta_3^i$ ,  $\theta_4^i$ , and  $\theta_5^i$  refer to the loading on VIX, CREDIT and FL, respectively, and the superscripts  $i = 1$  and  $2$  denote the loadings on sovereign and corporate, respectively.

**Table E: Contemporaneous correlations**

	EMEI	LAT-GI	EUR-GI	AS-GI	MID-GI
US equity indices					
Nasdaq	-0.43	-0.53	-0.58	-0.54	-0.42
FTSE	-0.42	-0.52	-0.47	-0.52	-0.42
S&P500	-0.52	-0.62	-0.68	-0.63	-0.51
US Treasury yields					
US $r^{3m}$	-0.21	-0.33	-0.25	-0.31	-0.21
US $r^{10yr}$	-0.01	-0.06	0.05	-0.08	-0.11
Slope	0.19	0.26	0.28	0.22	0.10
FX volatility					
USD-RV	0.62	0.63	0.69	0.69	0.59
EM-RV	0.79	0.84	0.64	0.87	0.62
Other measures					
Oil price	-0.49	-0.50	-0.52	-0.53	-0.50
Commodity	-0.53	-0.50	-0.53	-0.53	-0.49
CDX-EM	0.58	0.66	0.66	0.64	0.10

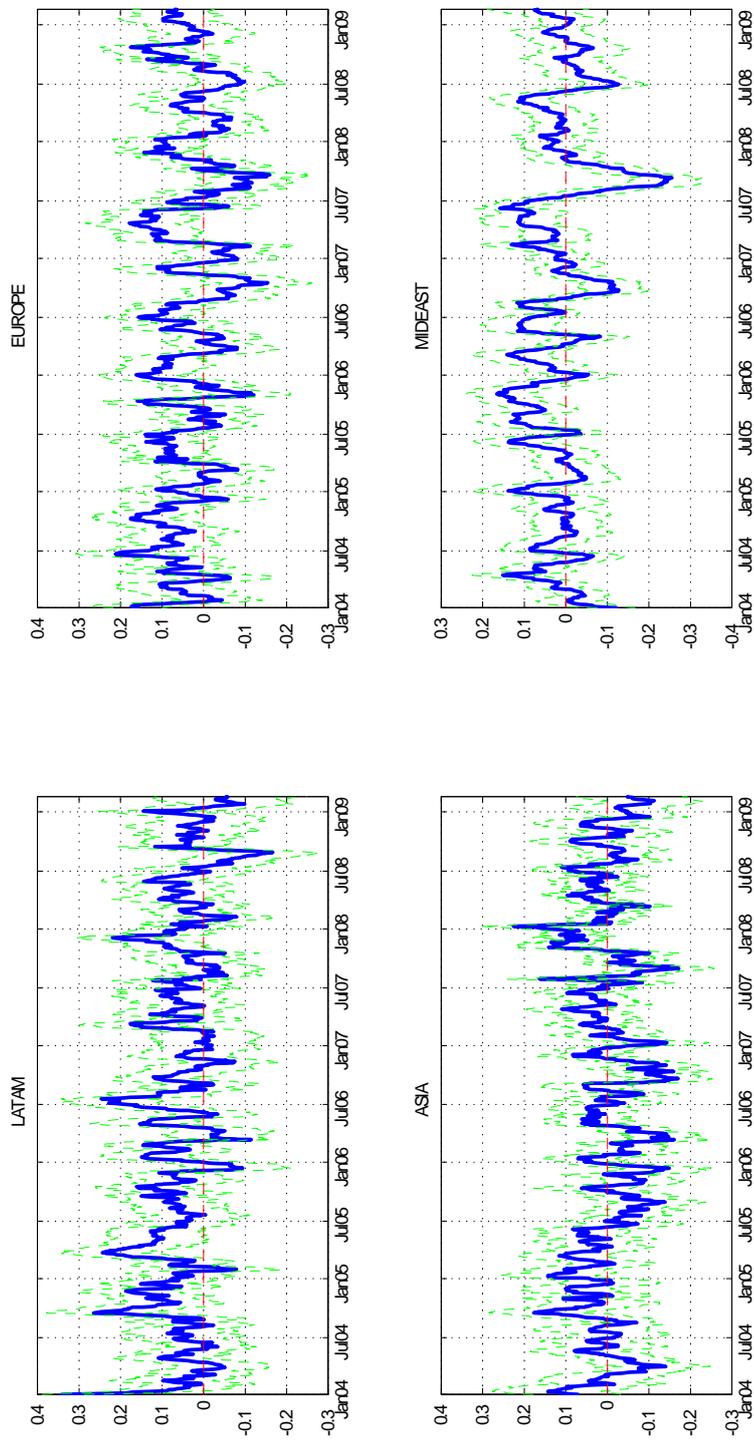
Notes: This table presents the correlation of the emerging market indicator (EMEI) and four regional global (REG-GI) indicators with several variables (in changes), listed in column 1, at a monthly frequency. Namely,  $REG^i-GI_t = EMEI_t + REGI_t^i$ , for example, LAT-GI equals EMEI plus the LatAm regional indicator  $REGI^1$ . As for the variables placed in the first column, we use three US equity indices, Nasdaq, FTSE, and S&P500. Two US Treasury yields, ie the three-month (US  $r^{3m}$ ) and ten-years (US  $r^{10yr}$ ), and the slope of the US term structure (Slope), ie  $US r^{10yr} - US r^{3m}$ . USD-RV refers to the realised volatility effective US-dollar exchange rate, whereas EM-RV consist of a global emerging market and four regional measures of realised volatility of the effective exchange rates. Other measures encompass the oil price, a commodity index, and the emerging market credit default index (CDX-EM). Sources: Datastream, JP Morgan, Yahoo Finance and author's calculations.

**Figure 1: Emerging market factor loading**



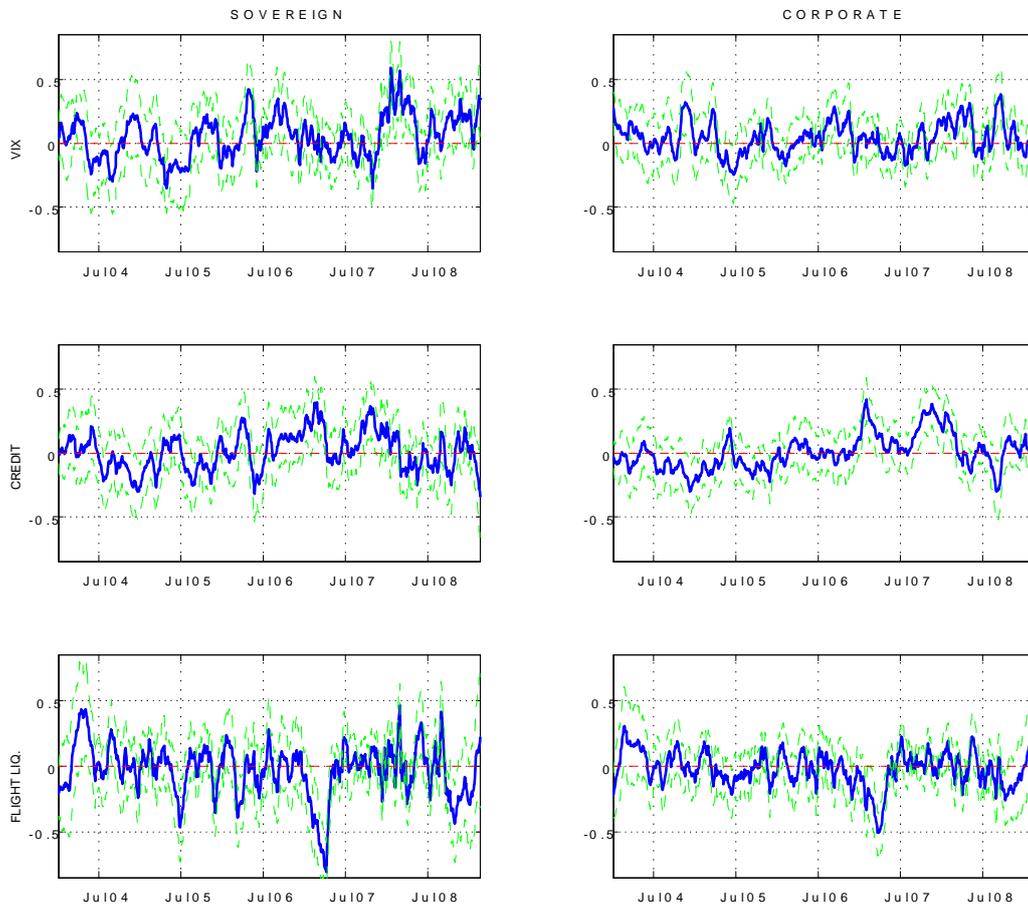
Notes: Posterior medians and one standard deviation confidence intervals.

**Figure 2: Regional factor loadings**



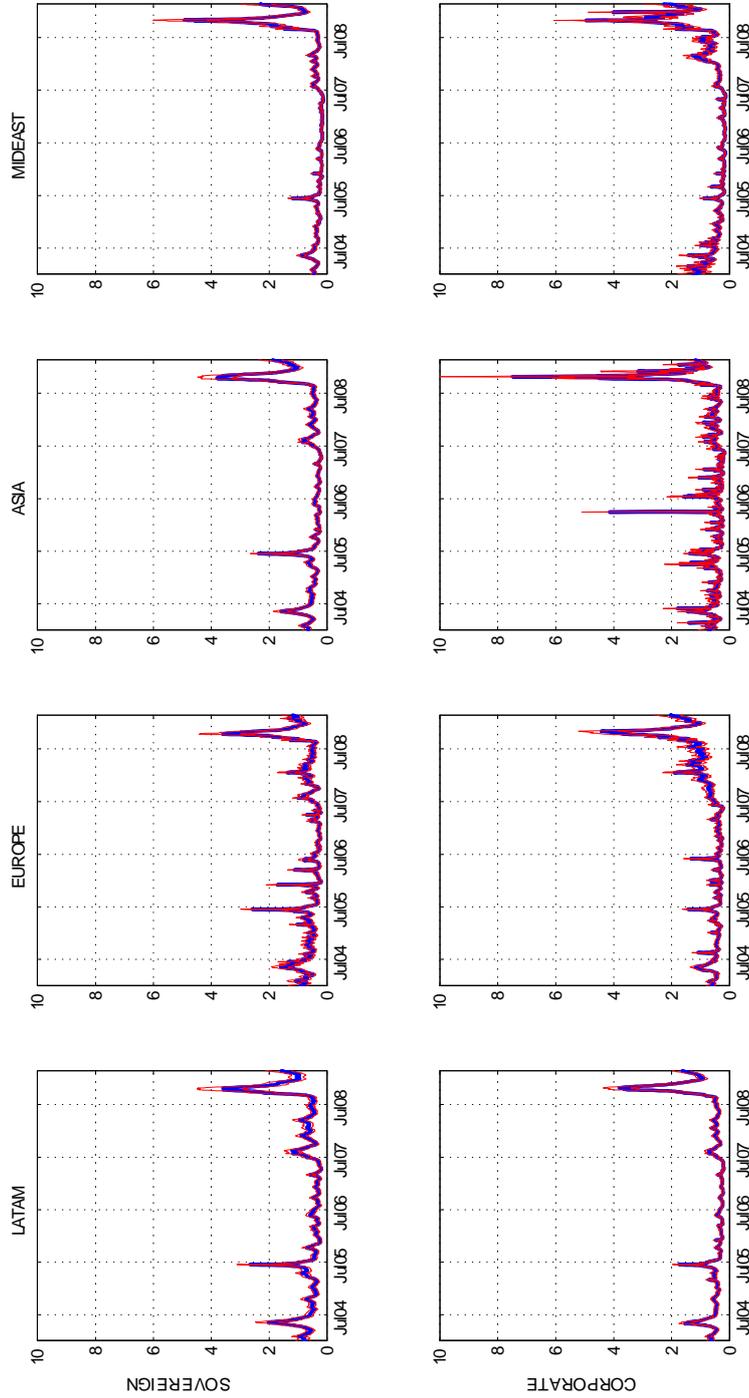
Notes: Posterior medians and one standard deviation confidence intervals of the regional factor loadings: LatAm, Europe, Asia and Mideast.

**Figure 3: Exogenous factor loadings**



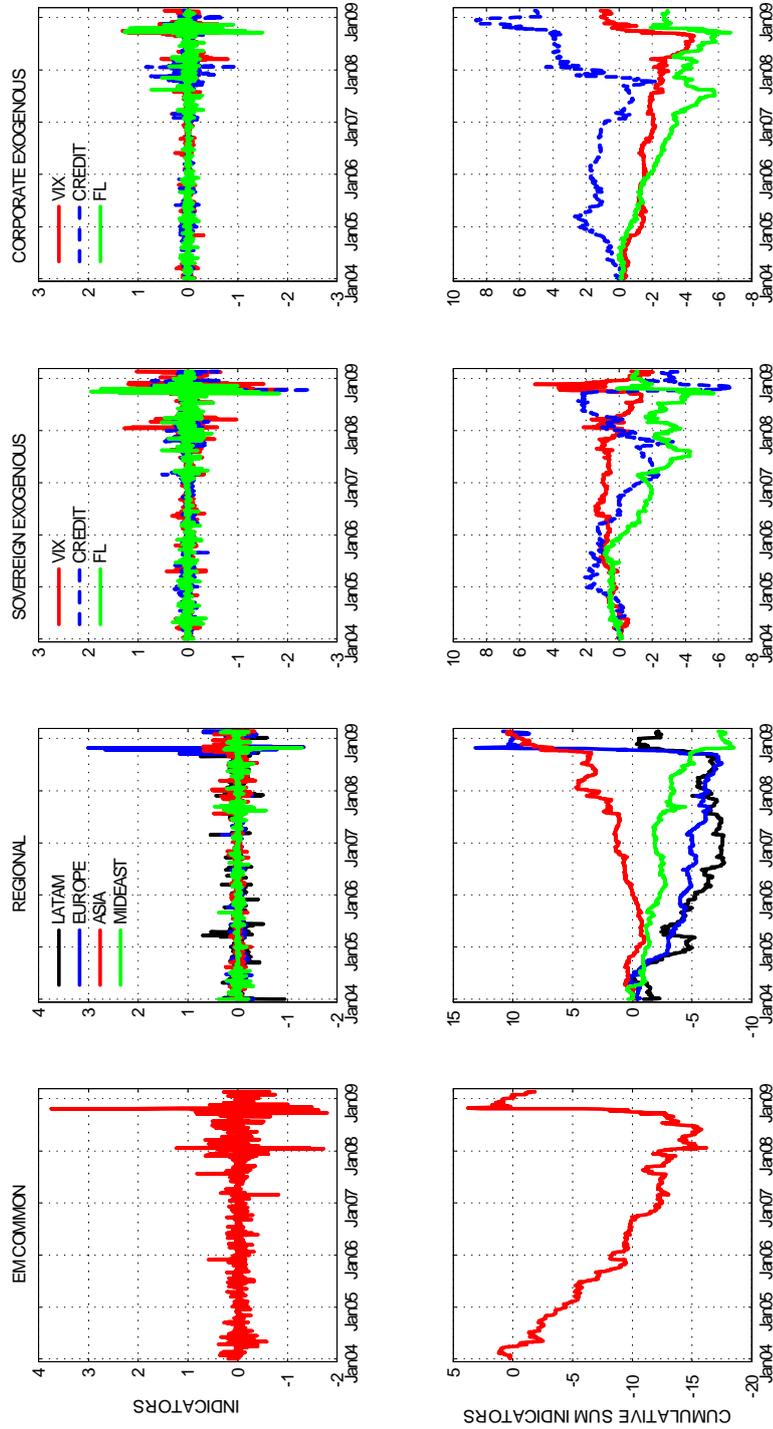
Notes: Posterior medians and one standard deviation confidence intervals of the exogenous factor loadings. There are three factors: CBOE Volatility Index (VIX), the spread between high-yield and investment-grade Merrill Lynch US corporate yields (CREDIT), and the spread between overnight index swap and three-month Treasury yields (FL). Left panels present the estimates for sovereigns, whereas right panels refer to corporates.

**Figure 4: Stochastic volatilities**



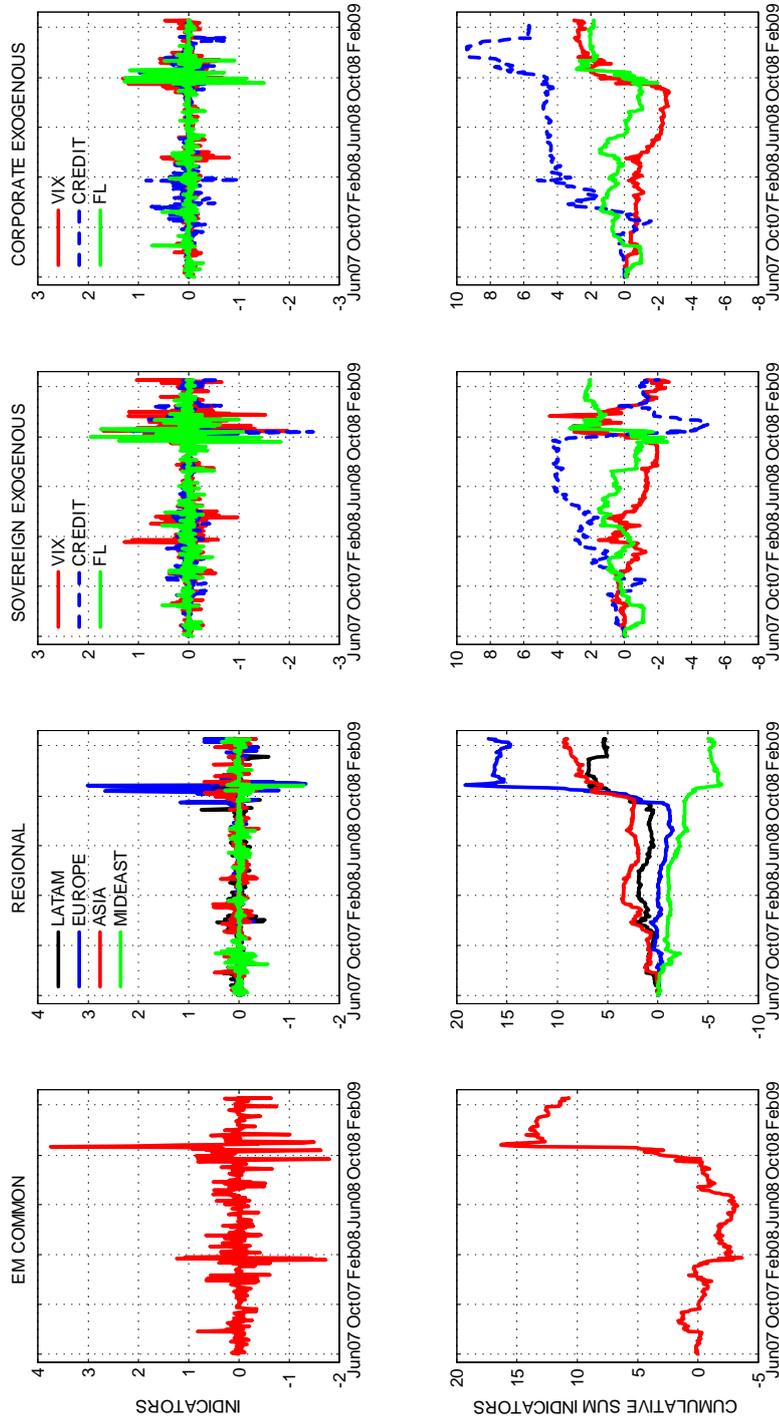
Notes: Standard deviations of smoothed stochastic volatilities estimates and one standard deviation confidence intervals.

Figure 5: Credit indicators



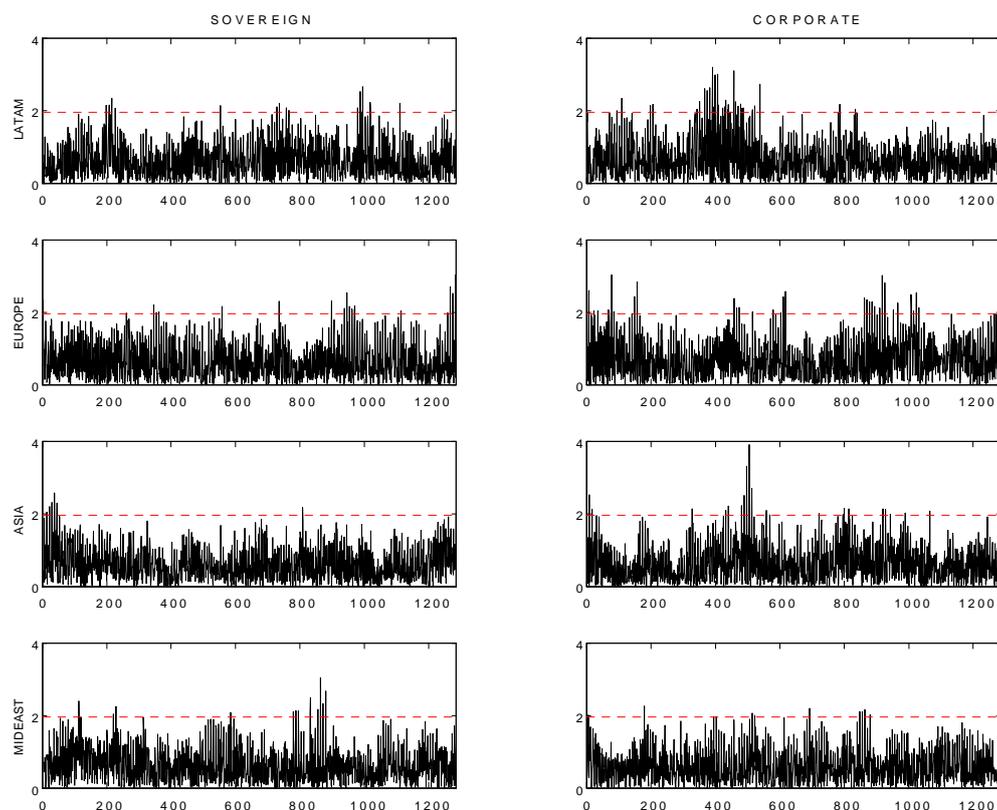
Notes: The top plots present the credit indicators on standardised spread changes: the EM common indicator, the regional indicators, the exogenous indicators for sovereign and corporate, from left to right. The bottom plots display the cumulative sum of the indicators.

**Figure 6: Credit Indicators from June 2007 to February 2009**



Notes: The top plots present the credit indicators on standardised spread changes: the EM common indicator, the regional indicators, the exogenous indicators for sovereign and corporate, from left to right. The bottom plots display the cumulative sum of the indicators.

**Figure 7: Convergence diagnostic stochastic volatilities**



Notes: Convergence diagnostics (CD) computed as in Geweke (1992). The red dotted line indicate 1.96. Recall, Geweke's CD is standard normal, thus a value of CD, in absolute value, which is less than 1.96 is in favour of convergence of the MCMC algorithm.

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