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TECHNICAL APPENDIX TO: UNDERSTANDING LIQUIDITY AND CREDIT RISKS IN THE FINANCIAL CRISIS

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Technical Appendix to: Understanding Liquidity and Credit Risks in the Financial Crisis*

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1 The Gibbs Sampler

This section describes the detailed Gibbs sampler for Bayesian estimation. For all notation, please see the original paper.

1.1 Generating L_{kt} and C_t

To generate L_{kt} and C_t , we first transform the dynamic factor model into a state space form.

Let $S_{ijkt}^* = S_{ijkt} - \beta_{ik}'X_t$, and $D_{jt}^* = D_{jt} - \gamma'Z_t$. The measurement

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equation of the model can be written as:

$$\begin{pmatrix} D_{1t}^* \\ D_{2t}^* \\ \dots \\ D_{Jt}^* \\ S_{111t}^* \\ S_{211t}^* \\ \dots \\ S_{I11t}^* \\ S_{121t}^* \\ S_{221t}^* \\ \dots \\ S_{I21t}^* \\ \dots \\ S_{IJ1t}^* \\ S_{112t}^* \\ S_{212t}^* \\ \dots \\ S_{IJ2t}^* \\ \dots \\ S_{1Kt}^* \\ S_{2Kt}^* \\ \dots \\ S_{IJKt}^* \end{pmatrix} = \begin{pmatrix} \psi_1^C & 0 & 0 & \dots & 0 \\ \psi_2^C & 0 & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ \psi_1^J & 0 & 0 & \dots & 0 \\ \psi_1^S & \lambda_{111}^S & 0 & \dots & 0 \\ \psi_{21}^S & \lambda_{111}^S & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ \psi_{I1}^S & \lambda_{111}^S & 0 & \dots & 0 \\ \psi_{12}^S & \lambda_{121}^S & 0 & \dots & 0 \\ \psi_{22}^S & \lambda_{221}^S & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ \psi_{I2}^S & \lambda_{I21}^S & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ \psi_{IJ}^S & \lambda_{IJ1}^S & 0 & \dots & 0 \\ \psi_{11}^S & 0 & \lambda_{112}^S & \dots & 0 \\ \psi_{21}^S & 0 & \lambda_{212}^S & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ \psi_{IJ}^S & 0 & \lambda_{IJ2}^S & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ \psi_{11}^S & 0 & 0 & \dots & \lambda_{11K}^S \\ \psi_{21}^S & 0 & 0 & \dots & \lambda_{21K}^S \\ \dots & \dots & \dots & \dots & \dots \\ \psi_{IJ}^S & 0 & 0 & \dots & \lambda_{IJK}^S \end{pmatrix} \begin{pmatrix} C_t \\ L_{1t} \\ \dots \\ L_{Kt} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t}^D \\ \epsilon_{2t}^D \\ \dots \\ \epsilon_{Jt}^D \\ \epsilon_{111t}^S \\ \epsilon_{211t}^S \\ \dots \\ \epsilon_{I11t}^S \\ \epsilon_{121t}^S \\ \epsilon_{221t}^S \\ \dots \\ \epsilon_{I21t}^S \\ \dots \\ \epsilon_{IJ1t}^S \\ \epsilon_{112t}^S \\ \epsilon_{212t}^S \\ \dots \\ \epsilon_{IJ2t}^S \\ \dots \\ \epsilon_{1Kt}^S \\ \epsilon_{2Kt}^S \\ \dots \\ \epsilon_{IJKt}^S \end{pmatrix} \quad (1)$$

$$(y_t = H\xi_t + e_t) \quad (2)$$

where $e_t \sim i.i.d.N(0, R)$, the size of y_t is $J + IJK$ by 1, the size of H is $J + IJK$ by $1 + K$, and the size of ξ_t is $1 + K$ by 1.

The transition equation can be written as

$$\begin{pmatrix} C_t \\ L_{1t} \\ \dots \\ L_{Kt} \end{pmatrix} = \begin{pmatrix} \phi_0^C(s_t^C) \\ \phi_{10}^L(s_t^L) \\ \dots \\ \phi_{K0}^L(s_t^L) \end{pmatrix} + \begin{pmatrix} \phi_1^C(s_t^C) & 0 & \dots & 0 \\ 0 & \phi_{11}^L(s_t^L) & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \phi_{K1}^L(s_t^L) \end{pmatrix} \begin{pmatrix} C_{t-1} \\ L_{1,t-1} \\ \dots \\ L_{K,t-1} \end{pmatrix} + \begin{pmatrix} \sigma_C(s_t^C)\nu_t^C \\ \sigma_{1L}(s_t^L)\nu_{1t}^L \\ \dots \\ \sigma_{KL}(s_t^L)\nu_{Kt}^L \end{pmatrix} \quad (3)$$

$$(\xi_t = \mu_t + F_t\xi_{t-1} + \epsilon_t) \quad (4)$$

where $\epsilon_t \sim i.i.d.N(0, Q_t)$, the size of ξ_t is $1 + K$ by 1, the size of μ_t is $1 + K$ by 1, and the size of F_t is $1 + K$ by $1 + K$.

Let $\tilde{y}_t = (y_1, y_2, \dots, y_t)'$. Following Kim and Nelson (1999, Ch. 8), we can draw the latent risk factors in the following two steps.

First run Kalman filter to calculate $\xi_{t|t} = E(\xi_t|\tilde{y}_t)$ and $P_{t|t} = Cov(\xi_t|\tilde{y}_t)$ for $t = 1, 2, \dots, T$:

$$\begin{aligned} \xi_{t|t-1} &= \mu_t + F_t\xi_{t-1} \\ P_{t|t-1} &= F_tP_{t-1}F_t' + Q_t \\ \xi_{t|t} &= \xi_{t|t-1} + P_{t|t-1}H'(HP_{t-1}H' + R)^{-1}(y_t - H\xi_{t|t-1}) \\ P_{t|t} &= P_{t|t-1} - P_{t|t-1}H'(HP_{t-1}H' + R)^{-1}HP_{t-1} \end{aligned}$$

Next, we draw ξ_T based on the last iteration of the Kalman filter:

$$\xi_T | \tilde{y}_T \sim N(\xi_{T|T}, P_{T|T})$$

Let $\xi_{t+1} = (C_{t+1}, L_{1,t+1}, \dots, L_{K,t+1})'$. We have

$$\xi_{t+1} = \mu_{t+1} + F_{t+1}\xi_t + \epsilon_{t+1}$$

Defining Q_{t+1} the variance of ϵ_{t+1} , for $t = T-1, T-2, \dots, 1$, we can derive $\xi_t | \tilde{y}_T$ backward from

$$\xi_t | \tilde{y}_t, \xi_{t+1} \sim N(\xi_{t|t, \xi_{t+1}}, P_{t|t, \xi_{t+1}})$$

where

$$\xi_{t|t, \xi_{t+1}} = \xi_{t|t} + P_{t|t} F_{t+1}' \{F_{t+1} P_{t|t} F_{t+1}' + Q_{t+1}\}^{-1} (\xi_{t+1} - \mu_{t+1} - F_{t+1} \xi_{t|t})$$

$$P_{t|t, \xi_{t+1}} = P_{t|t} - P_{t|t} F_{t+1}' \{F_{t+1} P_{t|t} F_{t+1}' + Q_{t+1}\}^{-1} F_{t+1} P_{t|t}$$

There are many observations missing, especially in the CDS data. To treat the missing elements in y_t , following Durbin and Koopman (2008, Ch. 4), we replace y_t , H and R by y_t^* , H_t^* and R_t^* , where $y_t^* = W_t y_t$, $H_t^* = W_t H$ and $R_t^* = W_t R W_t'$, with W_t being the known matrix whose rows are a subset of rows of the identity matrix I_{J+IJK} that correspond to the observed values in y_t . Thus, we adjust the dimensions of H and R to account for the fact that there is no new information added to the Kalman filter when data are missing.¹

1.2 Draw Parameters for the Measurement Equations

- **Generating σ_{ijkS}^2 , Conditional on $S_{ijk}, \lambda_{ijk}^S, \psi_{ij}^S, \beta_{ik}, L_{kt}$ and C_t .**

Prior

$$h_{ijkS} \sim G(\underline{s}_{ijkS}^{-2}, \underline{\nu}_{ijkS})$$

where $h_{ijkS} = \sigma_{ijkS}^{-2}$. G denotes a Gamma distribution. Details of the distribution can be found in Koop (2003, p.326).

¹Since generated missing observations contain no new data information aside from the parameters, we don't take them as observed in the Kalman filter. In practice, we find that otherwise the Gibbs sampler hardly converges. Using balanced panel data where rows with missing observations simply deleted, we find very similar results for latent risk factors.

Posterior

$$h_{ijkS}|S_{ijkt}, \lambda_{ijk}^S, \psi_{ij}^S, \beta_{ik}, L_{kt}, C_t \sim G(\bar{s}_{ijkS}^{-2}, \bar{\nu}_{ijkS})$$

where

$$\bar{\nu}_{ijkS} = T - T_{S_{ijk}}^m + \nu_{ijkS}$$

and

$$\bar{s}_{ijkS}^2 = \frac{\sum_{t=1}^T (e_{ijkt}^S)^2 + \nu_{ijkS} s_{ijkS}^2}{\bar{\nu}_{ijkS}}$$

where $e_{ijkt}^S = S_{ijkt} - \lambda_{ijk}^S L_{kt} - \psi_{ij}^S C_t - \beta_{ik}' X_t$ if S_{ijkt} is observed, $T_{S_{ijk}}^m$ is the number of missing observations in S_{ijk} .

- **Generating λ_{ijk}^S , Conditional on S_{ijkt} , ψ_{ij}^S , β_{ik} , h_{ijkS} , L_{kt} and C_t .**

Let $S_{ijkt}^\flat = S_{ijkt} - \beta_{ik}' X_t - \psi_{ij}^S C_t$ if S_{ijkt} is observed. We transform each measurement equation into the following form:

$$S_{ijkt}^\flat = \lambda_{ijk}^S L_{kt} + \varepsilon_{ijkt}^S \quad (5)$$

Prior

$$\lambda_{ijk}^S \sim N(\underline{b}_{\lambda_{ijk}^S}, \underline{V}_{\lambda_{ijk}^S}) \text{ with } \lambda_{ijk}^S > 0$$

Posterior

$$\lambda_{ijk}^S | S_{ijkt}, \psi_{ij}^S, \beta_{ik}, h_{ijkS}, L_{kt}, C_t \sim N(\bar{b}_{\lambda_{ijk}^S}, \bar{V}_{\lambda_{ijk}^S}) \text{ with } \lambda_{ijk}^S > 0$$

where

$$\bar{V}_{\lambda_{ijk}^S} = \{\underline{V}_{\lambda_{ijk}^S}^{-1} + h_{ijkS} L_k' L_k\}^{-1}$$

and

$$\bar{b}_{\lambda_{ijk}^S} = \bar{V}_{\lambda_{ijk}^S} \{\underline{V}_{\lambda_{ijk}^S}^{-1} \underline{b}_{\lambda_{ijk}^S} + h_{ijkS} L_k' S_{ijk}^\flat\}$$

where $S_{ijk}^\flat = [S_{ijk1}^\flat, S_{ijk2}^\flat, \dots, S_{ijkT}^\flat]'$ and $L_k = [L_{k,1}, L_{k,2}, \dots, L_{kT}]'$.

- **Generating ψ_{ij}^S , Conditional on S_{ijkt} , λ_{ijk}^S , β_{ik} , h_{ijkS} , L_{kt} and C_t .**

Let $S_{ijkt}^\natural = S_{ijkt} - \lambda_{ijk}^S L_{kt} - \beta_{ik}' X_t$ if S_{ijkt} is observed. The corresponding measurement equation can be rewritten as

$$S_{ijkt}^\natural = \psi_{ij}^S C_t + \varepsilon_{ijkt}^S \quad (6)$$

Prior

$$\psi_{ij}^S \sim N(\underline{b}_{\psi_{ij}^S}, \underline{V}_{\psi_{ij}^S}) \text{ with } \psi_{ij}^S > 0$$

Posterior

$\psi_{ij}^S | S_{ijkt}, \lambda_{ijk}^S, \beta_{ik}, h_{ijkS}, L_{kt}, C_t \sim N(\bar{b}_{\psi_{ij}^S}, \bar{V}_{\psi_{ij}^S})$ with $\psi_{ij}^S > 0$
where

$$\bar{V}_{\psi_{ij}^S} = \{V_{\psi_{ij}^S}^{-1} + \sum_{k=1}^{K} h_{ijk} C' C\}^{-1}$$

and

$$\bar{b}_{\psi_{ij}^S} = \bar{V}_{\psi_{ij}^S} \{V_{\psi_{ij}^S}^{-1} b_{\psi_{ij}^S} + \sum_{k=1}^{K} h_{ijk} C' S_{ijk}^{\sharp}\}$$

where $S_{ijk}^{\sharp} = [S_{ijk1}^{\sharp}, S_{ijk2}^{\sharp}, \dots, S_{ijkT}^{\sharp}]'$ and $C = [C_1, C_2, \dots, C_T]'$.

- **Generating β_{ik} , Conditional on S_{ijkt} , λ_{ijk}^S , ψ_{ij}^S , h_{ijkS} , L_{kt} and C_t .**

Let $S_{ijkt}^{\sharp} = S_{ijkt} - \lambda_{ijk}^S L_{kt} - \psi_{ij}^S C_t$ if S_{ijkt} is observed. The corresponding measurement equation can be transformed into:

$$S_{ijkt}^{\sharp} = \beta_{ik}' X_t + \varepsilon_{ijkt}^S \quad (7)$$

Prior

$$\beta_{ik} \sim N(\underline{b}_{\beta_{ik}}, \underline{V}_{\beta_{ik}})$$

Posterior

$$\beta_{ik} | S_{ijkt}, \lambda_{ijk}^S, \psi_{ij}^S, h_{ijkS}, L_{kt}, C_t \sim N(\bar{b}_{\beta_{ik}}, \bar{V}_{\beta_{ik}})$$

where

$$\bar{V}_{\beta_{ik}} = \{V_{\beta_{ik}}^{-1} + \sum_{j=1}^J h_{ijk} X' X\}^{-1}$$

and

$$\bar{b}_{\beta_{ik}} = \bar{V}_{\beta_{ik}} \{V_{\beta_{ik}}^{-1} \underline{b}_{\beta_{ik}} + \sum_{j=1}^J h_{ijk} X' S_{ijk}^{\sharp}\}$$

where $S_{ijk}^{\sharp} = [S_{ijk1}^{\sharp}, S_{ijk2}^{\sharp}, \dots, S_{ijkT}^{\sharp}]'$ and $X = [X_1, X_2, \dots, X_t]'$.

- **Generating σ_{jD}^2 , Conditional on D_{jt} , ψ_j^C , γ and C_t .**

Prior

$h_{jD} \sim G(\underline{s}_{jD}^{-2}, \underline{\nu}_{jD})$ where $h_{jD} = \sigma_{jD}^{-2}$

Posterior

$$h_{jD} | D_{jt}, \psi_j^C, \gamma, C_t \sim G(\bar{s}_{jD}^{-2}, \bar{\nu}_{jD})$$

where

$$\bar{\nu}_{jD} = T - T_{D_{jt}}^m + \underline{\nu}_{jD}$$

and

$$\bar{s}_{jD}^{-2} = \frac{\sum_{t=1}^T (e_{jt}^D)^2 + \underline{\nu}_{jD} \underline{s}_{jD}^2}{\bar{\nu}_{jD}}$$

where $T_{D_{jt}}^m$ is the total number of missing observations in D_j , $e_{jt}^D = D_{jt} - \psi_j^C C_t - \gamma' Z_t$ if D_{jt} is observed.

- **Generating ψ_j^C , Conditional on D_{jt} , γ , h_{jD} and C_t .**

Let $D_{jt}^b = D_{jt} - \gamma' Z_t$ if D_{jt} is observed. We rewrite the measurement equation for the credit default variable as:

$$D_{jt}^b = \psi_j^C C_t + \varepsilon_{jt}^D \quad (8)$$

Prior

$\psi_j^C \sim N(\underline{b}_{\psi_j^C}, \underline{V}_{\psi_j^C})$ with $\psi_j^C > 0$

Posterior

$\psi_j^C | D_{jt}, h_{jD}, \gamma, C_t \sim N(\bar{b}_{\psi_j^C}, \bar{V}_{\psi_j^C})$ with $\psi_j^C > 0$

where

$$\bar{V}_{\psi_j^C} = \{\underline{V}_{\psi_j^C}^{-1} + h_{jD} C' C\}^{-1}$$

and

$$\bar{b}_{\psi_j^C} = \bar{V}_{\psi_j^C} \{\underline{V}_{\psi_j^C}^{-1} \underline{b}_{\psi_j^C} + h_{jD} C' D_j^b\}$$

where $D_j^b = [D_{j1}^b, D_{j2}^b, \dots, D_{jT}^b]'$ and $C = [C_1, C_2, \dots, C_T]'$.

- **Generating γ , Conditional on D_{jt} , ψ_j^C , h_{jD} and C_t .**

Let $D_{jt}^b = D_{jt} - \psi_j^C C_t$ if D_{jt} is observed. We rewrite the corresponding measurement equation as:

$$D_{jt}^b = \gamma' Z_t + \varepsilon_{jt}^D \quad (9)$$

Prior

$$\gamma \sim N(\underline{b}_\gamma, \underline{V}_\gamma)$$

Posterior

$$\gamma | D_{jt}, h_{jD}, \psi_j^C, C_t \sim N(\bar{b}_\gamma, \bar{V}_\gamma) \text{ where}$$

$$\bar{V}_\gamma = \{\underline{V}_\gamma^{-1} + \sum_{j=1}^{j=J} h_{jD} Z' Z\}^{-1}$$

and

$$\bar{b}_\gamma = \bar{V}_\gamma \{\underline{V}_\gamma^{-1} \underline{b}_\gamma + \sum_{j=1}^{j=J} h_{jD} Z' D_j^\natural\}$$

where $D_j^\natural = [D_{j1}^\natural, D_{j2}^\natural, \dots, D_{jT}^\natural]'$ and $Z = [Z_1, Z_2, \dots, Z_T]'$.

1.3 Draw Parameters for the Latent Risk Equations

Without loss of generality, we set $s_t^L = 0$ if s_t^L is in ‘good’ state for liquidity risk, and $s_t^L = 1$ if s_t^L is in ‘bad’ state for liquidity risk. Likewise, we set $s_t^C = 0$ if s_t^C is in ‘good’ state for credit risk, and $s_t^C = 1$ if s_t^C is in ‘bad’ state for credit risk.

For notation convenience, we rewrite the state equations as follows:

$$L_{kt} = \phi_{k00}^L + \phi_{k01}^L s_t^L + (\phi_{k10}^L + \phi_{k11}^L s_t^L) L_{k,t-1} + \sigma_{kL}(s_t^L) v_{kt}^L \quad (10)$$

$$C_t = \phi_{00}^C + \phi_{01}^C s_t^C + (\phi_{10}^C + \phi_{11}^C s_t^C) C_{t-1} + \sigma_C(s_t^C) v_t^C \quad (11)$$

where

$$\phi_{k00}^L = \phi_{k0}^L(G_L), \phi_{k00}^L + \phi_{k01}^L = \phi_{k0}^L(B_L)$$

$$\phi_{k10}^L = \phi_{k1}^L(G_L), \phi_{k10}^L + \phi_{k11}^L = \phi_{k1}^L(B_L)$$

and

$$\phi_{00}^C = \phi_0^C(G_C), \phi_{00}^C + \phi_{01}^C = \phi_0^C(B_C)$$

$$\phi_{10}^C = \phi_1^C(G_C), \phi_{10}^C + \phi_{11}^C = \phi_1^C(B_C)$$

Considering that latent risks are more volatile on average in the bad states, we define

$$\sigma_{kL}^2(B_L) = \sigma_{kL}^2(G_L)(1 + h_{kLB})$$

$$\sigma_C^2(B_C) = \sigma_C^2(G_C)(1 + h_{CB})$$

where $h_{kLB} > 0$ and $h_{CB} > 0$.

- **Generating** $\phi_{k00}^L, \phi_{k01}^L, \phi_{k10}^L, \phi_{k11}^L$, **Conditional on** L_{kt} and $\sigma_{kL}(s_t^L)$.

Dividing both sides of the state equation by $\sigma_{kL}(s_t^L)$, we have

$$L_{kt}^\dagger = \phi_{k00}^L x_{1t}^\dagger + \phi_{k01}^L x_{1t}^{\dagger\dagger} + \phi_{k10}^L x_{2t}^\dagger + \phi_{k11}^L x_{2t}^{\dagger\dagger} + v_{kt}^L \quad (12)$$

where

$$L_{kt}^\dagger = \frac{L_{kt}}{\sigma_{kL}(s_t^L)}$$

$$x_{1t}^\dagger = \frac{1}{\sigma_{kL}(s_t^L)}$$

$$x_{1t}^{\dagger\dagger} = \frac{s_t^L}{\sigma_{kL}(s_t^L)}$$

$$x_{2t}^\dagger = \frac{L_{k,t-1}}{\sigma_{kL}(s_t^L)}$$

$$x_{2t}^{\dagger\dagger} = \frac{L_{k,t-1}s_t^L}{\sigma_{kL}(s_t^L)}$$

In matrix notation, equation (12) can be written as

$$L_k^\dagger = X_{kL}^\dagger b_{\phi_{kL}} + V_{kL} \quad V_{kL} \sim N(0, I_T) \quad (13)$$

where

$$X_{kLt}^\dagger = [x_{1t}^\dagger, x_{1t}^{\dagger\dagger}, x_{2t}^\dagger, x_{2t}^{\dagger\dagger}]$$

and

$$b_{\phi_{kL}} = [\phi_{k00}^L, \phi_{k01}^L, \phi_{k10}^L, \phi_{k11}^L]'$$

We assume Normal prior for $b_{\phi_{kL}}$:

Prior

$$b_{\phi_{kL}} \sim N(\underline{b}_{\phi_{kL}}, \underline{V}_{\phi_{kL}})$$

with the elements of $b_{\phi_{kL}}$ subject to the following restrictions:

$$\phi_{k10}^L \in (0, 1) \quad \phi_{k10}^L + \phi_{k11}^L \in (0, 1)$$

$$\frac{\phi_{k00}^L}{1 - \phi_{k10}^L} < \frac{\phi_{k00}^L + \phi_{k01}^L}{1 - \phi_{k10}^L - \phi_{k11}^L}$$

To save space, we use $R(b_{\phi_{kL}})$ to denote these additional restrictions.

Posterior

$$b_{\phi_{kL}} \sim N(\bar{b}_{\phi_{kL}}, \bar{V}_{\phi_{kL}}) R(b_{\phi_{kL}})$$

where

$$\bar{V}_{\phi_{kL}} = \{V_{\phi_{kL}}^{-1} + (X_{kL}^\dagger)' X_{kL}^\dagger\}^{-1}$$

and

$$\bar{b}_{\phi_{kL}} = \bar{V}_{\phi_{kL}} \{V_{\phi_{kL}}^{-1} b_{\phi_{kL}}^{-1} + (X_{kL}^\dagger)' L_k^\dagger\}$$

- **Generating $\sigma_{kL}^2(G_L)$, Conditional on L_{kt} , ϕ_{k00}^L , ϕ_{k01}^L , ϕ_{k10}^L , ϕ_{k11}^L and h_{kLB} .**

To generate $\sigma_{kL}^2(G_L)$, we divide both sides of equation (10) by $\sqrt{1 + h_{kLB}s_t^L}$

$$L_{kt}^\dagger = \phi_{k00}^L x_{1t}^\dagger + \phi_{k01}^L x_{1t}^{\dagger\dagger} + \phi_{k10}^L x_{2t}^\dagger + \phi_{k11}^L x_{2t}^{\dagger\dagger} + \sigma_{kL}(G_L) v_{kt}^L \quad (14)$$

where

$$\begin{aligned} L_{kt}^\dagger &= \frac{L_{kt}}{\sqrt{1 + h_{kLB}s_t^L}} \\ x_{1t}^\dagger &= \frac{1}{\sqrt{1 + h_{kLB}s_t^L}} \\ x_{1t}^{\dagger\dagger} &= \frac{s_t^L}{\sqrt{1 + h_{kLB}s_t^L}} \\ x_{2t}^\dagger &= \frac{L_{k,t-1}}{\sqrt{1 + h_{kLB}s_t^L}} \\ x_{2t}^{\dagger\dagger} &= \frac{L_{k,t-1}s_t^L}{\sqrt{1 + h_{kLB}s_t^L}} \end{aligned}$$

Prior

$$h_{kL} \sim G(\underline{s}_{kL}^{-2}, \underline{\nu}_{kL})$$

Posterior

$$h_{kL} \sim G(\bar{s}_{kL}^{-2}, \bar{\nu}_{kL})$$

where

$$\bar{\nu}_{kL} = T + \underline{\nu}_{kL}$$

and

$$\bar{s}_{kL}^2 = \frac{\underline{\nu}_{kL} \underline{s}_{kL}^2 + \sum_{t=1}^{t=T} (L_{kt}^\dagger - \phi_{k00}^L x_{1t}^\dagger - \phi_{k01}^L x_{1t}^{\dagger\dagger} - \phi_{k10}^L x_{2t}^\dagger - \phi_{k11}^L x_{2t}^{\dagger\dagger})^2}{\bar{\nu}_{kL}}$$

Given h_{kL} , we can derive $\sigma_{kL}(G_L)$ by $\sigma_{kL}(G_L) = \frac{1}{\sqrt{h_{kL}}}$.

- **Generating h_{kLB} , Conditional on L_{kt} , ϕ_{k00}^L , ϕ_{k01}^L , ϕ_{k10}^L , ϕ_{k11}^L and $\sigma_{kL}(G_L)$.**

To draw h_{kLB} , we divide both sides of equation (10) by $\sigma_{kL}(G_L)$:

$$L_{kt}^{\S} = \phi_{k00}^L x_{1t}^{\S} + \phi_{k01}^L x_{1t}^{\S\S} + \phi_{k10}^L x_{2t}^{\S} + \phi_{k11}^L x_{2t}^{\S\S} + v_{kt}^L \sqrt{1 + h_{kLB} s_t^L} \quad (15)$$

where

$$L_{kt}^{\S} = \frac{L_{kt}}{\sigma_{kL}(G_L)}$$

$$x_{1t}^{\S} = \frac{1}{\sigma_{kL}(G_L)}$$

$$x_{1t}^{\S\S} = \frac{s_t^L}{\sigma_{kL}(G_L)}$$

$$x_{2t}^{\S} = \frac{L_{k,t-1}}{\sigma_{kL}(G_L)}$$

$$x_{2t}^{\S\S} = \frac{L_{k,t-1} s_t^L}{\sigma_{kL}(G_L)}$$

Let $h_{kLB}^{\S} = \frac{1}{1+h_{kLB}}$, we set Gamma prior for h_{kLB}^{\S} :

Prior

$$h_{kLB}^{\S} \sim G(s_{kL^{\S}}^{-2}, \nu_{kL^{\S}})$$

subject to the restriction that $h_{kLB}^{\S} < 1$.

Posterior

$$h_{kLB}^{\S} \sim G(\bar{s}_{kL^{\S}}^{-2}, \bar{\nu}_{kL^{\S}})$$

subject to the restriction that $h_{kLB}^{\S} < 1$.

where

$$\bar{\nu}_{kL^{\S}} = \nu_{kL^{\S}} + T^{\S}$$

$$\bar{s}_{kL^{\S}}^{-2} = \frac{\nu_{kL^{\S}} s_{kL^{\S}}^2 + \sum^{T^{\S}} (L_{kt}^{\S} - \phi_{k00}^L x_{1t}^{\S} - \phi_{k01}^L x_{1t}^{\S\S} - \phi_{k10}^L x_{2t}^{\S} - \phi_{k11}^L x_{2t}^{\S\S})^2}{\bar{\nu}_{kL^{\S}}}$$

Note that $T^{\S} = \{t : s_t^L = 1\}$, also h_{kLB}^{\S} depends only on the values of L_{kt}^{\S} for which $s_t^L = 1$.

Once h_{kLB}^{\S} is drawn from the above posterior, we can calculate h_{kLB} by $h_{kLB} = \frac{1}{h_{kLB}^{\S}} - 1$.

- **Generating ϕ_{00}^C , ϕ_{01}^C , ϕ_{10}^C , ϕ_{11}^C , Conditional on $\sigma_C(s_t^C)$ and C_t .**

Dividing both sides of equation (11) by $\sigma_C(s_t^C)$, we have

$$C_t^\dagger = \phi_{00}^C z_{1t}^\dagger + \phi_{01}^C z_{1t}^{\dagger\dagger} + \phi_{10}^C z_{2t}^\dagger + \phi_{11}^C z_{2t}^{\dagger\dagger} + v_t^C \quad (16)$$

where

$$\begin{aligned} C_t^\dagger &= \frac{C_t}{\sigma_C(s_t^C)} \\ z_{1t}^\dagger &= \frac{1}{\sigma_C(s_t^C)} \\ z_{1t}^{\dagger\dagger} &= \frac{s_t^C}{\sigma_C(s_t^C)} \\ z_{2t}^\dagger &= \frac{C_{t-1}}{\sigma_C(s_t^C)} \\ z_{2t}^{\dagger\dagger} &= \frac{C_{t-1}s_t^C}{\sigma_C(s_t^C)} \end{aligned}$$

In matrix notation, equation (12) can be written as

$$C^\dagger = Z_C^\dagger b_{\phi_C} + V_C \quad V_C \sim N(0, I_T) \quad (17)$$

where

$$Z_{Ct}^\dagger = [z_{1t}^\dagger, z_{1t}^{\dagger\dagger}, z_{2t}^\dagger, z_{2t}^{\dagger\dagger}]$$

and

$$b_{\phi_C} = [\phi_{00}^C, \phi_{01}^C, \phi_{10}^C, \phi_{11}^C]'$$

We assume Normal prior for b_{ϕ_C} :

Prior

$$b_{\phi_C} \sim N(\underline{b}_{\phi_C}, \underline{V}_{\phi_C})$$

with the elements of b_{ϕ_C} subject to the following restrictions:

$$\begin{aligned} \phi_{10}^C &\in (0, 1) & \phi_{10}^C + \phi_{11}^C &\in (0, 1) \\ \frac{\phi_{00}^C}{1 - \phi_{10}^C} &< \frac{\phi_{00}^C + \phi_{01}^C}{1 - \phi_{10}^C - \phi_{11}^C} \end{aligned}$$

To save space, we use $R(b_{\phi_C})$ to denote these additional restrictions.

Posterior

$$b_{\phi_C} \sim N(\bar{b}_{\phi_C}, \bar{V}_{\phi_C}) R(b_{\phi_C})$$

where

$$\bar{V}_{\phi_C} = \{\underline{V}_{\phi_C}^{-1} + (Z_C^\dagger)' Z_C^\dagger\}^{-1}$$

and

$$\bar{b}_{\phi_C} = \bar{V}_{\phi_C} \{\underline{V}_{\phi_C}^{-1} \underline{b}_{\phi_C} + (Z_C^\dagger)' C^\dagger\}$$

- **Generating $\sigma_C^2(G_C)$, Conditional on $C_t, \phi_{00}^C, \phi_{01}^C, \phi_{10}^C, \phi_{11}^C$ and h_{CB} .**

To generate $\sigma_C^2(G_C)$, we divide both sides of equation (11) by $\sqrt{1 + h_{CB}s_t^C}$

$$C_t^\dagger = \phi_{00}^C z_{1t}^\dagger + \phi_{01}^C z_{1t}^{\dagger\dagger} + \phi_{10}^C z_{2t}^\dagger + \phi_{11}^C z_{2t}^{\dagger\dagger} + \sigma_C(G_C) v_t^C \quad (18)$$

where

$$\begin{aligned} C_t^\dagger &= \frac{C_t}{\sqrt{1 + h_{CB}s_t^C}} \\ z_{1t}^\dagger &= \frac{1}{\sqrt{1 + h_{CB}s_t^C}} \\ z_{1t}^{\dagger\dagger} &= \frac{s_t^C}{\sqrt{1 + h_{CB}s_t^C}} \\ z_{2t}^\dagger &= \frac{C_{t-1}}{\sqrt{1 + h_{CB}s_t^C}} \\ z_{2t}^{\dagger\dagger} &= \frac{C_{t-1}s_t^C}{\sqrt{1 + h_{CB}s_t^C}} \end{aligned}$$

Prior

$$h_C \sim G(\underline{s}_C^{-2}, \underline{\nu}_C) \text{ where } h_C = \sigma_C^{-2}(G_C)$$

Posterior

$$h_C \sim G(\bar{s}_C^{-2}, \bar{\nu}_C)$$

where

$$\bar{\nu}_C = T + \underline{\nu}_C$$

and

$$\bar{s}_C^2 = \frac{\underline{\nu}_C \underline{s}_C^2 + \sum_{t=1}^{t=T} (C_t^\dagger - \phi_{00}^C z_{1t}^\dagger - \phi_{01}^C z_{1t}^{\dagger\dagger} - \phi_{10}^C z_{2t}^\dagger - \phi_{11}^C z_{2t}^{\dagger\dagger})^2}{\bar{\nu}_C}$$

Given h_C , we can derive $\sigma_C(G_C)$ by $\sigma_C(G_C) = \frac{1}{\sqrt{h_C}}$.

- **Generating h_{CB} , Conditional on $C_t, \phi_{00}^C, \phi_{01}^C, \phi_{10}^C, \phi_{11}^C$ and $\sigma_C(G_C)$.**

To draw h_{CB} , we divide both sides of equation (11) by $\sigma_C(G_C)$:

$$C_t^{\S} = \phi_{00}^C z_{1t}^{\S} + \phi_{01}^C z_{1t}^{\S\S} + \phi_{10}^C z_{2t}^{\S} + \phi_{11}^C z_{2t}^{\S\S} + v_t^C \sqrt{1 + h_{CB} s_t^C} \quad (19)$$

where

$$C_t^{\S} = \frac{C_t}{\sigma_C(G_C)}$$

$$z_{1t}^{\S} = \frac{1}{\sigma_C(G_C)}$$

$$z_{1t}^{\S\S} = \frac{s_t^C}{\sigma_C(G_C)}$$

$$z_{2t}^{\S} = \frac{C_{t-1}}{\sigma_C(G_C)}$$

$$z_{2t}^{\S\S} = \frac{C_{t-1} s_t^C}{\sigma_C(G_C)}$$

Let $h_{CB}^{\S} = \frac{1}{1+h_{CB}}$, we set Gamma prior for h_{CB}^{\S} :

Prior

$$h_{CB}^{\S} \sim G(\underline{s}_{C^{\S}}^{-2}, \underline{\nu}_{C^{\S}})$$

subject to the restriction that $h_{CB}^{\S} < 1$.

Posterior

$$h_{CB}^{\S} \sim G(\bar{s}_{C^{\S}}^{-2}, \bar{\nu}_{C^{\S}})$$

subject to the restriction that $h_{CB}^{\S} < 1$.

where

$$\bar{\nu}_{C^{\S}} = \underline{\nu}_{C^{\S}} + T_C^{\S}$$

$$\bar{s}_{C^{\S}}^2 = \frac{\underline{\nu}_{C^{\S}} \underline{s}_{C^{\S}}^2 + \sum T_C^{\S} (C_t^{\S} - \phi_{00}^C z_{1t}^{\S} - \phi_{01}^C z_{1t}^{\S\S} - \phi_{10}^C z_{2t}^{\S} - \phi_{11}^C z_{2t}^{\S\S})^2}{\bar{\nu}_{C^{\S}}}$$

Note that $T_C^{\S} = \{t : s_t^C = 1\}$, and h_{CB}^{\S} depends only on the values of C_t^{\S} for which $s_t^C = 1$.

Once h_{CB}^{\S} is drawn from the above posterior, h_{CB} can be calculated by $h_{CB} = \frac{1}{h_{CB}^{\S}} - 1$.

1.4 Generating s_t^L , s_t^C and M

- **Generate s_t^L and s_t^C , Conditional on M , L_{kt} , C_t and the other model parameters**

We use the multimove Gibbs-sampling method described in Kim and Nelson (1999, Ch 9) to draw the latent Markov-Switching states.

To summarize, we first run Hamilton's (1989) filter to get the probability $f(s_t|\tilde{L}_{kt}, \tilde{C}_t)$ for $t = 1, 2, \dots, T$ and save them, where $\tilde{L}_{kt} = [L_{k1}, L_{k2}, \dots, L_{kt}]'$ and $\tilde{C}_t = [C_1, C_2, \dots, C_t]'$. Then we generate s_T from the last iteration of the filter. After that, we recursively generate s_t conditional on \tilde{L}_{kt} , \tilde{C}_t and s_{t+1} for $t = T - 1, T - 2, \dots, 1$.

- **Generate M , Conditional on s_t^L , s_t^C , L_{kt} , C_t and the other model parameters**

As explained in Chib (1996), given \tilde{s}_T , the posterior distribution of the transition matrix M can be derived without regard to the sampling model.

Let vector m_b be the b^{th} column of M . We elicit a Dirichlet prior for m_b :

$$m_b \sim D(\alpha_{1,b}, \alpha_{2,b}, \dots, \alpha_{a,b})$$

Thus, the posterior for m_b is:

$$m_b|\tilde{s}_T \sim D(\alpha_{1,b} + q_{1,b}, \alpha_{2,b} + q_{2,b}, \dots, \alpha_{a,b} + q_{a,b})$$

where $q_{a,b}$ is the number of transitions from $s_t = b$ to $s_{t+1} = a$ in the vector \tilde{s}_T .

2 Priors and Prior Sensitivity Analysis

2.1 Elicited Priors

The results presented in the paper involve the following priors:

$$\begin{aligned} \underline{s}_{ijkS}^{-2} &= 10, & \underline{\nu}_{ijkS} &= 0.1 \\ \underline{b}_{\lambda_{ijk}^S} &= 1, & \underline{V}_{\lambda_{ijk}^S} &= 10 \\ \underline{b}_{\psi_{ij}^S} &= 1, & \underline{V}_{\psi_{ij}^S} &= 10 \\ \underline{b}_{\gamma} &= 0, & \underline{V}_{\gamma} &= 10 \\ \underline{b}_{\beta_{ik}} &= 0, & \underline{V}_{\beta_{ik}} &= 10 \\ \underline{s}_{jD}^{-2} &= 10, & \underline{\nu}_{jD} &= 0.1 \end{aligned}$$

$$\begin{aligned}
\underline{b}_{\psi_j^C} &= 1, \quad \underline{V}_{\psi_j^C} = 10 \\
\underline{b}_{\phi_{kL}} &= 0_{4 \times 1}, \quad \underline{V}_{\phi_{kL}} = 10 * I_4 \\
\underline{s}_{kL}^{-2} &= 10, \quad \underline{\nu}_{kL} = 0.1 \\
\underline{s}_{kL}^{-2} &= 0.1, \quad \underline{\nu}_{kL}^{\S} = 10 \\
\underline{b}_{\phi_C} &= 0_{4 \times 1}, \quad \underline{V}_{\phi_C} = 10 * I_4 \\
\underline{s}_C^{-2} &= 10, \quad \underline{\nu}_C = 0.1 \\
\underline{s}_C^{-2} &= 0.1, \quad \underline{\nu}_C^{\S} = 10 \\
\alpha_{a,b} &= 1 \text{ for } a, b \in \{1, 2, 3, 4\}.
\end{aligned}$$

2.2 Prior Sensitivity Analysis

The following priors are used for prior sensitivity analysis.

$$\begin{aligned}
\underline{s}_{ijkS}^{-2} &= 1, \quad \underline{\nu}_{ijkS} = 1 \\
\underline{b}_{\lambda_{ijk}^S} &= 0, \quad \underline{V}_{\lambda_{ijk}^S} = 100 \\
\underline{b}_{\psi_{ij}^S} &= 0, \quad \underline{V}_{\psi_{ij}^S} = 100 \\
\underline{b}_{\gamma} &= 0, \quad \underline{V}_{\gamma} = 100 \\
\underline{b}_{\beta_{ik}} &= 0, \quad \underline{V}_{\beta_{ik}} = 100 \\
\underline{s}_{jD}^{-2} &= 1, \quad \underline{\nu}_{jD} = 1 \\
\underline{b}_{\psi_j^C} &= 1, \quad \underline{V}_{\psi_j^C} = 100 \\
\underline{b}_{\phi_{kL}} &= 0_{4 \times 1}, \quad \underline{V}_{\phi_{kL}} = 4 * I_4 \\
\underline{s}_{kL}^{-2} &= 1, \quad \underline{\nu}_{kL} = 1 \\
\underline{s}_{kL}^{-2} &= 0.1, \quad \underline{\nu}_{kL}^{\S} = 10 \\
\underline{b}_{\phi_C} &= 0_{4 \times 1}, \quad \underline{V}_{\phi_C} = 4 * I_4 \\
\underline{s}_C^{-2} &= 1, \quad \underline{\nu}_C = 1 \\
\underline{s}_C^{-2} &= 0.1, \quad \underline{\nu}_C^{\S} = 10 \\
\alpha_{a,b} &= 2 \text{ for } a, b \in \{1, 2, 3, 4\}.
\end{aligned}$$

Empirical results using these new priors are as follows.

Table 1: Model Comparison		
	BIC	AIC
Model A	-2.802	-3.901
Model B	-2.492	-3.565
Model C	-2.664	-3.737
Model D	-2.321	-3.369
Model E	-2.909	-3.932
Model F	-2.601	-3.617
Model G	-2.744	-3.760
Model H	-2.386	-3.396

Table 2: Posterior Mean of Transition Probabilities (Posterior standard deviations in parentheses)				
	(G_L, G_C)	(B_L, G_C)	(G_L, B_C)	(B_L, B_C)
(G_L, G_C)	0.972 (0.007)	0.231 (0.127)	0.246 (0.132)	0.221 (0.096)
(B_L, G_C)	0.009 (0.005)	0.258 (0.140)	0.235 (0.132)	0.198 (0.111)
(G_L, B_C)	0.009 (0.005)	0.187 (0.113)	0.251 (0.128)	0.149 (0.087)
(B_L, B_C)	0.010 (0.005)	0.324 (0.150)	0.267 (0.142)	0.432 (0.145)

Table 3: Proportion of Variance of Spreads Attributable to Each Component (USD)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays</i> _{1m}	0.8918	0.0000	0.0008	0.0000	0.0020	0.0000	0.1054
<i>barclays</i> _{3m}	0.8208	0.0720	0.0000	0.0966	-0.0002	0.0000	0.0108
<i>barclays</i> _{12m}	0.2720	0.4217	0.0000	0.1345	0.0000	0.0000	0.1718
<i>btmufj</i> _{1m}	0.8755	0.0042	0.0011	0.0239	0.0023	0.0000	0.0930
<i>btmufj</i> _{3m}	0.7801	0.1027	0.0000	0.1125	-0.0003	0.0000	0.0050
<i>btmufj</i> _{12m}	0.2129	0.5345	0.0000	0.1340	0.0000	0.0000	0.1186
<i>citibank</i> _{1m}	0.8963	0.0015	0.0013	0.0146	0.0025	0.0000	0.0836
<i>citibank</i> _{3m}	0.7715	0.1101	0.0000	0.1158	-0.0003	0.0000	0.0029
<i>citibank</i> _{12m}	0.1991	0.5585	0.0000	0.1325	0.0000	0.0000	0.1099
<i>deutschebank</i> _{1m}	0.9094	0.0000	0.0014	0.0002	0.0026	0.0000	0.0864
<i>deutschebank</i> _{3m}	0.7876	0.0982	0.0000	0.1106	-0.0003	0.0000	0.0039
<i>deutschebank</i> _{12m}	0.2908	0.4672	0.0000	0.1465	0.0000	0.0000	0.0956
<i>hbos</i> _{1m}	0.8682	0.0000	0.0009	0.0001	0.0020	0.0000	0.1287
<i>hbos</i> _{3m}	0.8352	0.0038	0.0000	0.0221	-0.0002	0.0000	0.1391
<i>hbos</i> _{12m}	0.6070	0.0496	0.0000	0.0688	0.0000	0.0000	0.2747
<i>hsbc</i> _{1m}	0.9085	0.0001	0.0013	0.0028	0.0025	0.0000	0.0848
<i>hsbc</i> _{3m}	0.7876	0.0992	0.0000	0.1111	-0.0003	0.0000	0.0024
<i>hsbc</i> _{12m}	0.2660	0.4843	0.0000	0.1426	0.0000	0.0000	0.1070
<i>jpmc</i> _{1m}	0.9009	0.0000	0.0015	0.0003	0.0027	0.0000	0.0946
<i>jpmc</i> _{3m}	0.7692	0.1076	0.0000	0.1144	-0.0003	0.0000	0.0091
<i>jpmc</i> _{12m}	0.1849	0.5484	0.0000	0.1265	0.0000	0.0000	0.1403
<i>lloyds</i> _{1m}	0.9186	0.0000	0.0013	0.0005	0.0026	0.0000	0.0770
<i>lloyds</i> _{3m}	0.7716	0.1103	0.0000	0.1160	-0.0003	0.0000	0.0024
<i>lloyds</i> _{12m}	0.1903	0.5624	0.0000	0.1300	0.0000	0.0000	0.1173
<i>rabobank</i> _{1m}	0.8999	0.0006	0.0015	0.0089	0.0027	0.0000	0.0864
<i>rabobank</i> _{3m}	0.7460	0.1237	0.0000	0.1208	-0.0003	0.0000	0.0098
<i>rabobank</i> _{12m}	0.2110	0.5224	0.0000	0.1319	0.0000	0.0000	0.1346
<i>rboscotland</i> _{1m}	0.9163	0.0001	0.0012	0.0036	0.0024	0.0000	0.0764
<i>rboscotland</i> _{3m}	0.7686	0.1099	0.0000	0.1155	-0.0003	0.0000	0.0062
<i>rboscotland</i> _{12m}	0.1867	0.5159	0.0000	0.1233	0.0000	0.0000	0.1741
<i>ubs</i> _{1m}	0.9148	0.0001	0.0012	0.0045	0.0024	0.0000	0.0769
<i>ubs</i> _{3m}	0.7560	0.1217	0.0000	0.1206	-0.0003	0.0000	0.0021
<i>ubs</i> _{12m}	0.1929	0.5353	0.0000	0.1276	0.0000	0.0000	0.1441
<i>westlb</i> _{1m}	0.8708	0.0015	0.0013	0.0145	0.0024	0.0000	0.1095
<i>westlb</i> _{3m}	0.7369	0.1307	0.0000	0.1234	-0.0003	0.0000	0.0093
<i>westlb</i> _{12m}	0.1818	0.5561	0.0000	0.1263	0.0000	0.0000	0.1358

Table 4: Proportion of Variance of Spreads Attributable to Each Component (GBP)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays</i> _{1m}	0.9964	0.0000	0.0000	0.0000	0.0000	0.0000	0.0036
<i>barclays</i> _{3m}	0.6936	0.1117	0.0000	0.1493	0.0000	0.0000	0.0454
<i>barclays</i> _{12m}	0.3393	0.4224	0.0000	0.2031	0.0000	0.0000	0.0352
<i>btmufj</i> _{1m}	0.9363	0.0081	0.0000	0.0466	0.0000	0.0000	0.0091
<i>btmufj</i> _{3m}	0.6632	0.1297	0.0000	0.1574	0.0000	0.0000	0.0497
<i>btmufj</i> _{12m}	0.4042	0.3832	0.0000	0.2112	0.0000	0.0000	0.0013
<i>citibank</i> _{1m}	0.9627	0.0025	0.0000	0.0263	0.0000	0.0000	0.0084
<i>citibank</i> _{3m}	0.6614	0.1204	0.0000	0.1515	0.0000	0.0000	0.0668
<i>citibank</i> _{12m}	0.3860	0.4004	0.0000	0.2110	0.0000	0.0000	0.0027
<i>deutschebank</i> _{1m}	0.9893	0.0000	0.0000	0.0004	0.0000	0.0000	0.0103
<i>deutschebank</i> _{3m}	0.6811	0.1194	0.0000	0.1530	0.0000	0.0000	0.0464
<i>deutschebank</i> _{12m}	0.4663	0.3144	0.0000	0.2055	0.0000	0.0000	0.0138
<i>hbos</i> _{1m}	0.8170	0.0000	0.0000	0.0003	0.0000	0.0000	0.1828
<i>hbos</i> _{3m}	0.6717	0.0046	0.0000	0.0295	0.0000	0.0000	0.2943
<i>hbos</i> _{12m}	0.5569	0.0366	0.0000	0.0764	0.0000	0.0000	0.3301
<i>hsbc</i> _{1m}	0.9705	0.0001	0.0000	0.0057	0.0000	0.0000	0.0236
<i>hsbc</i> _{3m}	0.6560	0.1306	0.0000	0.1571	0.0000	0.0000	0.0563
<i>hsbc</i> _{12m}	0.4222	0.3599	0.0000	0.2092	0.0000	0.0000	0.0087
<i>jpmc</i> _{1m}	0.9895	0.0000	0.0000	0.0005	0.0000	0.0000	0.0099
<i>jpmc</i> _{3m}	0.6919	0.1078	0.0000	0.1465	0.0000	0.0000	0.0538
<i>jpmc</i> _{12m}	0.4497	0.3364	0.0000	0.2087	0.0000	0.0000	0.0052
<i>lloyds</i> _{1m}	0.9978	0.0000	0.0000	0.0009	0.0000	0.0000	0.0012
<i>lloyds</i> _{3m}	0.6791	0.1208	0.0000	0.1537	0.0000	0.0000	0.0465
<i>lloyds</i> _{12m}	0.3867	0.4010	0.0000	0.2113	0.0000	0.0000	0.0010
<i>rabobank</i> _{1m}	0.9702	0.0008	0.0000	0.0149	0.0000	0.0000	0.0141
<i>rabobank</i> _{3m}	0.6683	0.1207	0.0000	0.1524	0.0000	0.0000	0.0587
<i>rabobank</i> _{12m}	0.4470	0.3355	0.0000	0.2078	0.0000	0.0000	0.0097
<i>rboscotland</i> _{1m}	0.9907	0.0002	0.0000	0.0067	0.0000	0.0000	0.0024
<i>rboscotland</i> _{3m}	0.6555	0.1367	0.0000	0.1606	0.0000	0.0000	0.0471
<i>rboscotland</i> _{12m}	0.3503	0.4340	0.0000	0.2093	0.0000	0.0000	0.0064
<i>ubs</i> _{1m}	0.9861	0.0003	0.0000	0.0084	0.0000	0.0000	0.0052
<i>ubs</i> _{3m}	0.6411	0.1411	0.0000	0.1614	0.0000	0.0000	0.0564
<i>ubs</i> _{12m}	0.4013	0.3863	0.0000	0.2113	0.0000	0.0000	0.0011
<i>westlb</i> _{1m}	0.9665	0.0025	0.0000	0.0265	0.0000	0.0000	0.0045
<i>westlb</i> _{3m}	0.6500	0.1459	0.0000	0.1653	0.0000	0.0000	0.0388
<i>westlb</i> _{12m}	0.3917	0.3959	0.0000	0.2113	0.0000	0.0000	0.0011

Table 5: Proportion of Variance of Spreads Attributable to Each Component (EUR)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays</i> _{1m}	0.8953	0.0000	0.0000	0.0000	0.0000	0.0000	0.1047
<i>barclays</i> _{3m}	0.6521	0.1986	0.0000	0.1391	0.0000	0.0000	0.0101
<i>barclays</i> _{12m}	0.2183	0.5940	0.0000	0.1392	0.0000	0.0000	0.0485
<i>btmufj</i> _{1m}	0.8509	0.0154	0.0000	0.0441	0.0000	0.0000	0.0896
<i>btmufj</i> _{3m}	0.6115	0.2391	0.0000	0.1478	0.0000	0.0000	0.0015
<i>btmufj</i> _{12m}	0.2308	0.5804	0.0000	0.1415	0.0000	0.0000	0.0474
<i>citibank</i> _{1m}	0.8573	0.0045	0.0000	0.0240	0.0000	0.0000	0.1142
<i>citibank</i> _{3m}	0.6327	0.2208	0.0000	0.1445	0.0000	0.0000	0.0020
<i>citibank</i> _{12m}	0.2288	0.5784	0.0000	0.1406	0.0000	0.0000	0.0522
<i>deutschebank</i> _{1m}	0.8600	0.0000	0.0000	0.0004	0.0000	0.0000	0.1396
<i>deutschebank</i> _{3m}	0.5914	0.2377	0.0000	0.1449	0.0000	0.0000	0.0260
<i>deutschebank</i> _{12m}	0.2786	0.5370	0.0000	0.1495	0.0000	0.0000	0.0348
<i>hbos</i> _{1m}	0.8276	0.0000	0.0000	0.0003	0.0000	0.0000	0.1721
<i>hbos</i> _{3m}	0.7510	0.0077	0.0000	0.0290	0.0000	0.0000	0.2123
<i>hbos</i> _{12m}	0.5575	0.0610	0.0000	0.0711	0.0000	0.0000	0.3104
<i>hsbc</i> _{1m}	0.8616	0.0003	0.0000	0.0051	0.0000	0.0000	0.1330
<i>hsbc</i> _{3m}	0.6458	0.2079	0.0000	0.1416	0.0000	0.0000	0.0047
<i>hsbc</i> _{12m}	0.2908	0.5170	0.0000	0.1499	0.0000	0.0000	0.0423
<i>jpmc</i> _{1m}	0.9018	0.0000	0.0000	0.0005	0.0000	0.0000	0.0977
<i>jpmc</i> _{3m}	0.6562	0.2013	0.0000	0.1405	0.0000	0.0000	0.0020
<i>jpmc</i> _{12m}	0.2787	0.5280	0.0000	0.1483	0.0000	0.0000	0.0450
<i>lloyds</i> _{1m}	0.8918	0.0000	0.0000	0.0009	0.0000	0.0000	0.1073
<i>lloyds</i> _{3m}	0.6309	0.2220	0.0000	0.1447	0.0000	0.0000	0.0024
<i>lloyds</i> _{12m}	0.2037	0.6015	0.0000	0.1353	0.0000	0.0000	0.0595
<i>rabobank</i> _{1m}	0.8816	0.0015	0.0000	0.0137	0.0000	0.0000	0.1032
<i>rabobank</i> _{3m}	0.6043	0.2301	0.0000	0.1442	0.0000	0.0000	0.0214
<i>rabobank</i> _{12m}	0.2736	0.5323	0.0000	0.1475	0.0000	0.0000	0.0467
<i>rboscotland</i> _{1m}	0.8773	0.0003	0.0000	0.0060	0.0000	0.0000	0.1164
<i>rboscotland</i> _{3m}	0.6107	0.2350	0.0000	0.1465	0.0000	0.0000	0.0078
<i>rboscotland</i> _{12m}	0.1847	0.6213	0.0000	0.1309	0.0000	0.0000	0.0630
<i>ubs</i> _{1m}	0.8353	0.0005	0.0000	0.0078	0.0000	0.0000	0.1564
<i>ubs</i> _{3m}	0.5832	0.2578	0.0000	0.1499	0.0000	0.0000	0.0091
<i>ubs</i> _{12m}	0.2277	0.5860	0.0000	0.1412	0.0000	0.0000	0.0451
<i>westlb</i> _{1m}	0.8539	0.0043	0.0000	0.0234	0.0000	0.0000	0.1184
<i>westlb</i> _{3m}	0.5929	0.2518	0.0000	0.1494	0.0000	0.0000	0.0059
<i>westlb</i> _{12m}	0.2337	0.5835	0.0000	0.1427	0.0000	0.0000	0.0400

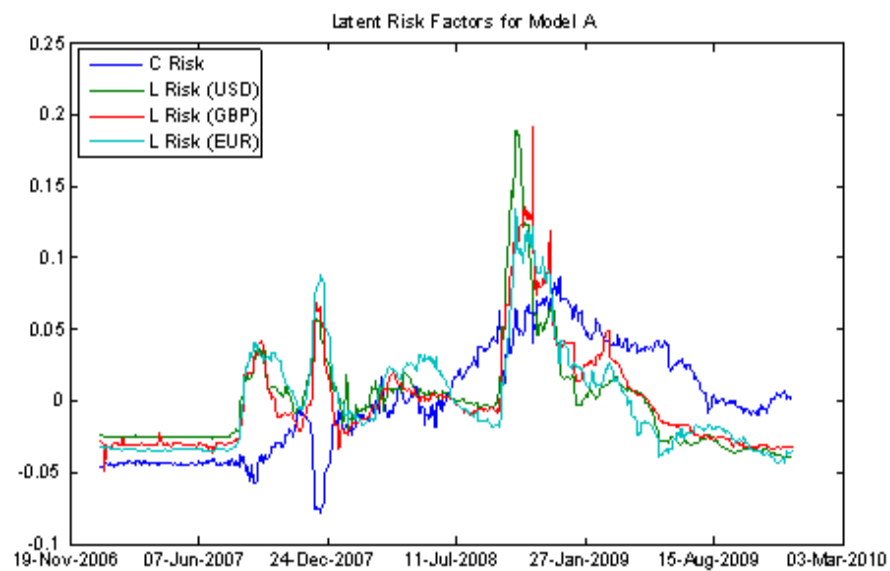


Figure 1

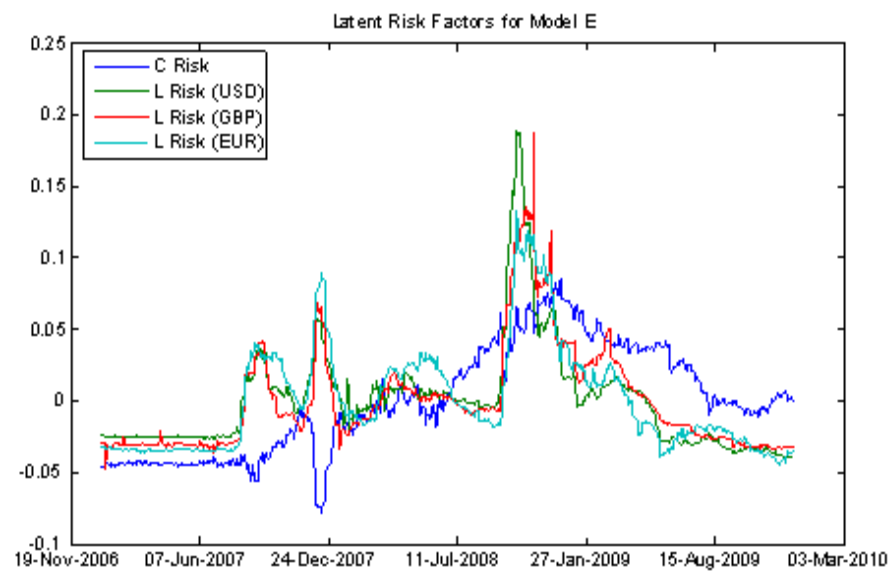


Figure 2

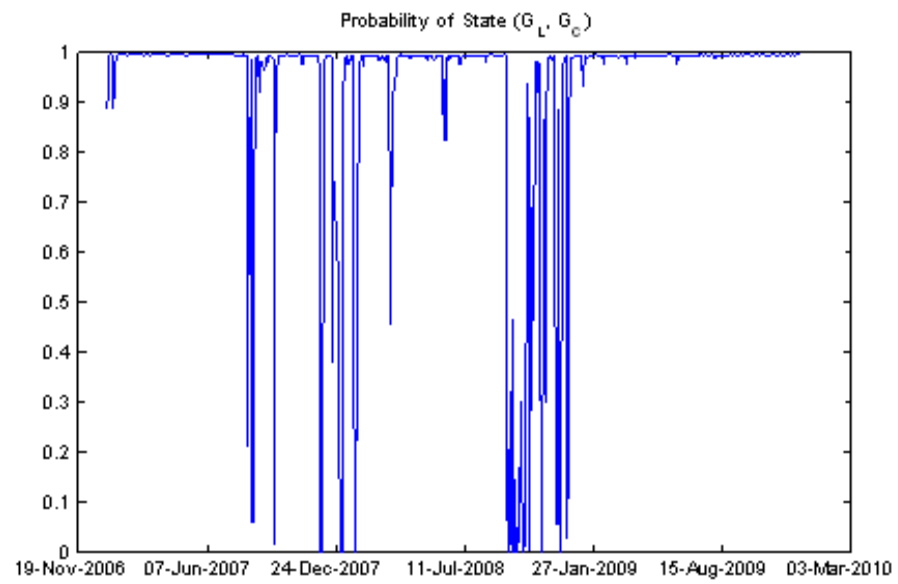


Figure 3

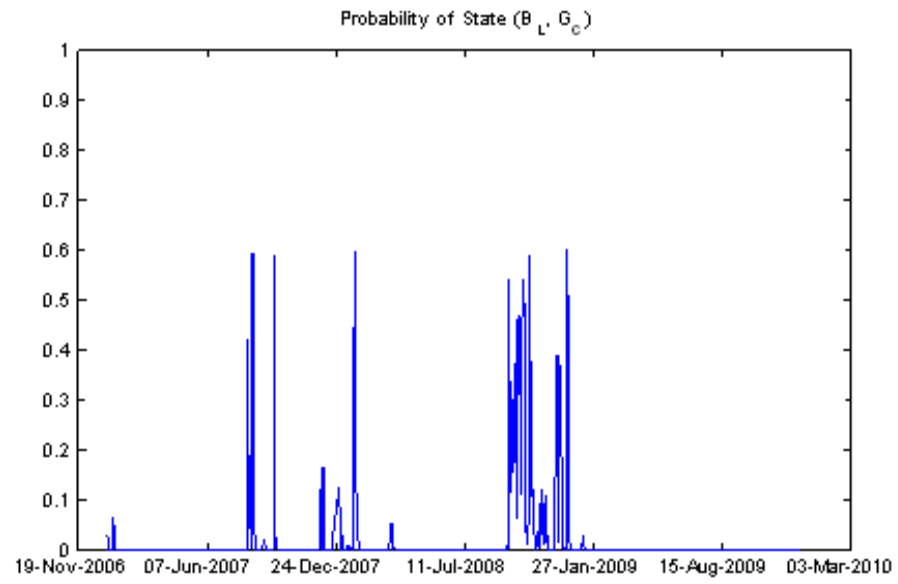


Figure 4

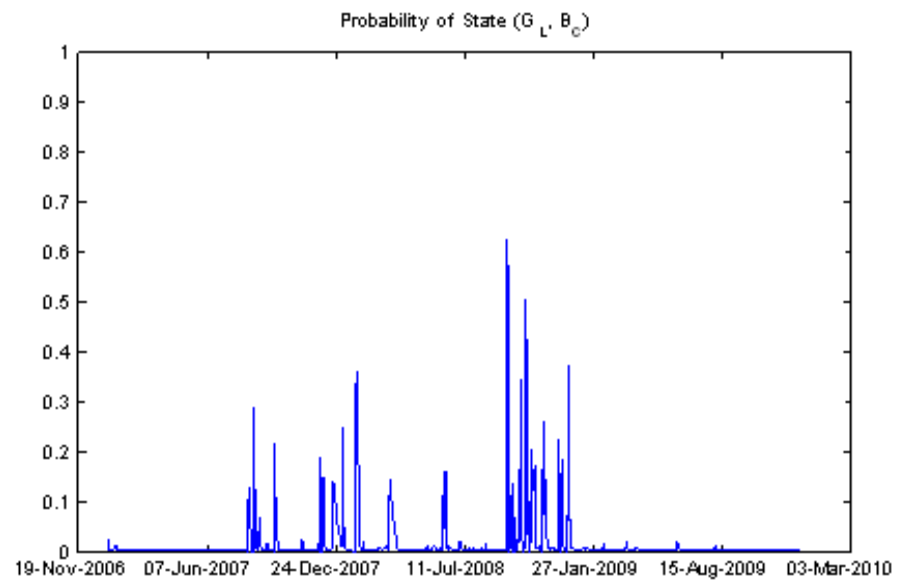


Figure 5

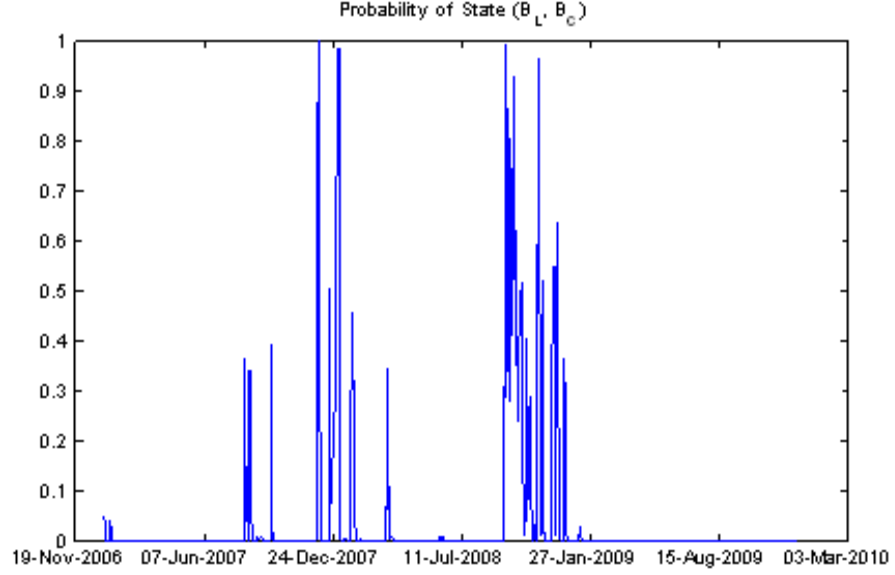


Figure 6

3 Empirical Results Involving Only Eight Banks

Empirical results reported in this section using data of the eight banks for which we do not have any missing observations.

Table 6: Model Comparison		
	BIC	AIC
Model A	-3.227	-4.325
Model B	-2.853	-3.926
Model C	-3.013	-4.086
Model D	-2.593	-3.641
Model E	-3.273	-4.296
Model F	-2.886	-3.902
Model G	-3.093	-4.109
Model H	-2.620	-3.630

Table 7: Posterior Mean of Transition Probabilities (Posterior standard deviations in parentheses)				
	(G_L, G_C)	(B_L, G_C)	(G_L, B_C)	(B_L, B_C)
(G_L, G_C)	0.950 (0.013)	0.311 (0.134)	0.179 (0.093)	0.047 (0.038)
(B_L, G_C)	0.019 (0.009)	0.375 (0.149)	0.061 (0.054)	0.069 (0.062)
(G_L, B_C)	0.018 (0.010)	0.109 (0.096)	0.658 (0.108)	0.107 (0.050)
(B_L, B_C)	0.013 (0.008)	0.205 (0.141)	0.101 (0.063)	0.777 (0.077)

Table 8: Proportion of Variance of Spreads Attributable to Each Component (USD)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays</i> _{1m}	0.8977	0.0000	0.0008	0.0000	0.0019	0.0000	0.0996
<i>barclays</i> _{3m}	0.7277	0.1088	0.0000	0.1521	-0.0002	0.0000	0.0117
<i>barclays</i> _{12m}	0.1120	0.6091	0.0000	0.1409	0.0000	0.0000	0.1380
<i>citibank</i> _{1m}	0.9021	0.0011	0.0013	0.0172	0.0024	0.0000	0.0758
<i>citibank</i> _{3m}	0.6746	0.1506	0.0000	0.1723	-0.0002	0.0000	0.0027
<i>citibank</i> _{12m}	0.0620	0.7329	0.0000	0.1150	0.0000	0.0000	0.0901
<i>deutschebank</i> _{1m}	0.9155	0.0000	0.0014	0.0004	0.0025	0.0000	0.0803
<i>deutschebank</i> _{3m}	0.7000	0.1319	0.0000	0.1642	-0.0002	0.0000	0.0041
<i>deutschebank</i> _{12m}	0.1412	0.6161	0.0000	0.1593	0.0000	0.0000	0.0835
<i>jpmc</i> _{1m}	0.9095	0.0000	0.0015	0.0006	0.0026	0.0000	0.0859
<i>jpmc</i> _{3m}	0.7100	0.1232	0.0000	0.1598	-0.0002	0.0000	0.0073
<i>jpmc</i> _{12m}	0.0572	0.7153	0.0000	0.1091	0.0000	0.0000	0.1183
<i>lloyds</i> _{1m}	0.9199	0.0001	0.0013	0.0038	0.0025	0.0000	0.0724
<i>lloyds</i> _{3m}	0.6662	0.1572	0.0000	0.1749	-0.0002	0.0000	0.0020
<i>lloyds</i> _{12m}	0.0581	0.7330	0.0000	0.1114	0.0000	0.0000	0.0975
<i>rabobank</i> _{1m}	0.9022	0.0006	0.0015	0.0120	0.0026	0.0000	0.0810
<i>rabobank</i> _{3m}	0.6442	0.1685	0.0000	0.1781	-0.0002	0.0000	0.0094
<i>rabobank</i> _{12m}	0.0740	0.6867	0.0000	0.1216	0.0000	0.0000	0.1177
<i>rboscotland</i> _{1m}	0.9102	0.0006	0.0012	0.0122	0.0023	0.0000	0.0735
<i>rboscotland</i> _{3m}	0.6388	0.1751	0.0000	0.1808	-0.0002	0.0000	0.0055
<i>rboscotland</i> _{12m}	0.0592	0.6820	0.0000	0.1083	0.0000	0.0000	0.1505
<i>ubs</i> _{1m}	0.9131	0.0004	0.0012	0.0108	0.0023	0.0000	0.0721
<i>ubs</i> _{3m}	0.6595	0.1621	0.0000	0.1767	-0.0002	0.0000	0.0019
<i>ubs</i> _{12m}	0.0617	0.7026	0.0000	0.1123	0.0000	0.0000	0.1234

Table 9: Proportion of Variance of Spreads Attributable to Each Component (GBP)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays_{1m}</i>	0.9964	0.0000	0.0000	0.0000	0.0000	0.0000	0.0036
<i>barclays_{3m}</i>	0.5686	0.1710	0.0000	0.2161	0.0000	0.0000	0.0442
<i>barclays_{12m}</i>	0.1462	0.6117	0.0000	0.2071	0.0000	0.0000	0.0349
<i>citibank_{1m}</i>	0.9605	0.0019	0.0000	0.0292	0.0000	0.0000	0.0084
<i>citibank_{3m}</i>	0.5556	0.1660	0.0000	0.2105	0.0000	0.0000	0.0679
<i>citibank_{12m}</i>	0.2036	0.5581	0.0000	0.2337	0.0000	0.0000	0.0046
<i>deutschebank_{1m}</i>	0.9894	0.0000	0.0000	0.0006	0.0000	0.0000	0.0100
<i>deutschebank_{3m}</i>	0.5797	0.1621	0.0000	0.2124	0.0000	0.0000	0.0458
<i>deutschebank_{12m}</i>	0.3039	0.4289	0.0000	0.2503	0.0000	0.0000	0.0169
<i>jpmc_{1m}</i>	0.9899	0.0000	0.0000	0.0009	0.0000	0.0000	0.0092
<i>jpmc_{3m}</i>	0.6276	0.1232	0.0000	0.1928	0.0000	0.0000	0.0564
<i>jpmc_{12m}</i>	0.2736	0.4696	0.0000	0.2484	0.0000	0.0000	0.0084
<i>lloyds_{1m}</i>	0.9924	0.0001	0.0000	0.0064	0.0000	0.0000	0.0011
<i>lloyds_{3m}</i>	0.5633	0.1735	0.0000	0.2167	0.0000	0.0000	0.0464
<i>lloyds_{12m}</i>	0.2064	0.5553	0.0000	0.2346	0.0000	0.0000	0.0037
<i>rabobank_{1m}</i>	0.9661	0.0008	0.0000	0.0191	0.0000	0.0000	0.0140
<i>rabobank_{3m}</i>	0.5645	0.1652	0.0000	0.2117	0.0000	0.0000	0.0586
<i>rabobank_{12m}</i>	0.2704	0.4706	0.0000	0.2473	0.0000	0.0000	0.0117
<i>rboscotland_{1m}</i>	0.9746	0.0010	0.0000	0.0219	0.0000	0.0000	0.0024
<i>rboscotland_{3m}</i>	0.5044	0.2201	0.0000	0.2309	0.0000	0.0000	0.0446
<i>rboscotland_{12m}</i>	0.1706	0.5986	0.0000	0.2215	0.0000	0.0000	0.0093
<i>ubs_{1m}</i>	0.9749	0.0008	0.0000	0.0191	0.0000	0.0000	0.0052
<i>ubs_{3m}</i>	0.5332	0.1896	0.0000	0.2204	0.0000	0.0000	0.0568
<i>ubs_{12m}</i>	0.2207	0.5369	0.0000	0.2386	0.0000	0.0000	0.0037

Table 10: Proportion of Variance of Spreads Attributable to Each Component (EUR)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays</i> _{1m}	0.9792	0.0000	0.0000	0.0000	0.0000	0.0000	0.0208
<i>barclays</i> _{3m}	0.4124	0.2921	0.0000	0.2244	0.0000	0.0000	0.0711
<i>barclays</i> _{12m}	0.0401	0.7761	0.0000	0.1137	0.0000	0.0000	0.0701
<i>citibank</i> _{1m}	0.9506	0.0033	0.0000	0.0362	0.0000	0.0000	0.0099
<i>citibank</i> _{3m}	0.4276	0.2956	0.0000	0.2299	0.0000	0.0000	0.0468
<i>citibank</i> _{12m}	0.0587	0.7392	0.0000	0.1346	0.0000	0.0000	0.0675
<i>deutschebank</i> _{1m}	0.9394	0.0000	0.0000	0.0008	0.0000	0.0000	0.0598
<i>deutschebank</i> _{3m}	0.3835	0.3139	0.0000	0.2243	0.0000	0.0000	0.0783
<i>deutschebank</i> _{12m}	0.1060	0.6813	0.0000	0.1737	0.0000	0.0000	0.0391
<i>jpmc</i> _{1m}	0.9963	0.0000	0.0000	0.0012	0.0000	0.0000	0.0025
<i>jpmc</i> _{3m}	0.4955	0.2289	0.0000	0.2177	0.0000	0.0000	0.0579
<i>jpmc</i> _{12m}	0.0945	0.6812	0.0000	0.1639	0.0000	0.0000	0.0604
<i>lloyds</i> _{1m}	0.9866	0.0002	0.0000	0.0081	0.0000	0.0000	0.0051
<i>lloyds</i> _{3m}	0.4056	0.3084	0.0000	0.2287	0.0000	0.0000	0.0573
<i>lloyds</i> _{12m}	0.0439	0.7628	0.0000	0.1180	0.0000	0.0000	0.0753
<i>rabobank</i> _{1m}	0.9554	0.0014	0.0000	0.0237	0.0000	0.0000	0.0194
<i>rabobank</i> _{3m}	0.3925	0.3066	0.0000	0.2243	0.0000	0.0000	0.0767
<i>rabobank</i> _{12m}	0.0895	0.6890	0.0000	0.1604	0.0000	0.0000	0.0611
<i>rboscotland</i> _{1m}	0.9639	0.0018	0.0000	0.0269	0.0000	0.0000	0.0074
<i>rboscotland</i> _{3m}	0.3519	0.3569	0.0000	0.2291	0.0000	0.0000	0.0620
<i>rboscotland</i> _{12m}	0.0340	0.7848	0.0000	0.1053	0.0000	0.0000	0.0758
<i>ubs</i> _{1m}	0.9394	0.0015	0.0000	0.0244	0.0000	0.0000	0.0346
<i>ubs</i> _{3m}	0.3877	0.3353	0.0000	0.2331	0.0000	0.0000	0.0438
<i>ubs</i> _{12m}	0.0628	0.7438	0.0000	0.1396	0.0000	0.0000	0.0538

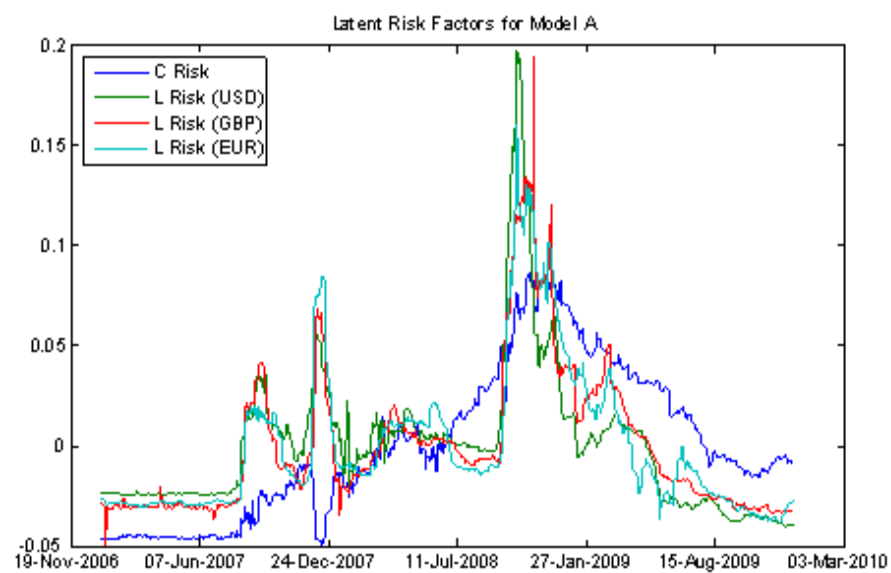


Figure 7

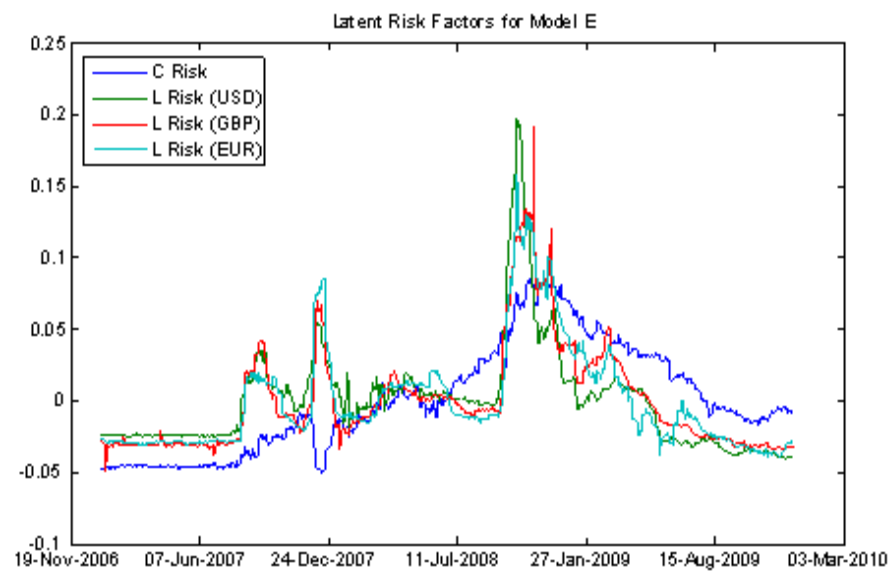


Figure 8

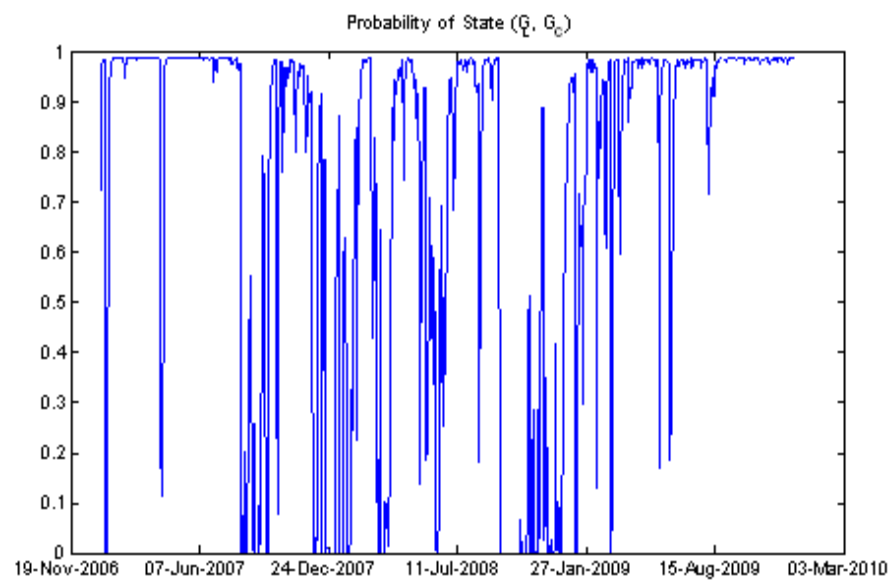


Figure 9

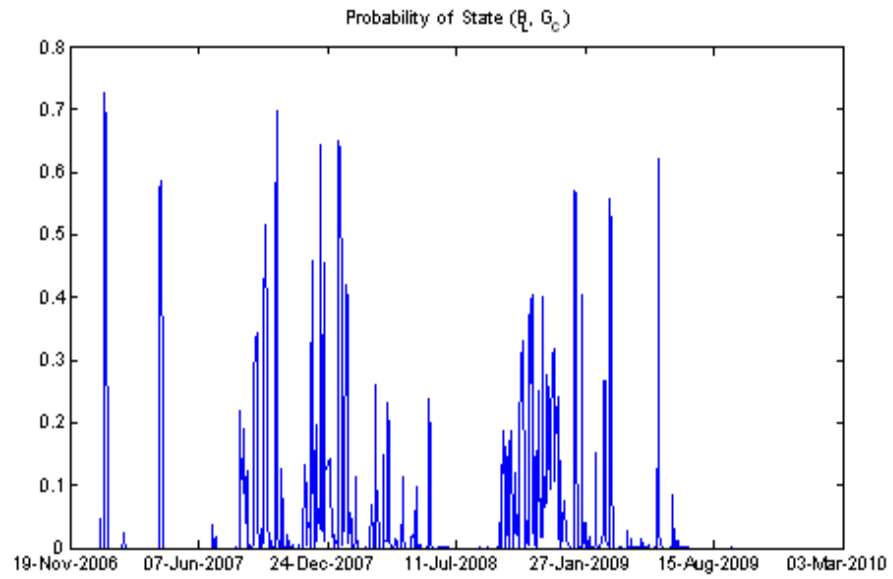


Figure 10

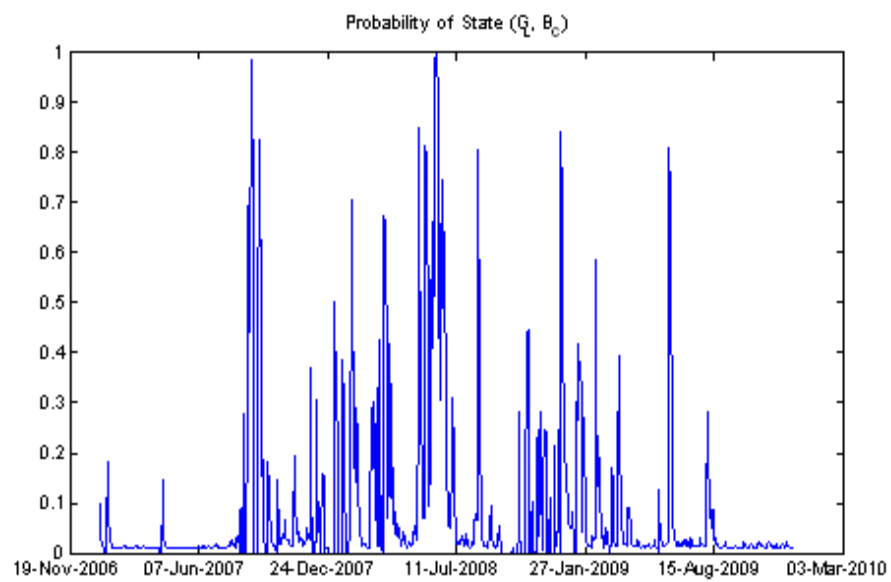


Figure 11

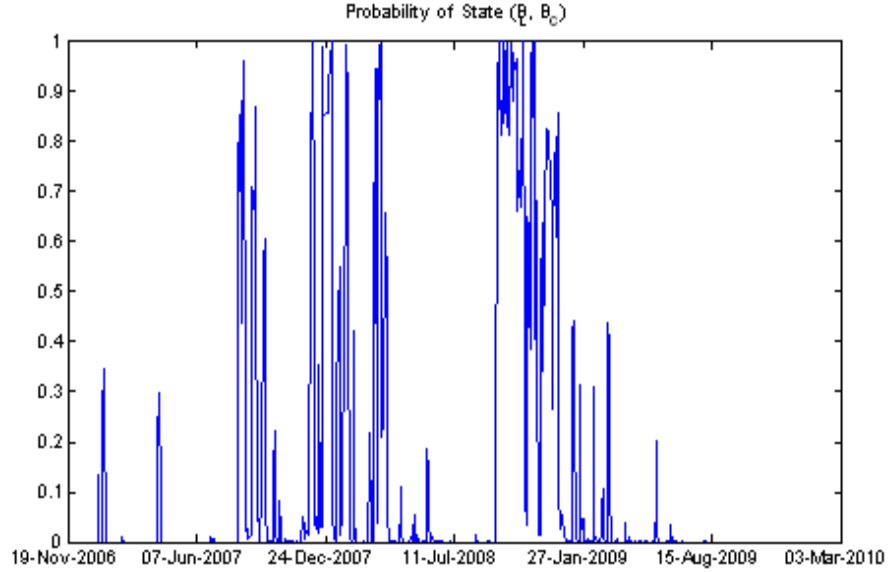


Figure 12

4 Empirical Results Involving Different Identification Assumptions

In this section, we present the empirical results where we restrict the factor loading for the term $i = 2$ to unity. Variance decomposition results for EUR show a pattern that differs from that of USD and GBP, which might be caused by the non-negligible correlation between L for EUR and C .

Table 11: Model Comparison		
	BIC	AIC
Model A	-3.048	-4.146
Model B	-2.697	-3.770
Model C	-2.873	-3.946
Model D	-2.467	-3.515
Model E	-3.115	-4.137
Model F	-2.779	-3.795
Model G	-2.915	-3.931
Model H	-2.495	-3.505

Table 12: Posterior Mean of Transition Probabilities (Posterior standard deviations in parentheses)				
	(G_L, G_C)	(B_L, G_C)	(G_L, B_C)	(B_L, B_C)
(G_L, G_C)	0.948 (0.012)	0.257 (0.165)	0.225 (0.127)	0.086 (0.039)
(B_L, G_C)	0.010 (0.007)	0.273 (0.157)	0.059 (0.064)	0.028 (0.025)
(G_L, B_C)	0.015 (0.010)	0.157 (0.140)	0.283 (0.144)	0.094 (0.049)
(B_L, B_C)	0.027 (0.012)	0.312 (0.195)	0.432 (0.150)	0.791 (0.052)

Table 13: Proportion of Variance of Spreads Attributable to Each Component (USD)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays</i> _{1m}	0.8649	0.1428	0.0000	-0.0449	0.0000	0.0000	0.0373
<i>barclays</i> _{3m}	0.6123	0.4063	0.0008	-0.0636	-0.0019	-0.0007	0.0470
<i>barclays</i> _{12m}	0.1026	0.9225	0.0000	-0.0393	0.0000	0.0000	0.0142
<i>btmufj</i> _{1m}	0.8287	0.2160	0.0000	-0.0540	0.0000	0.0000	0.0094
<i>btmufj</i> _{3m}	0.5612	0.4765	0.0009	-0.0660	-0.0020	-0.0008	0.0302
<i>btmufj</i> _{12m}	0.1157	0.9216	0.0000	-0.0417	0.0000	0.0000	0.0044
<i>citibank</i> _{1m}	0.8590	0.1899	0.0000	-0.0516	0.0000	0.0000	0.0028
<i>citibank</i> _{3m}	0.4396	0.0000	0.0011	0.0000	-0.0020	0.0000	0.5613
<i>citibank</i> _{12m}	0.1135	0.9235	0.0000	-0.0413	0.0000	0.0000	0.0043
<i>deutschebank</i> _{1m}	0.8673	0.1761	0.0000	-0.0499	0.0000	0.0000	0.0066
<i>deutschebank</i> _{3m}	0.5621	0.4564	0.0009	-0.0646	-0.0020	-0.0008	0.0482
<i>deutschebank</i> _{12m}	0.1462	0.8921	0.0000	-0.0461	0.0000	0.0000	0.0079
<i>hbos</i> _{1m}	0.8996	0.1120	0.0000	-0.0405	0.0000	0.0000	0.0289
<i>hbos</i> _{3m}	0.7227	0.2078	0.0007	-0.0494	-0.0020	-0.0005	0.1207
<i>hbos</i> _{12m}	0.4815	0.3007	0.0000	-0.0485	0.0000	0.0000	0.2663
<i>hsbc</i> _{1m}	0.8724	0.1748	0.0000	-0.0499	0.0000	0.0000	0.0027
<i>hsbc</i> _{3m}	0.5461	0.4757	0.0010	-0.0650	-0.0021	-0.0009	0.0452
<i>hsbc</i> _{12m}	0.1311	0.9090	0.0000	-0.0441	0.0000	0.0000	0.0040
<i>jpmc</i> _{1m}	0.8877	0.1540	0.0000	-0.0472	0.0000	0.0000	0.0056
<i>jpmc</i> _{3m}	0.5126	0.4980	0.0010	-0.0645	-0.0021	-0.0009	0.0558
<i>jpmc</i> _{12m}	0.0927	0.9356	0.0000	-0.0376	0.0000	0.0000	0.0094
<i>lloyds</i> _{1m}	0.8598	0.1902	0.0000	-0.0516	0.0000	0.0000	0.0016
<i>lloyds</i> _{3m}	0.5172	0.5038	0.0010	-0.0651	-0.0020	-0.0009	0.0460
<i>lloyds</i> _{12m}	0.1100	0.9256	0.0000	-0.0408	0.0000	0.0000	0.0051
<i>rabobank</i> _{1m}	0.8415	0.1997	0.0000	-0.0523	0.0000	0.0000	0.0111
<i>rabobank</i> _{3m}	0.4892	0.5206	0.0010	-0.0644	-0.0020	-0.0009	0.0565
<i>rabobank</i> _{12m}	0.1051	0.9238	0.0000	-0.0398	0.0000	0.0000	0.0109
<i>rboscotland</i> _{1m}	0.8413	0.1979	0.0000	-0.0521	0.0000	0.0000	0.0129
<i>rboscotland</i> _{3m}	0.5271	0.4993	0.0009	-0.0654	-0.0019	-0.0008	0.0410
<i>rboscotland</i> _{12m}	0.0880	0.9349	0.0000	-0.0366	0.0000	0.0000	0.0137
<i>ubs</i> _{1m}	0.8592	0.1911	0.0000	-0.0517	0.0000	0.0000	0.0014
<i>ubs</i> _{3m}	0.5241	0.5035	0.0009	-0.0656	-0.0020	-0.0008	0.0398
<i>ubs</i> _{12m}	0.0992	0.9304	0.0000	-0.0388	0.0000	0.0000	0.0091
<i>westlb</i> _{1m}	0.8273	0.2133	0.0000	-0.0536	0.0000	0.0000	0.0131
<i>westlb</i> _{3m}	0.5125	0.5246	0.0009	-0.0662	-0.0019	-0.0009	0.0310
<i>westlb</i> _{12m}	0.1058	0.9223	0.0000	-0.0399	0.0000	0.0000	0.0118

Table 14: Proportion of Variance of Spreads Attributable to Each Component (GBP)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays</i> _{1m}	0.6467	0.3521	0.0000	-0.0024	0.0000	0.0000	0.0036
<i>barclays</i> _{3m}	0.3563	0.6093	0.0000	-0.0023	0.0000	0.0000	0.0367
<i>barclays</i> _{12m}	0.1239	0.8419	0.0000	-0.0016	0.0000	0.0000	0.0358
<i>btmufj</i> _{1m}	0.5813	0.4139	0.0000	-0.0024	0.0000	0.0000	0.0073
<i>btmufj</i> _{3m}	0.3382	0.6222	0.0000	-0.0023	0.0000	0.0000	0.0419
<i>btmufj</i> _{12m}	0.2363	0.7215	0.0000	-0.0021	0.0000	0.0000	0.0442
<i>citibank</i> _{1m}	0.6523	0.3411	0.0000	-0.0024	0.0000	0.0000	0.0090
<i>citibank</i> _{3m}	0.3353	0.0000	0.0000	0.0000	0.0000	0.0000	0.6647
<i>citibank</i> _{12m}	0.2295	0.7222	0.0000	-0.0020	0.0000	0.0000	0.0503
<i>deutschebank</i> _{1m}	0.7115	0.2830	0.0000	-0.0022	0.0000	0.0000	0.0077
<i>deutschebank</i> _{3m}	0.4049	0.5467	0.0000	-0.0023	0.0000	0.0000	0.0508
<i>deutschebank</i> _{12m}	0.2835	0.6578	0.0000	-0.0022	0.0000	0.0000	0.0609
<i>hbos</i> _{1m}	0.6838	0.1970	0.0000	-0.0018	0.0000	0.0000	0.1211
<i>hbos</i> _{3m}	0.5251	0.2344	0.0000	-0.0018	0.0000	0.0000	0.2422
<i>hbos</i> _{12m}	0.4683	0.2377	0.0000	-0.0017	0.0000	0.0000	0.2956
<i>hsbc</i> _{1m}	0.6205	0.3569	0.0000	-0.0024	0.0000	0.0000	0.0249
<i>hsbc</i> _{3m}	0.3494	0.5983	0.0000	-0.0023	0.0000	0.0000	0.0545
<i>hsbc</i> _{12m}	0.2348	0.7103	0.0000	-0.0020	0.0000	0.0000	0.0569
<i>jpmc</i> _{1m}	0.7423	0.2568	0.0000	-0.0022	0.0000	0.0000	0.0031
<i>jpmc</i> _{3m}	0.3885	0.5590	0.0000	-0.0023	0.0000	0.0000	0.0548
<i>jpmc</i> _{12m}	0.2803	0.6619	0.0000	-0.0021	0.0000	0.0000	0.0599
<i>lloyds</i> _{1m}	0.6755	0.3258	0.0000	-0.0023	0.0000	0.0000	0.0010
<i>lloyds</i> _{3m}	0.3529	0.6085	0.0000	-0.0023	0.0000	0.0000	0.0409
<i>lloyds</i> _{12m}	0.2328	0.7231	0.0000	-0.0020	0.0000	0.0000	0.0461
<i>rabobank</i> _{1m}	0.6685	0.3194	0.0000	-0.0023	0.0000	0.0000	0.0144
<i>rabobank</i> _{3m}	0.3734	0.5736	0.0000	-0.0023	0.0000	0.0000	0.0553
<i>rabobank</i> _{12m}	0.2675	0.6775	0.0000	-0.0021	0.0000	0.0000	0.0570
<i>rboscotland</i> _{1m}	0.6490	0.3507	0.0000	-0.0024	0.0000	0.0000	0.0027
<i>rboscotland</i> _{3m}	0.3411	0.6222	0.0000	-0.0023	0.0000	0.0000	0.0390
<i>rboscotland</i> _{12m}	0.1804	0.7846	0.0000	-0.0019	0.0000	0.0000	0.0369
<i>ubs</i> _{1m}	0.6455	0.3514	0.0000	-0.0024	0.0000	0.0000	0.0055
<i>ubs</i> _{3m}	0.3429	0.6103	0.0000	-0.0023	0.0000	0.0000	0.0491
<i>ubs</i> _{12m}	0.2311	0.7277	0.0000	-0.0020	0.0000	0.0000	0.0433
<i>westlb</i> _{1m}	0.6291	0.3694	0.0000	-0.0024	0.0000	0.0000	0.0039
<i>westlb</i> _{3m}	0.3393	0.6287	0.0000	-0.0023	0.0000	0.0000	0.0343
<i>westlb</i> _{12m}	0.2340	0.7215	0.0000	-0.0020	0.0000	0.0000	0.0466

Table 15: Proportion of Variance of Spreads Attributable to Each Component (EUR)							
	var(L)	var (C)	var(X)	cov(L,C)	cov(L,X)	cov(C,X)	var(e)
<i>barclays</i> _{1m}	0.6491	0.5159	0.0000	-0.2411	0.0000	0.0000	0.0760
<i>barclays</i> _{3m}	0.4585	0.7826	0.0000	-0.2496	0.0000	0.0000	0.0085
<i>barclays</i> _{12m}	0.2422	0.9011	0.0000	-0.1947	0.0000	0.0000	0.0515
<i>btmufj</i> _{1m}	0.5530	0.6240	0.0000	-0.2447	0.0000	0.0000	0.0678
<i>btmufj</i> _{3m}	0.4101	0.8287	0.0000	-0.2429	0.0000	0.0000	0.0041
<i>btmufj</i> _{12m}	0.2682	0.8998	0.0000	-0.2047	0.0000	0.0000	0.0367
<i>citibank</i> _{1m}	0.5867	0.5385	0.0000	-0.2341	0.0000	0.0000	0.1088
<i>citibank</i> _{3m}	0.1026	0.0000	0.0000	0.0000	0.0000	0.0000	0.8974
<i>citibank</i> _{12m}	0.2819	0.8877	0.0000	-0.2084	0.0000	0.0000	0.0389
<i>deutschebank</i> _{1m}	0.5419	0.5523	0.0000	-0.2278	0.0000	0.0000	0.1337
<i>deutschebank</i> _{3m}	0.3563	0.8570	0.0000	-0.2302	0.0000	0.0000	0.0170
<i>deutschebank</i> _{12m}	0.2400	0.9240	0.0000	-0.1962	0.0000	0.0000	0.0322
<i>hbos</i> _{1m}	0.7479	0.3678	0.0000	-0.2183	0.0000	0.0000	0.1026
<i>hbos</i> _{3m}	0.7527	0.3800	0.0000	-0.2225	0.0000	0.0000	0.0897
<i>hbos</i> _{12m}	0.6471	0.3828	0.0000	-0.2070	0.0000	0.0000	0.1771
<i>hsbc</i> _{1m}	0.5913	0.5363	0.0000	-0.2346	0.0000	0.0000	0.1070
<i>hsbc</i> _{3m}	0.4396	0.8014	0.0000	-0.2473	0.0000	0.0000	0.0063
<i>hsbc</i> _{12m}	0.2940	0.8817	0.0000	-0.2122	0.0000	0.0000	0.0364
<i>jpmc</i> _{1m}	0.6433	0.4592	0.0000	-0.2263	0.0000	0.0000	0.1237
<i>jpmc</i> _{3m}	0.4418	0.8012	0.0000	-0.2479	0.0000	0.0000	0.0049
<i>jpmc</i> _{12m}	0.2953	0.8774	0.0000	-0.2121	0.0000	0.0000	0.0393
<i>lloyds</i> _{1m}	0.6050	0.5360	0.0000	-0.2372	0.0000	0.0000	0.0962
<i>lloyds</i> _{3m}	0.4216	0.8181	0.0000	-0.2447	0.0000	0.0000	0.0050
<i>lloyds</i> _{12m}	0.2640	0.8976	0.0000	-0.2028	0.0000	0.0000	0.0413
<i>rabobank</i> _{1m}	0.5975	0.5292	0.0000	-0.2342	0.0000	0.0000	0.1074
<i>rabobank</i> _{3m}	0.4043	0.8192	0.0000	-0.2398	0.0000	0.0000	0.0163
<i>rabobank</i> _{12m}	0.2819	0.8855	0.0000	-0.2082	0.0000	0.0000	0.0407
<i>rboscotland</i> _{1m}	0.5819	0.5626	0.0000	-0.2383	0.0000	0.0000	0.0938
<i>rboscotland</i> _{3m}	0.4365	0.8029	0.0000	-0.2467	0.0000	0.0000	0.0072
<i>rboscotland</i> _{12m}	0.2298	0.9102	0.0000	-0.1906	0.0000	0.0000	0.0506
<i>ubs</i> _{1m}	0.5319	0.5929	0.0000	-0.2339	0.0000	0.0000	0.1091
<i>ubs</i> _{3m}	0.3893	0.8410	0.0000	-0.2384	0.0000	0.0000	0.0081
<i>ubs</i> _{12m}	0.2556	0.9024	0.0000	-0.2001	0.0000	0.0000	0.0421
<i>westlb</i> _{1m}	0.5440	0.5820	0.0000	-0.2343	0.0000	0.0000	0.1083
<i>westlb</i> _{3m}	0.3895	0.8430	0.0000	-0.2387	0.0000	0.0000	0.0063
<i>westlb</i> _{12m}	0.2550	0.9133	0.0000	-0.2010	0.0000	0.0000	0.0328

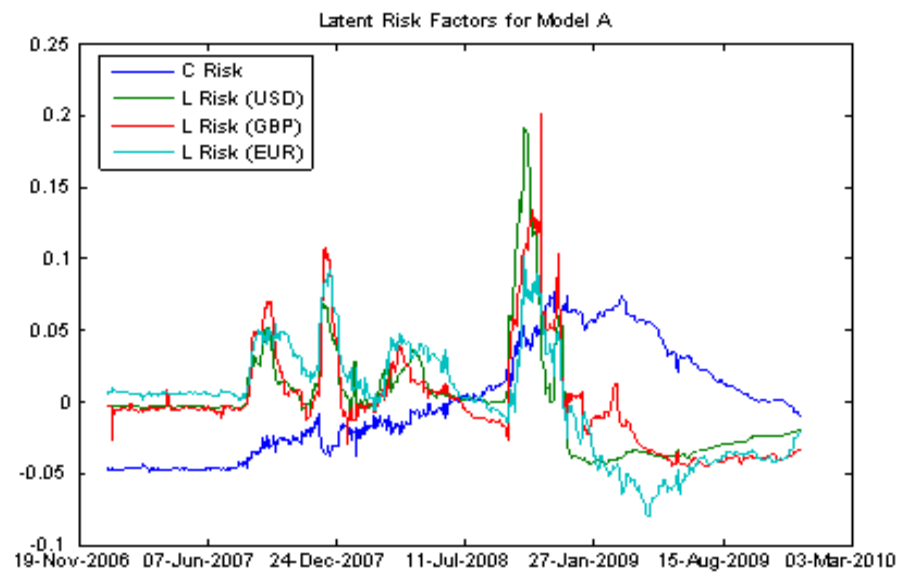


Figure 13

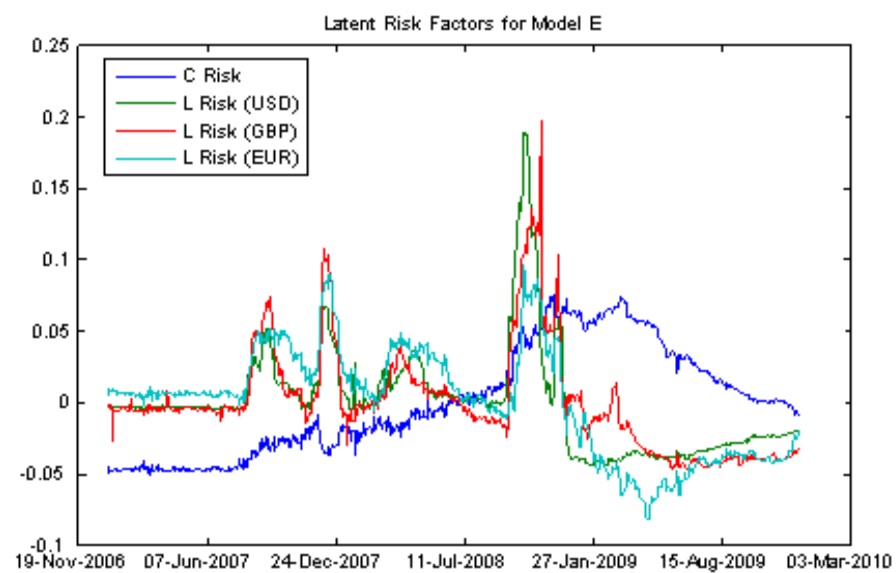


Figure 14

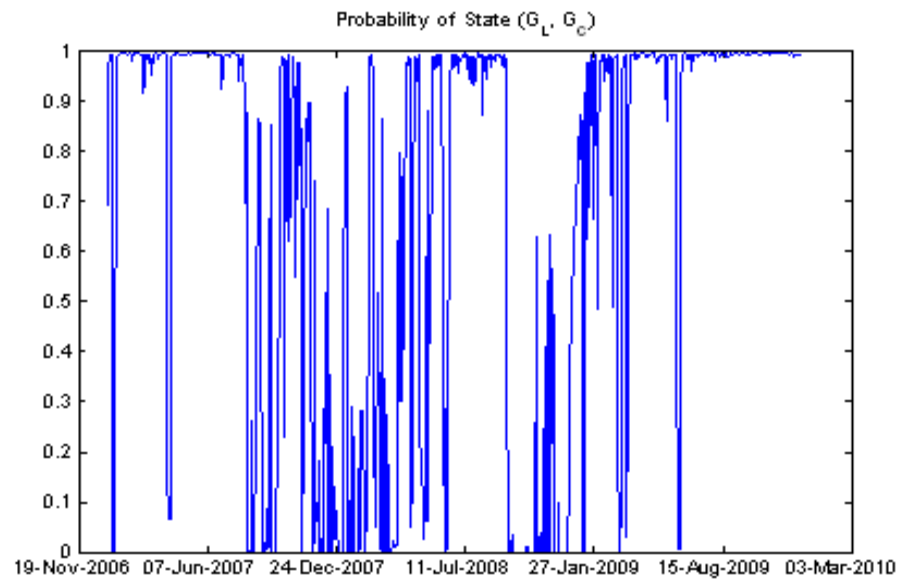


Figure 15

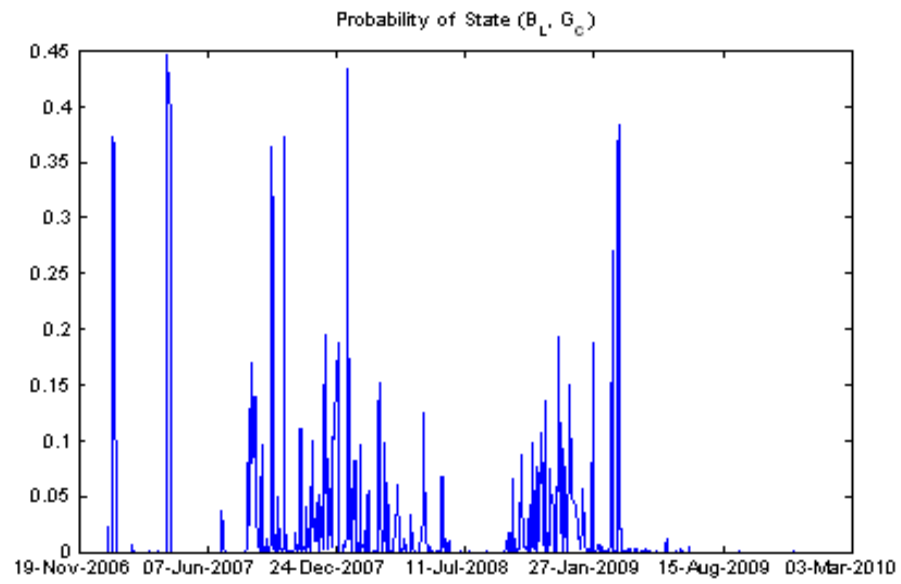


Figure 16

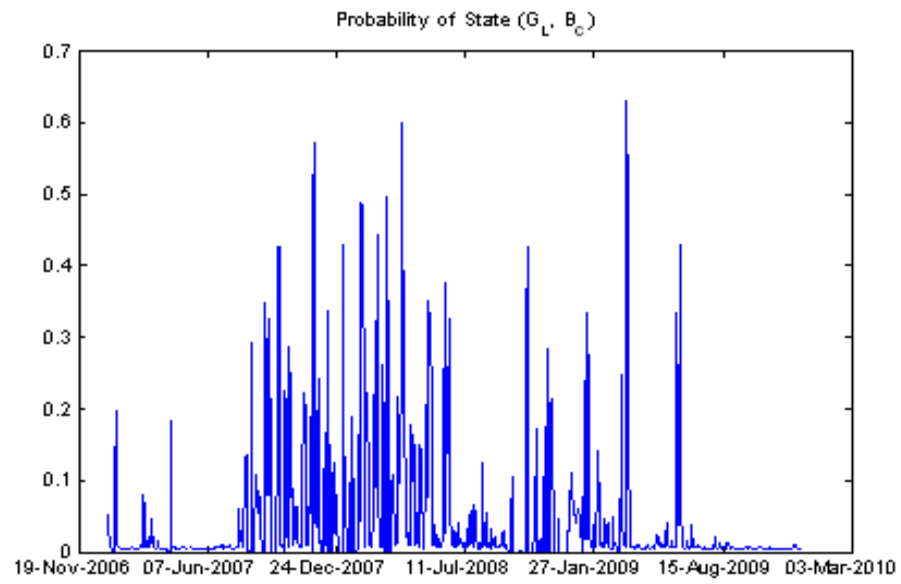


Figure 17

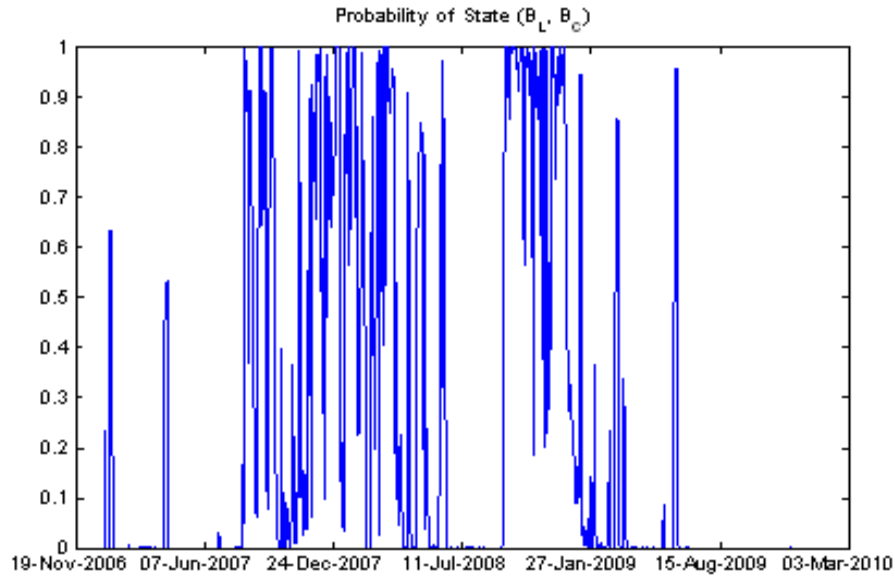


Figure 18

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