Online Appendix to

'Finance and Synchronization'

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During the estimation period we consider (1980-2012), global goods and financial markets have grown at fast pace as countries integrated. The responsiveness of countries to global developments is likely to have changed, as well. In this Section we address this possibility, by estimating a model where country-specific factor loadings are allowed to vary over time.

Consider a version of equation (4) of the main text, where factor loadings are allowed to be time-varying:

$$y_t = a_t^y + b_t^y \mathcal{F}_t^y + e_t^y, \tag{A-1}$$

where, for ease of notation, the country subscripts i are ignored. Assume that the coefficients a_t^y and b_t^y evolve as random walks. In state-space form this model can be expressed as:

$$y_t = \mathbf{X}_t \boldsymbol{\beta}_t + e_t^y. \tag{A-2}$$

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + v_t \tag{A-3}$$

where $\mathbf{X}_t = (1, \mathcal{F}_t^y)$, $\boldsymbol{\beta}_t = (a_t^y, b_t^y)'$, and $Var(e_t^y) = R$ and $Var(v_t) = Q$.

The model (A-2)-(A-3) can be easily estimated *via* Gibbs sampling (see Blake and Mumtaz, 2012). Specifically, if the time-varying coefficients $\boldsymbol{\beta}_t$ are known, then the conditional posterior distribution of R is inverse Gamma, and the distribution of Q is inverse Wishart. Conditional on R and Q the model (A-2)-(A-3) is a linear Gaussian state space model. Since the conditional posterior of $\boldsymbol{\beta}_t$ is normal, the mean and the variance of $\boldsymbol{\beta}_t$ can be derived with the Kalman filter.

Specifically, the Gibbs sampling algorithm consists of the following steps:

1. Set starting values (i.e., β_0,$.Var(\beta_0)$, R_0, Q_0) and priors

$$\mathcal{P}(R) \sim \mathcal{IG}(\frac{T_0}{2}, \frac{\theta^R}{2}) \tag{A-4}$$

$$\mathcal{P}(Q) \sim \mathcal{IW}(\frac{T_0}{2}, \frac{\theta^Q}{2}) \tag{A-5}$$

2. Sample the state variable β_t conditional on R and Q from its conditional posterior distribution using the Kalman filter

3. Using β_0 and $Var(\beta_0)$ run Kalman Filter to get mean and variance of β_t at each point in time

4. Conditional on β_t, sample Q and R from their posterior distributions.

5. Repeat steps 1 to 3 until convergence is detected.

Below we describe how we proceed in detail.

Setting $\beta_{0,i}$, $Var\left(\beta_{0,i}\right)$, and $R_{0,i}$.

We compute a fixed parameter version of model (A-1) on the full sample for all countries. Therefore, for each country i, we get an estimate of $\beta_{0,i}$, $Var\left(\beta_{0,i}\right)$, and $R_{0,i}$:

$$\beta_0 = \left(X_t' X_t\right)^{-1}\left(X_t' Y_t\right) \tag{A-6}$$

$$Var\left(\beta_0\right) = R_0 \otimes \left(X_t' X_t\right)^{-1} \tag{A-7}$$

$$R_0 = \frac{\left(y_t - X_t\beta_t\right)\left(y_t - X_t\beta_t\right)'}{(T-K)} \tag{A-8}$$

where T denotes the number of observations.

Setting $Q_{0,i}$.

Since Q_0 is unobserved, one could do a rolling window OLS estimation of the fixed parameter model to get a time-varying estimate of β_0. Then, an estimate of Q_0 can be obtained by running an VAR(1) model on the rolling estimates of β_0:

$$\beta_{0,t} = \Phi\beta_{0,t-1} + \xi_\tau. \tag{A-9}$$

and recovering the covariance matrix of ξ_t in equation (A-9) as:

$$Q_0 = \frac{\left(\beta_{0,t} - \Phi\beta_{0,t-1}\right)\left(\beta_{0,t} - \Phi\beta_{0,t-1}\right)'}{(T-K)}. \tag{A-10}$$

For the above procedure to work we clearly need a large number of observations. The sample has to be large enough to allow for a rolling window estimation. The annual frequency of our data set creates a limitation for the implementation of the strategy. We increase the number of available observations using a quarterly data set that is comparable to our annual data set (quarterly real GDP data from the OECD from 1980:Q1 to 2012:Q4).

We then estimate a fixed parameter version of model (A-1) using a rolling window. To do that, we use a window of 40 quarters.

We then estimate a VAR(1) model as in (A-9) on the rolling estimates and compute variance-covariance $Q_{0,i}$ for each country.

Setting the priors

Conditional on β_t the posterior distribution of R is inverse Gamma and the posterior distribution of Q is inverse Wishart:

$$\mathcal{P}(R) \sim \mathcal{IG}(T_0, \theta^R) \qquad \text{and} \qquad \mathcal{P}(Q) \sim \mathcal{IW}(T_0, \theta^Q). \tag{A-11}$$

We set $T_0 = 32$, i.e. the number of observations in our (annual) sample. We then set θ^R so that the mean of $\mathcal{IG}(\frac{T_0}{2}, \frac{\theta^R}{2})$ matches $Var(e_t) \equiv R_0$ and the mean of $\mathcal{IW}(\frac{T_0}{2}, \frac{\theta^Q}{2})$

matches $Var(v_t) \equiv Q_0$. Therefore, for $\mathcal{P}(R_i) \sim \mathcal{IG}(T_{0,i}, \theta_i^R)$ we set $\theta_i^R = R_{0,i}(T_{0,i} - 1)$. For $\mathcal{P}(Q_i) \sim \mathcal{IW}(T_0, \theta_i^Q)$ we set the diagonal element $\theta_{nn,i}^Q = Q_{0,i}(T_0 - n - 1)$.

Implementation

We run 100,000 replications, discard the first 99,000, and use the remaining 1,000 draws to form the empirical distribution of the parameters of (A-2)-(A-3). Figure A-1 reports the time-varying estimates of the loadings on the first principal component as against their static counterpart for the 18 countries in the sample.[1] The results show that, while some variation is apparent, the time-varying estimates of factor loadings are rarely significantly different from their constant counterparts.

Table A-1 BANKING INTEGRATION AND BUSINESS CYCLE SYNCHRONIZATION ("WITHIN" ESTIMATES): TIME-VARYING PARAMETERS

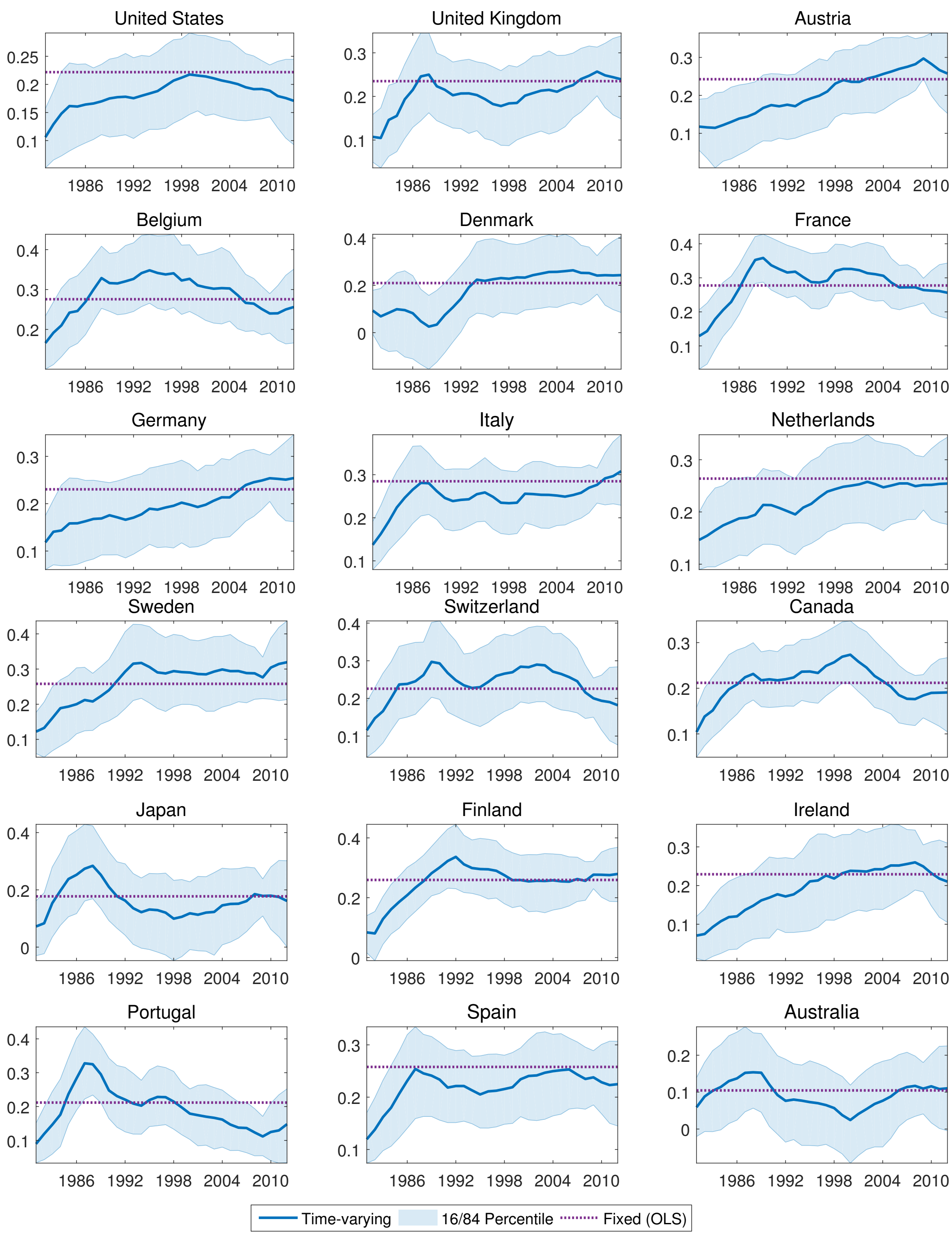
	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$	$\mathcal{S}$	$\mathcal{S}^{\mathcal{F}}$	$\mathcal{S}^{\varepsilon}$
	(1)	(2)	(3)	(4)	(5)	(6)
Banking / Pop.	-0.144	-0.195	0.033			
	(0.040)	(0.037)	(0.012)			
	[-3.63]	[-5.21]	[2.68]			
Banking / GDP				-0.148	-0.199	0.031
				(0.042)	(0.040)	(0.013)
				[-3.56]	[-5.03]	[2.46]
Observations	4863	4863	4863	4863	4863	4863
R2	0.099	0.198	0.161	0.099	0.197	0.161
Country Pairs	153	153	153	153	153	153

NOTE. All regression specifications include a vector of country-pair fixed effects and a vector of year fixed effects. Estimation is performed over the 1980-2012 period. Standard errors are adjusted for country-pair-level heteroskedasticity and autocorrelation.

The estimates of the coefficients and residuals in (A-2)-(A-3) allow us to run our baseline regression when the time-varying estimates of b_t^y are used to decompose $\mathcal{S}_{ij,t}$ into $\mathcal{S}_{ij,t}^{\mathcal{F}}$, and $\mathcal{S}_{ij,t}^{\varepsilon}$. Table A-1 reports the results. The estimates of β continue to switch signs as in the main text of the paper: negative when $\mathcal{S}_{ij,t}$ or $\mathcal{S}_{ij,t}^{\mathcal{F}}$ are the dependent variable, but positive and significant when $\mathcal{S}_{ij,t}^{\varepsilon}$ is used.

[1]The time-varying estimates of the loadings on the second and third principal components are not reported here for brevity, but are available from the authors upon request.

Figure A-1 TIME-VARYING ESTIMATES OF THE LOADINGS ON THE FIRST PRINCIPAL COMPONENT



NOTE. Mean (dotted line) and median (solid line) estimates of the time-varying parameters in model (A-2)-(A-3). Shaded areas display the 68 percent credible intervals. The dashed line reports the OLS fixed estimates.

References

Blake, A. and H. Mumtaz (2012, 07). *Applied Bayesian econometrics for central bankers*. Number 4 in Technical Books. Centre for Central Banking Studies, Bank of England.