

Time-varying stock market integration and institutions in Europe: a Bayesian dynamic factor analysis*

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Abstract

This paper investigates stock market integration using a panel of monthly stock market returns for 19 European countries over the period 1970-2015. We focus on the potentially time-varying nature of integration and on the role played by EU and euro area membership. To this end, we set up a dynamic factor model that decomposes equity risk premiums into a country-specific and a common European risk factor, with time-varying factor loadings and stochastic volatilities. We estimate our model using Bayesian Markov Chain Monte Carlo (MCMC) methods. We suggest a time-varying measure for the degree of integration that is corrected for the bias induced by temporary volatility shocks to the risk factors. The results suggest - in line with the existing literature - that integration has increased in most European countries from the late 1980s/early 1990s onward but also - more controversially - that neither EU nor euro area membership has increased stock market integration.

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1 Introduction

The environment in which European financial markets operate has changed drastically in recent decades. From the mid 1980s onward, most European economies have implemented important financial reforms such as credit and capital control relaxations, interest rate liberalization, and banking and securities markets reforms (see e.g., Abiad et al., 2008). These reforms have been implemented to such an extent that most European countries were almost fully liberalized by the end of the 1990s. During the same period, the European economic and monetary unification process has complemented and reinforced these reforms with measures like the Single European Act (1986), the Maastricht Treaty (1992) and the introduction of the euro (1999). It is therefore not surprising that a considerable amount of research has been devoted to investigate the implications of these changes for the development and - in particular - the integration of financial markets in Europe.

A large part of the research on European financial market integration has focused on stock market integration. There seems to be a consensus in the literature that stock market integration has increased in European countries in recent decades (see e.g., Pukthuanthong and Roll, 2009; Eiling and Gerard, 2011; Bekaert et al., 2009). There is less agreement however on whether this increase was mainly part of a global integration process or whether it was to a large extent regionally driven, stemming in particular from the European economic and monetary unification process. A number of studies have investigated the impact of the start of EMU (European Monetary Union) and the introduction of the euro on European financial market integration, see e.g., Fratzscher (2002), Baele et al. (2004), Hardouvelis et al. (2006) and Cappiello et al. (2006). These studies document an increase in stock market integration of countries joining the euro while other studies like Berben and Jos Jansen (2005) argue that stock market integration evolved largely independent of monetary unification. Bekaert et al. (2013) assess the contribution of both the EU (European Union) and the euro on equity market integration and find that EU membership increased integration while the adoption of the euro had only minimal effects on European stock market integration. Bekaert et al. (2009) however argue that the global integration of Europe was a more important reason for measured permanent increases in equity return correlations than regional EU-driven stock market integration.

This paper revisits these issues using a new methodological approach. In particular, we investigate European stock market integration for 19 European countries over the period 1970-2015 focussing on the potentially time-varying nature of integration and on the impact of institutions - i.e., of EU and euro area membership - on integration. To this end, we set up a dynamic factor model which decomposes equity risk premiums into a country-specific and a common European risk factor with time-varying factor loadings

and stochastic volatilities. This type of decomposition can be rationalized by existing asset pricing theories like the (international) CAPM. Estimates for the distributions of the unobserved factors, factor loadings, stochastic volatilities and parameters are obtained through Bayesian Markov Chain Monte Carlo (MCMC) methods. From a time-varying variance decomposition applied to the dynamic factor model, time-varying stock market integration measures (i.e., variance ratios) are calculated for every country. In the paper we provide a discussion of the advantages of using variance ratios as measures of stock market integration. While variance ratios have been used before to estimate financial market integration (see e.g., Errunza and Losq, 1985; Carrieri et al., 2007; Pukthuanthong and Roll, 2009), the method used in the paper to estimate them is new.

Our methodology fits into the recent and growing empirical literature on the Bayesian estimation of dynamic factor models with time-varying coefficients, i.e., time-varying factor persistence parameters, time-varying factor volatilities, time-varying factor loadings, and time-varying factor covariances (see e.g., Canova et al., 2007; Del Negro and Otrok, 2008; Mumtaz and Surico, 2012). To the best of our knowledge, these Bayesian state space methods have not yet been applied in the context of the measurement of financial market integration.¹ Besides the obvious advantages of these methods such as the possibility of simultaneously analyzing a large number of countries, it is our contention that these methods provide a number of useful properties that are of particular interest to the analysis of time-varying financial market integration.

First, as noted by Kose et al. (2012) in the context of the measurement of common business cycles, dynamic factor models allow for the estimation of common factors for which country weights are implicitly derived as part of the estimation process. This is important in the analysis of stock market integration as the country weights in the common factor are most likely endogenous to the degree of stock market integration. For example, more segmented European countries should receive smaller weights in the construction of the European portfolio and the weights received should increase as these countries become more integrated. The common practice in the literature on stock market integration, however, is to proxy the common risk factor using portfolio returns that are constructed as (weighted) averages of country-specific equity returns or, alternatively, using existing equity indices which are themselves also constructed as (weighted) averages of country-specific indices.² The country weights used in these cases are often fixed or even identical across countries. As a result, the use of these constructed returns may lead to biased financial market integration estimates.

¹While state space methods have been used previously to estimate CAPM models, they have *not* been used to simultaneously filter both factors and factor loadings. Typically, CAPM models are estimated as regression equations with time-varying parameters (i.e., the states) and a proxy for the common factor (see e.g., Tsay, 2005, p. 510)

²It is furthermore worth noting that existing equity indices are not necessarily representative for the countries that are included in the considered sample. The MSCI Europe index, for example, is based on only 15 out of the 19 European countries that we analyze in this paper.

Second, our state space approach is naturally well-suited to measure time-varying stock market integration through the use of variance ratios. These are constructed from factor loadings and factor volatilities which in a state space framework can be easily modelled as time-varying stochastic processes.³ An additional advantage of our Bayesian state space approach is that the Gibbs sampler used to estimate the dynamic factor model provides the empirical distribution of the stock market integration measure in every period. The obtained distributions are then used in the statistical tests that we conduct to investigate whether the degree of stock market integration differs across country groups (i.e., EU countries, euro area countries) and subperiods.

Third, our approach makes it possible to correct our stock market integration measure for a potential volatility or heteroskedasticity bias. In an influential paper, Forbes and Rigobon (2002) show that cross-country correlations between stock returns are high when common volatility is high. A similar bias can occur in our stock market integration measure which is a variance share that depends on the potentially time-varying volatilities of the common and idiosyncratic factors. More specifically, if uncorrected, our stock market integration measure may erroneously point to higher (lower) integration if the volatility of the common factor is *temporarily* high (low) and/or if the volatility of the country-specific factor is *temporarily* low (high). The bias-corrected measure of stock market integration calculated in this paper avoids this problem since only the trend components of the volatilities are used in its construction.

Our results suggest that stock market integration has structurally increased in most European countries over the sample period, particularly from the late 1980s and early 1990s onward. Nonetheless, the evolution was sometimes quite different across countries with some countries experiencing modest increases and others integrating more rapidly. In most European countries the evolution of stock market integration has followed the increasing trend in financial liberalization. From 2010 onward - i.e., after the global financial crisis, the ensuing Great Recession and the euro area debt crisis - the trend increase in stock market integration seems to have come to an end in all countries. At the end of the sample period, the degree of stock market integration was well below 100% in all countries (with an average degree of about 70% across all countries in the sample). This stands in contrast to the high degrees of financial market liberalization - i.e., between 80% and 100% - attained in all European countries already by the end of the 1990s. With respect to the impact of institutions, we find no evidence that countries belonging to the EU or to the euro area have experienced higher levels of stock market integration or have integrated faster than countries that are not members of these institutions. The core members of the EU (i.e., the initial member states of the EU) and the so-called core members of the euro area (i.e., dubbed as such by

³By allowing equity excess returns to be characterized by time-varying *and* persistent variances, our approach also exploits the typical characteristics of financial market data (see e.g., Tsay, 2005).

the press in the recent media coverage of the euro area debt crisis) *did* however experience consistently higher degrees of stock market integration compared to countries that do not belong to either the EU or the euro core.

The remainder of the paper is organized as follows. Section 2 lays out the dynamic factor model together with the estimation approach and shows how this model can be used to set up a bias-corrected measure of time-varying stock market integration. Section 3 presents the data used. Section 4 reports and discusses the estimation results. Section 5 concludes.

2 Empirical specification and methodology

In this section, we first lay out a dynamic factor model that is consistent with the international CAPM and write down its state space representation. Next, we suggest a bias-corrected measure for stock market integration. Finally, we present our econometric approach to estimate the state space system.

2.1 Dynamic factor model and state space representation

2.1.1 Dynamic factor model and link with asset pricing theory

Define r_{it} as the period t excess return or risk premium for country i in deviation from its country-specific mean⁴, then write

$$r_{it} = \mu_{it} + \beta_{it}r_{pt} + e_{it}, \quad i = 1, \dots, N, \quad t = \tau_i, \dots, T, \quad (1)$$

where μ_{it} is the unobserved country-specific risk factor, r_{pt} is the unobserved common European risk factor which can be interpreted as the excess return or risk premium of a European equity portfolio, β_{it} is the country-specific time-varying loading on the common European risk factor and e_{it} is measurement error. As for a number of countries data are missing for the first years of the sample period (see Section 3 below), τ_i denotes the first available observation for country i .

Eq.(1) is consistent with asset pricing theory, in particular with the international CAPM (see e.g., Harvey, 1991; Bekaert and Harvey, 1995). If μ_{it} equals 0 (for all i and t) then eq.(1) is the full integration international CAPM formulation for equity returns with the country-specific excess returns being proportional to the international portfolio excess return. If μ_{it} is not equal to 0, then integration of country i is incomplete as a country-specific risk premium affects equity returns, i.e., the higher the variance of μ_{it} relative to the variance of r_{it} , the more country i is segmented. This characteristic of our dynamic

⁴The reason for this demeaning is that prior inspection of the mean of the excess return showed no signs of time variation. This was confirmed by Chow breakpoint tests. As such, it is not necessary to allow for a time-varying mean in (the components of) r_{it} and prior demeaning is sufficient to remove the time-invariant mean in excess returns.

factor model constitutes the basis of the stock market integration measure discussed in section 2.2.

2.1.2 State space representation

Eq.(1) constitutes the *observation equation* from a state space model relating the observed excess return r_{it} to the unobserved states, i.e., the idiosyncratic risk factor μ_{it} , the unobserved factor loading β_{it} , the unobserved common European risk factor r_{pt} and the additive noise e_{it} , which we assume to be generated as $e_{it} \sim iid\mathcal{N}(0, \sigma_{e_i}^2)$. The state space model can be completed by assuming stochastic laws of motion for each of the unobserved states. This is done in the *state equations* (2)-(8) below.

The idiosyncratic risk factor μ_{it} is assumed to follow a zero-mean $AR(1)$ process with stochastic volatility in the innovations

$$\mu_{i,t+1} = \theta_i \mu_{it} + e^{h_{it}} \sigma_{\psi_i} \psi_{it}, \quad \psi_{it} \sim iid\mathcal{N}(0, 1), \quad (2)$$

for $i = 1, \dots, N$ and $t = \tau_i, \dots, T$. As it is well known that equity excess returns are typically characterized by both temporary and persistent volatility changes (see e.g., Tsay, 2005), we model stochastic volatility $e^{h_{it}}$ as the sum of two distinct components, i.e., $e^{h_{it}} = e^{\bar{h}_{it} + \tilde{h}_{it}}$ where \bar{h}_{it} is a permanent trend component modeled as a driftless random walk process

$$\bar{h}_{i,t+1} = \bar{h}_{it} + \sigma_{\bar{\gamma}_i} \bar{\gamma}_{it}, \quad \bar{\gamma}_{it} \sim iid\mathcal{N}(0, 1), \quad (3)$$

and \tilde{h}_{it} is a temporary component modeled as a stationary $AR(1)$ process

$$\tilde{h}_{i,t+1} = \pi_i \tilde{h}_{it} + \sigma_{\tilde{\gamma}_i} \tilde{\gamma}_{it}, \quad |\pi_i| < 1, \quad \tilde{\gamma}_{it} \sim iid\mathcal{N}(0, 1). \quad (4)$$

The innovations ψ_{it} , $\bar{\gamma}_{it}$ and $\tilde{\gamma}_{it}$ are assumed to be mutually independent and *iid* over time and over cross-sections. The latter assumption implies that any comovement in the data is attributed to the common factor.

Likewise, the common factor r_{pt} is assumed to follow a zero-mean $AR(1)$ process with stochastic volatility in the innovations

$$r_{p,t+1} = \rho r_{pt} + e^{g_t} \sigma_{\xi} \xi_t, \quad \xi_t \sim iid\mathcal{N}(0, 1), \quad (5)$$

for $t = 1, \dots, T$. The stochastic volatility e^{g_t} is again modeled as consisting of two distinct components,

i.e., $e^{g_t} = e^{\bar{g}_t + \tilde{g}_t}$ where \bar{g}_t is a permanent trend component modeled as a driftless random walk

$$\bar{g}_{t+1} = \bar{g}_t + \sigma_{\bar{\lambda}} \bar{\lambda}_t, \quad \bar{\lambda}_t \sim iid\mathcal{N}(0, 1), \quad (6)$$

and \tilde{g}_t is a stationary component modeled as a stationary $AR(1)$ process

$$\tilde{g}_{t+1} = \varrho \tilde{g}_t + \sigma_{\tilde{\lambda}} \tilde{\lambda}_t, \quad |\varrho| < 1, \quad \tilde{\lambda}_t \sim iid\mathcal{N}(0, 1). \quad (7)$$

The innovations ξ_t , $\bar{\lambda}_t$ and $\tilde{\lambda}_t$ are assumed to be mutually independent and *iid* over time.

The time variation in the factor loadings β_{it} is modeled as a driftless random walk

$$\beta_{i,t+1} = \beta_{it} + \sigma_{\omega_i} \omega_{it}, \quad \omega_{it} \sim iid\mathcal{N}(0, 1), \quad (8)$$

for $i = 1, \dots, N$ and $t = \tau_i, \dots, T$. The innovations ω_{it} are assumed to be *iid* over time and over cross-sections.

2.2 Measuring stock market integration

There is no generally accepted measure of financial market integration. Although some authors argue that stock market integration can be measured directly via the factor loadings on the common factor (i.e., the β 's in our model) (see e.g., Fratzscher, 2002; Baele et al., 2004), we do not believe that these constitute an adequate measure of stock market integration. A country i can be fully integrated even if its loading β_{it} is low. And integration of a country can increase even if its loading β_{it} falls, for instance when its country-specific risk premium falls. In line with the international CAPM, a country is fully integrated if its excess return is proportional to the international (European) portfolio excess return (i.e., if $\mu_{it} = 0$), irrespective of the magnitude of the factor of proportionality β_{it} .

A measure of stock market integration frequently used in the literature that focuses on the (relative) importance of the country-specific risk factor μ_{it} in stock excess returns is the variance share, i.e., the proportion of a country's excess return that can be explained by the common risk factor (see e.g., Errunza and Losq, 1985; Carrieri et al., 2007; Pukthuanthong and Roll, 2009). From eq.(1), a time-varying measure for the degree of stock market integration of country i in period t is therefore given by

$$FMI_{it} = \frac{V_t(\beta_{it} r_{pt})}{V_t(r_{it} - e_{it})} = \frac{V_t(\beta_{it} r_{pt})}{V_t(\mu_{it} + \beta_{it} r_{pt})} = 1 - \frac{V_t(\mu_{it})}{V_t(\mu_{it} + \beta_{it} r_{pt})}, \quad (9)$$

where $0 \leq FMI_{it} \leq 1$. If $FMI_{it} = 0$, there is full segmentation or detachment of country i from the international financial markets. This is the case if the variance of the country-specific risk factor

$V_t(\mu_{it})$ is relatively high compared to the variance induced by the common risk factor $V_t(\beta_{it}r_{pt})$ such that $V_t(\beta_{it}r_{pt}) \ll V_t(\mu_{it} + \beta_{it}r_{pt})$. This may be due to a low loading ($\beta_{it} \approx 0$) of country i on an important common risk factor ($V_t(r_{pt}) \gg 0$) or to the common risk factor being absent from the model ($V_t(r_{pt}) \approx 0$). In the former case, country i is segmented from a relatively more integrated European market constituting of countries other than country i , while in the latter case all countries are segmented. If $FMI_{it} = 1$, there is full international integration of country i . This is the case if the variance of the country-specific risk factor $V_t(\mu_{it})$ is relatively low and, as a result, $V_t(\beta_{it}r_{pt}) \approx V_t(\mu_{it} + \beta_{it}r_{pt})$. Note from eq.(9) that stock market integration as measured by FMI_{it} increases when - ceteris paribus - the loading on the common factor β_{it} increases, when the volatility of the common factor r_{pt} increases, or when the volatility of the country-specific factor μ_{it} falls. If $\mu_{it} = 0$ however, changes in β_{it} have no further impact on stock market integration as FMI_{it} equals 1 in this case.

Using the state space model in eqs.(1)-(8), the variance ratio based FMI measure proposed in eq.(9) can be calculated as

$$FMI_{it} = \frac{\beta_{it}^2 (e^{g_{t-1}})^2 \sigma_{\xi}^2 / (1 - \rho^2)}{(e^{h_{i,t-1}})^2 \sigma_{\psi_i}^2 / (1 - \theta_i^2) + \beta_{it}^2 (e^{g_{t-1}})^2 \sigma_{\xi}^2 / (1 - \rho^2)}. \quad (10)$$

A potentially important limitation of using the variance ratio in eq.(9) or (10) as a measure for stock market integration is that it can be contaminated by a so-called heteroskedasticity or volatility bias (see e.g., Pukthuanthong and Roll, 2009). Forbes and Rigobon (2002) argue that during periods of turmoil, when the volatility of stock markets increases temporarily, standard (unadjusted) estimates of cross-market correlations will be biased upward.⁵ A similar bias occurs when stock market integration is measured using a variance share. The reason is that the variance share calculated in eq.(9) or (10) depends on the potentially time-varying volatilities of the common and idiosyncratic factors. More specifically, the variance share in eq.(9) or (10) may erroneously point to higher (lower) integration if the volatility of the common factor is *temporarily* high (low) and/or if the volatility of the country-specific factor is *temporarily* low (high).

To deal with this issue, we calculate a corrected version of the stock market integration measure presented above. This corrected measure is based on the disentanglement of the transitory and permanent components from the volatilities of the common and idiosyncratic risk premiums r_{pt} and μ_{it} as presented

⁵This problem has been acknowledged in (early) studies on stock market integration that calculate correlations between equity returns. Longin and Solnik (1995) find that, over the period 1960 – 1990, correlations between the stock markets of 6 major economies and the US increase in periods when the conditional volatility of these markets is high. King et al. (1994) argue that estimates pointing toward increased integration in the late 1980s are confounding transitory increases in stock market correlations (i.e., due to the 1987 crash) with permanent ones. Similarly, Brooks and Del Negro (2002) argue that the increase in comovement across national stock markets measured at the end of the 1990s and early 2000s is due to large IT shocks rather than to increased stock market integration.

in section 2.1. More specifically, our bias-corrected measure of stock market integration

$$FMI_{it}^c = \frac{\beta_{it}^2 (e^{\bar{g}_{t-1}})^2 \sigma_{\xi}^2 / (1 - \rho^2)}{\left(e^{\bar{h}_{i,t-1}}\right)^2 \sigma_{\psi_i}^2 / (1 - \theta_i^2) + \beta_{it}^2 (e^{\bar{g}_{t-1}})^2 \sigma_{\xi}^2 / (1 - \rho^2)}, \quad (11)$$

is constructed using only the permanent trend components \bar{h}_{it} and \bar{g}_t of the stochastic volatilities of the factors μ_{it} and r_{pt} . These should not be clouded by temporary volatility swings but reflect more structural evolutions in the relative importance of country-specific and common risk factors and hence signal the underlying trend in stock market integration.

2.3 Estimation method

2.3.1 Identification and normalization

As it stands, the model in eqs.(1)-(8) is not identified. We therefore impose a number of normalizations. First, the relative scale of the loadings and the common factor in the product $\beta_{it}r_{pt}$ is not identified as β_{it} can be multiplied by a constant and r_{pt} divided by the same constant without changing their product. We address this identification issue by normalizing the average of the factor loadings $\frac{1}{N} \sum_{i=1}^N \frac{1}{T-\tau_i+1} \sum_{t=\tau_i}^T \beta_{it} = 1$ over both t and i . This has the additional advantage that, unlike normalizations on one of the variances, the sign of the loadings and the common factor is determined. Second, a similar identification problem arises in the products $e^{\bar{h}_{it}+\tilde{h}_{it}}\sigma_{\psi_i}\psi_{it}$ and $e^{\bar{g}_t+\tilde{g}_t}\sigma_{\xi}\xi_t$, where the level of \bar{h}_{it} and \bar{g}_t and the scale of the variances $\sigma_{\psi_i}^2$ and σ_{ξ}^2 are not separately identified⁶, e.g., $e^{\bar{h}_{it}+\tilde{h}_{it}}\sigma_{\psi_i} = e^{(a+\bar{h}_{it})+\tilde{h}_{it}}(\sigma_{\psi_i}/e^a)$. Therefore, we impose the normalizations $\frac{1}{T-\tau_i+1} \sum_{t=\tau_i}^T e^{\bar{h}_{it}} = 1$ for each i and $\frac{1}{T} \sum_{t=1}^T e^{\bar{g}_t} = 1$. As such, $\sigma_{\psi_i}^2 / (1 - \theta_i^2)$ and $\sigma_{\xi}^2 / (1 - \rho^2)$ represent the unconditional variances of μ_{it} and r_{pt} respectively.

2.3.2 Gibbs sampling algorithm

Let $r_i = \{r_{it}\}_{t=1}^T$ denote r_{it} stacked over the available time period and $r = \{r_i\}_{i=1}^N$ denote r_i stacked over the available countries. Similar notation is used for the other variables r_p , μ , β , \bar{h} , \tilde{h} , \bar{g} and \tilde{g} . Likewise, we define $\theta = \{\theta_i\}_{i=1}^N$ and similarly for the other parameter vectors.

In a standard linear Gaussian state space model, the Kalman filter can be used to filter the unobserved components from the data and construct the likelihood function such that the unknown parameters can be estimated using maximum likelihood. The introduction of the time-varying factor loadings β_{it} and the stochastic volatilities h_{it} and g_t implies that the state space model becomes non-linear such that the standard Kalman filter is inapplicable and the exact likelihood function is hard to evaluate. Al-

⁶The levels of \bar{h}_{it} and \bar{g}_t are not identified as these are random walk processes. The levels of \tilde{h}_{it} and \tilde{g}_t in contrast are identified as these are zero-mean AR(1) processes.

though approximate filters for the unobserved states and maximum likelihood estimates for the unknown parameters $\phi = [\theta, \rho, \pi, \varrho, \sigma_e^2, \sigma_\gamma^2, \sigma_\gamma^2, \sigma_\lambda^2, \sigma_\lambda^2, \sigma_\omega^2, \sigma_\psi^2, \sigma_\xi^2]$ are available, an exact treatment is feasible using simulation-based methods. More specifically, we use the Gibbs sampler (see e.g., Kim and Nelson, 1999, for an application of Gibbs-sampling to state space models) which is a Markov Chain Monte Carlo (MCMC) method to simulate draws from the intractable joint and marginal posterior distributions of the unknown parameters and the unobserved states using only tractable conditional distributions. Intuitively, this amounts to reducing the complex non-linear model into a sequence of blocks for subsets of parameters/states that are tractable conditional on the other blocks in the sequence.

The posterior density of interest is $f(r_p, \mu, \beta, \bar{h}, \tilde{h}, \bar{g}, \tilde{g}, \phi|r)$. Given an arbitrary set of starting values $(r_p^0, \mu^0, \beta^0, \bar{h}^0, \tilde{h}^0, \bar{g}^0, \tilde{g}^0, \phi^0)$:

1. sample r_p^1 from $f(r_p|r, \mu^0, \beta^0, \bar{g}^0, \tilde{g}^0, \phi^0)$
2. sample (μ_i^1, β_i^1) from $f(\mu_i, \beta_i|r, r_p^1, \bar{h}^0, \tilde{h}^0, \phi^0)$ for $i = 1, \dots, N$
3. (a) sample \bar{h}_i^1 and \tilde{h}_i^1 from $f(\bar{h}_i, \tilde{h}_i|\mu_i^1, \phi^0)$ for $i = 1, \dots, N$
(b) sample \bar{g}^1 and \tilde{g}^1 from $f(\bar{g}, \tilde{g}|r_p^1, \phi^0)$
4. sample ϕ^1 from $f(\phi|r, r_p^1, \mu^1, \beta^1, \bar{h}^1, \tilde{h}^1, \bar{g}^1, \tilde{g}^1)$

Sampling from these blocks can then be iterated J times and, after a sufficiently long burn-in period B , the sequence of draws $(B+1, \dots, J)$ approximates a sample from the virtual posterior distribution $f(r_p, \mu, \beta, \bar{h}, \tilde{h}, \bar{g}, \tilde{g}, \phi|r)$. Details on the exact implementation of each of the blocks can be found in Appendix A. The FMI measures defined in eqs.(9)-(10) are calculated in each sweep of the Gibbs sampler to obtain their posterior distribution. The same holds for the different cross-country and time averages of FMI_{it} that are calculated to investigate European stock market integration in Section 4.2. The results reported below are based on 15000 draws, with the first 10000 used as burn-in draws and the last 5000 used to construct the posterior distributions of states, hyperparameters, statistics and FMI measures.

2.3.3 Priors

For the AR parameters we use a Gaussian prior $\mathcal{N}(b_0, V_0)$ defined by setting a *prior mean* b_0 and *prior variance* V_0 . For the variance parameters we use the inverse Gamma prior $IG(s_0, S_0)$ where the shape $s_0 = \nu_0 T$ and scale $S_0 = s_0 \sigma_0^2$ parameters are calculated from the *prior belief* σ_0^2 about the variance parameter and the *prior strength* ν_0 which is expressed as a fraction of the sample size T^7 . Details on

⁷Since this prior is conjugate, $\nu_0 T$ can be interpreted as the number of fictitious observations used to construct the prior belief σ_0^2 .

the notation and implementation are provided in Appendix A.4.

Our prior choices are reported in Table 1. For the AR parameters of the factors μ_{it} and r_{pt} we note that under the efficient market hypothesis equity excess returns are unpredictable. Therefore we set the prior mean to zero for the AR(1) parameters θ_i ($\forall i$) and ρ . For the AR parameters π_i ($\forall i$) and ϱ in the stationary components of the stochastic volatilities, \tilde{h}_{it} and \tilde{g}_t , we set the prior mean equal to 0.8. Given the monthly frequency of our dataset, this implies the prior belief that the half-life of transitory shocks to the variances of the factors is about 3 months or a quarter. We set relatively uninformative priors for all of these AR parameters.

Table 1: Details on prior choices

Gaussian priors $\mathcal{N}(b_0, V_0)$			Percentiles		
AR(1) parameters		mean (b_0)	stdv ($\sqrt{V_0}$)	5%	95%
Common factor	ρ	0.00	0.25	-0.4113	0.4113
Transitory SV common factor	ϱ	0.80	0.50	-0.0225	1.6225
Idiosyncratic factor	θ	0.00	0.25	-0.4113	0.4113
Transitory SV idiosyncratic factor	π	0.80	0.50	-0.0225	1.6225
Inverse Gamma priors $IG(\nu_0 T, \nu_0 T \sigma_0^2)$			Percentiles		
Standard deviations		belief (σ_0)	strength (ν_0)	5%	95%
Measurement error	σ_e	0.01	0.10	0.0086	0.0120
Shock to factor loadings	σ_ω	0.01	0.10	0.0086	0.0120
Shock to common factor	σ_ξ	1.00	0.01	0.6728	2.0866
Shock to idiosyncratic factor	σ_ψ	3.00	0.01	2.0298	6.1289
Permanent shock to SV common factor	$\sigma_{\bar{\gamma}}$	0.01	0.10	0.0086	0.0120
Transitory shock to SV common factor	$\sigma_{\tilde{\gamma}}$	0.05	0.10	0.0432	0.0595
Permanent shock to SV idiosyncratic factor	$\sigma_{\bar{\lambda}}$	0.01	0.10	0.0086	0.0120
Transitory shock to SV idiosyncratic factor	$\sigma_{\tilde{\lambda}}$	0.05	0.10	0.0432	0.0595

Notes: We set IG priors on the variance parameters σ^2 but in the bottom panel of this table we report details on the implied prior distribution for the standard deviations σ as these are easier to interpret. Likewise, in the top panel of the table we report the prior standard deviation $\sqrt{V_0}$ instead of the prior variance V_0 .

For the variances, our prior belief for $\sigma_{e_i}^2$ ($\forall i$) embodies the belief that measurement error in eq.(1) is small and is therefore set to 0.01^2 . Our prior beliefs for the random walk error variances $\sigma_{\tilde{\gamma}_i}^2$ ($\forall i$), $\sigma_{\tilde{\lambda}}^2$ and $\sigma_{\omega_i}^2$ ($\forall i$) are also set to the relatively low value of 0.01^2 , which embodies the belief that the permanent components of the stochastic volatilities, \bar{h}_{it} and \bar{g}_t , and the factor loadings β_{it} are slowly evolving over time and pick up permanent structural changes in the economy. Given the more volatile transitory components of the volatilities, \tilde{h}_{it} and \tilde{g}_t , the prior beliefs for the variances $\sigma_{\tilde{\gamma}_i}^2$ ($\forall i$) and $\sigma_{\tilde{\lambda}}^2$ are set to a somewhat higher value, namely 0.05^2 . The prior beliefs for the variances $\sigma_{\psi_i}^2$ ($\forall i$) and σ_{ξ}^2 are set to 9 and 1 respectively.⁸ The reason for the smaller prior on the variance of the shock to the common factor σ_{ξ}^2 is that we do not want to put too much prior weight on financial market integration. Robustness checks with smaller values for $\sigma_{\psi_i}^2$ and larger values for σ_{ξ}^2 do not show any marked differences

⁸Note that the unconditional variances of the actual equity excess returns (expressed in percentage terms) over the sample period 1970:1-2015:12 lie between 30 and 120.

compared to the results of the baseline simulation, though. We use relatively loose priors by setting the prior strength equal to either 0.1 or 0.01. Note that we use the least informative priors for the innovations to the idiosyncratic and common factors as we do not want to be informative on the relative importance of these two factors.

3 Data

We use monthly data over the period 1970:1-2015:12 on the excess returns for 19 European countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and the UK. The maximum number of observations per country is 552. For some countries we have fewer observations. This makes the panel unbalanced. Those countries are Finland, for which the sample starts in 1982:1 (408 observations), Greece, Ireland and Portugal, for which the sample starts in 1988:1 (336 observations), Poland, for which the sample starts in 1993:1 (276 observations), and Czech Republic and Hungary, for which the sample starts in 1995:1 (252 observations). To calculate monthly excess returns in % we use continuously compounded returns in deviation from the risk free rate

$$R_{it} = \left(\log \left(\frac{S_{it}}{S_{i,t-1}} \right) \right) \cdot 100 - R_{ft}$$

where S_{it} is the value of the stock market index in country i at time t and R_{ft} is the risk-free rate in the US at time t . This calculation of country equity excess returns follows Bekaert et al. (2009). For S_{it} we use the country-specific MSCI equity return index expressed in USD⁹ provided by Morgan Stanley (and obtained from Datastream). The MSCI index is widely used in the literature. It covers 90-95% of the investable market capitalization. Note that the MSCI country indices are value weighted and are calculated with dividend reinvestment. For R_{ft} we use the 3-month US Treasury Bill rate. It is provided by the US Federal Reserve in annualized % terms (and obtained from Datastream). We convert it to monthly numbers by dividing it by 12. We then subtract the country-specific means from R_{it} for each i to obtain the variable r_{it} used in the estimations.

4 Estimation results

In this section we report the results of estimating the dynamic factor model in state space form as given by equations (1)-(8). We first present the estimated stochastic factor volatilities and the factor loadings,

⁹To alleviate exchange rate noise, it is common practice in the literature to work with equity returns expressed into a common currency (see e.g., Pukthuanthong and Roll, 2009).

both of which are expected to drive stock market integration. Second, we discuss the estimated measures of time-varying European stock market integration. The discussion tackles the country-specific FMI measures as well as cross-country and time averages of the FMI measures.

4.1 Factor volatilities and factor loadings

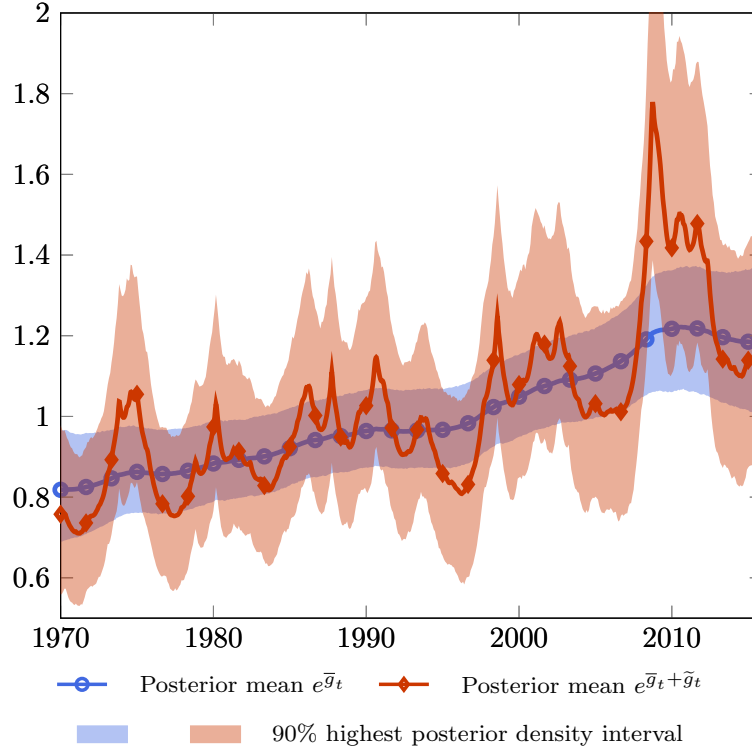
The estimation of the dynamic factor model in state space form given by equations (1)-(8) provides estimates for the country-specific factors μ_{it} , the common European factor r_{pt} and corresponding factor loadings β_{it} , the stochastic volatilities h_{it} and g_t , and the hyperparameters ϕ . The components β_{it} , h_{it} and g_t that, from eqs.(9)-(11), are expected to drive stock market integration are presented in Figures 1-3. Figures for the factors μ_{it} and r_{pt} as well as figures with histograms of the posterior distributions of the parameters ϕ are not reported but are available from the authors upon request.

The graph of the estimated stochastic volatility $e^{\bar{g}_t + \tilde{g}_t}$ of the common European risk factor is presented in Figure 1. A number of familiar episodes of global financial turmoil are clearly visible. The 1973-1975 period was characterized by the end of the Bretton Woods era, the first oil crisis and the ensuing recession which led to a sharp drop in global stock prices and in excess returns and to a sharp increase in their volatility. In October 1987 stock markets around the world crashed (“Black Monday”). In the period 1997-2003 several global events occurred that also affected European financial markets, i.e., the crisis in Asia, Argentina and Russia, the failure of the LTCM hedge fund, and the dot com bubble burst. The last spike in volatility that can be observed in the figure reflects the financial crisis, the ensuing Great Recession of 2008-2009 and the euro area debt crisis of 2010-2012. As we note in Section 2.2 however, the measurement of stock market integration should not depend on such transitory episodes. In Figure 1 we also report the estimated trend component of the volatility of the common European factor, i.e., $e^{\bar{g}_t}$. From the figure it is clear that there is a moderate structural increase in the volatility of the common factor over the sample period up until 2010, signaling an increase in the importance of the common European factor. After 2010, this upward trend seems to have been reversed.

The estimated stochastic volatilities $e^{\bar{h}_{it} + \tilde{h}_{it}}$ of the country-specific risk factors are presented in Figure 2 for each of the 19 countries in our sample. On these graphs, it is possible to discern certain country-specific episodes of financial turmoil. Examples are the property price crash and banking crisis in the UK in the period 1973-1975 and an increase in uncertainty in Germany after the federal election in West Germany in January 1987. Again, these are temporary changes in volatility that should not be included in a measure of stock market integration. To adequately measure stock market integration, it is the structural evolution in the stochastic volatility of the country-specific risk factors that matters. The estimated trend components in the volatilities of the country-specific risk factors, i.e., $e^{\bar{h}_{it}}$, are also

presented in Figure 2. From the figure it is clear that, over the sample period, the volatility of the country-specific risk factors decreases substantially in almost all European countries. Notable exceptions are Ireland for which the trend volatility $e^{\bar{h}_{it}}$ of its country-specific risk premium μ_{it} has been stable over the sample period and Greece for which we observe a trend decline in the volatility of μ_{it} until the end of the 2000s, after which the trend in the volatility increases quite substantially again.

Figure 1: Stochastic volatility in the common European risk factor



In Figure 3 we present the time-varying loadings β_{it} on the common European factor for each of the 19 countries in our sample. Some countries fluctuate (slightly) more than the European portfolio return (i.e., those countries with β 's that tend to be higher than 1) while others fluctuate (slightly) less (i.e., those countries with β 's that tend to be lower than 1).¹⁰ From the figure we note that the country-specific exposures to the common European risk factor have remained relatively stable over the sample period for most countries.¹¹ The finding of relatively stable factor loadings suggests that if our stock market integration measures FMI_{it} and FMI_{it}^c do reveal structural changes in European stock market integration, these changes are mainly driven by structural volatility changes of the risk factors (common and/or country-specific) rather than by structural changes in the exposures to common risk. This conclusion reemphasizes the inadequacy of using factor loadings in and of themselves as measures

¹⁰Note that imposing the average of the β 's (over i and t) to be equal to 1 as an identification restriction (see the discussion in Section 2.3.1) provides a natural benchmark value (i.e., 1) for the sensitivity of country i 's return to the European portfolio return (i.e., for the loading β_{it}).

¹¹The exceptions are Austria which shows an increase in β_{it} and the UK and Switzerland which show a decline in β_{it} .

of stock market integration as we have discussed in Section 2.2.

Figure 2: Stochastic volatility in the country-specific risk factors

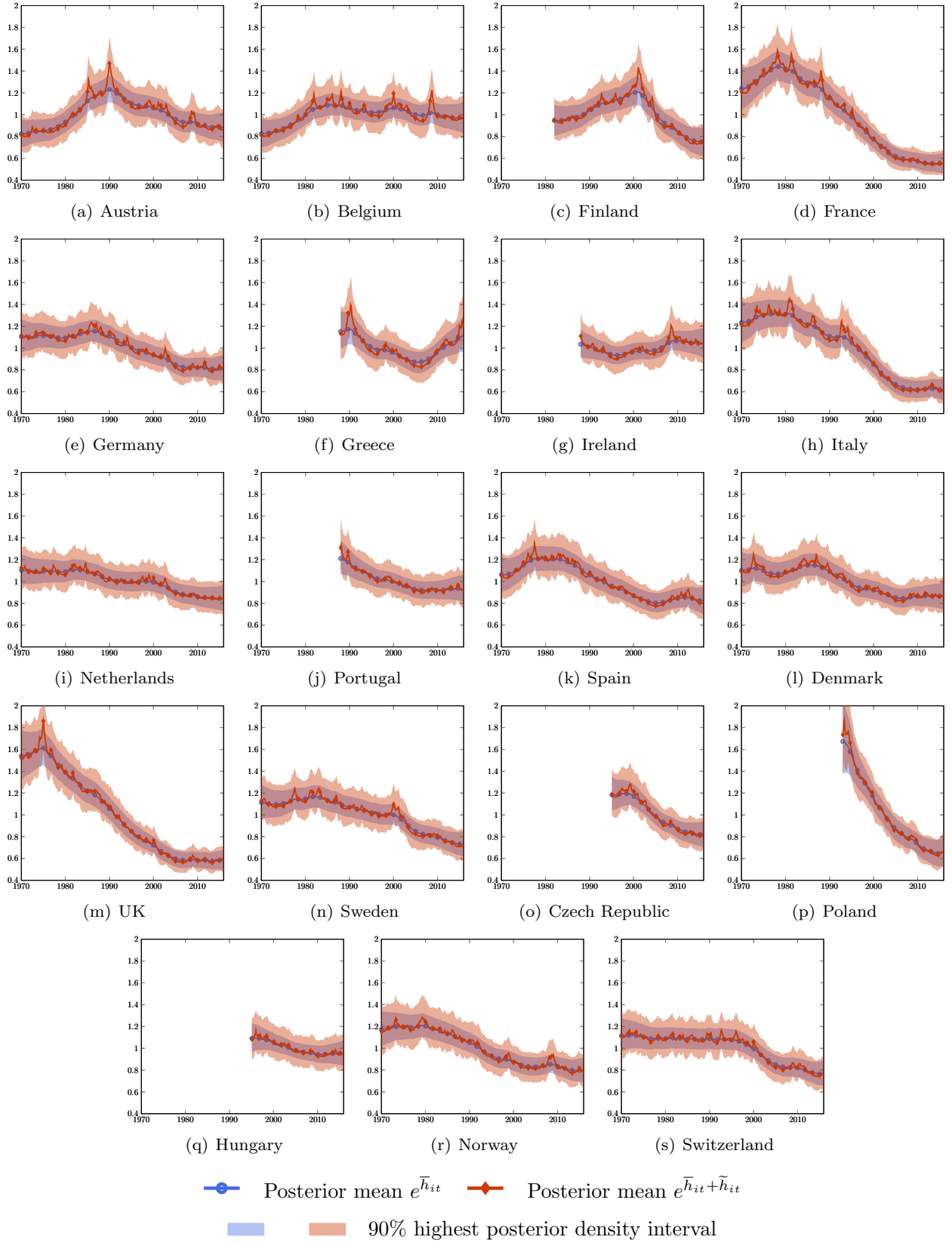
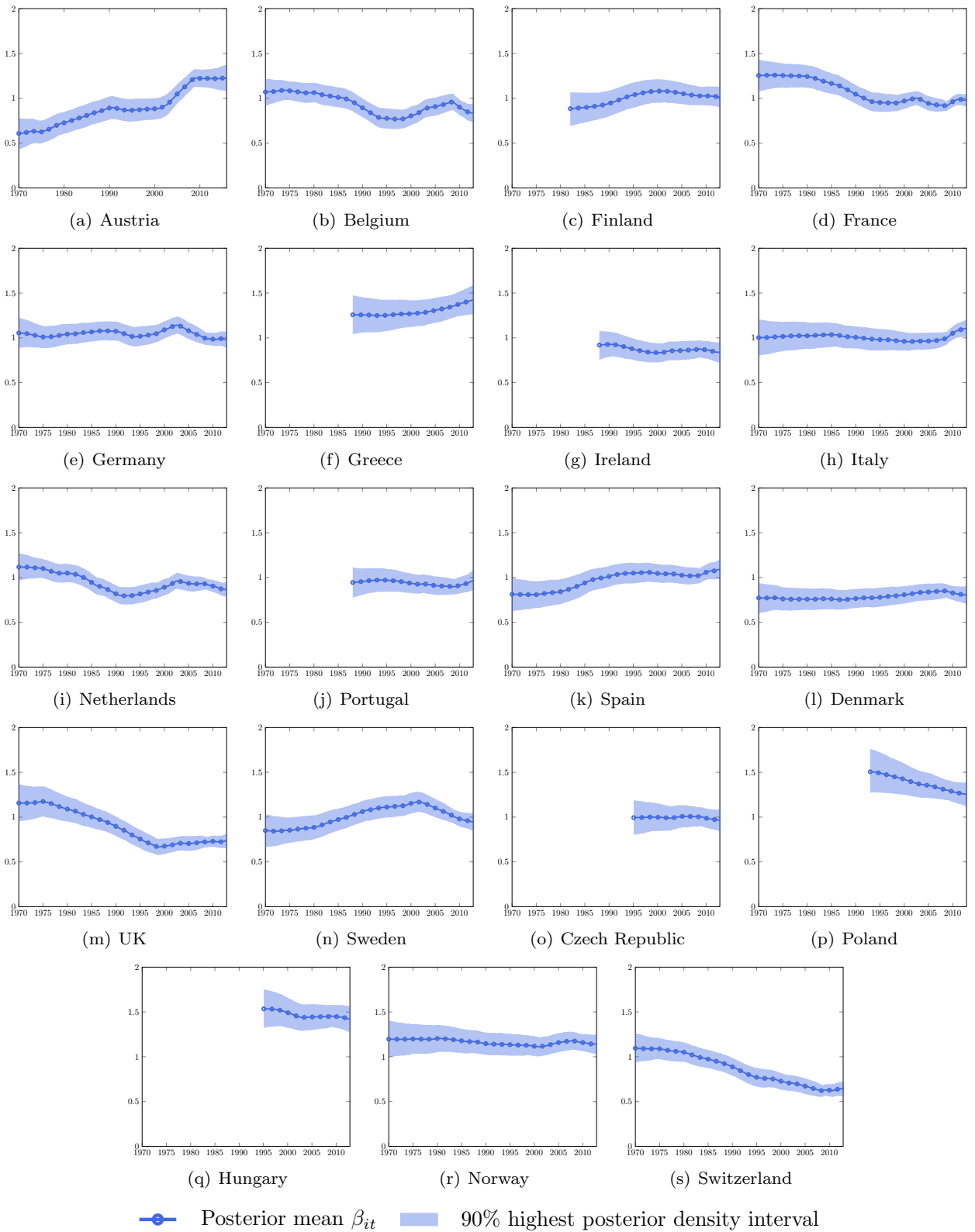


Figure 3: Factor loadings on the common European risk factor



4.2 Measures of stock market integration

4.2.1 Individual country results and average over all countries

In Table 2 we report country-specific time averages of the estimated measures of stock market integration over balanced subsamples with starting dates according to data availability (see Section 3 for details on data availability). In particular, we report $\overline{FMI}_i^c = \frac{1}{T-\tau_i+1} \sum_{t=\tau_i}^T FMI_{it}^c$ where τ_i denotes the first period for which data is available for country i . Since we are looking at time averages, the integration measures corrected for volatility bias are very close to the uncorrected integration measures, so we only report the former ones. We also report the cross-country average of \overline{FMI}_i^c over all countries, namely $\overline{FMI}^c = \frac{1}{N} \sum_{i=1}^N \overline{FMI}_i^c$. From the table we note that the average degree of stock market integration across countries lies between 0.58 and 0.63 depending on the subsample considered. Of course, while indicative of the average degree of integration of all European countries in recent decades, this number may hide important differences in the degree of stock market integration across countries. For instance, the numbers in column 1 in the table - where countries are included for which data are available from 1970:1 onward - show stock market integration time averages that vary between low values of about 0.5 for Austria, Italy and Denmark to high values of about 0.7 for France, Germany and the Netherlands. These numbers, however, are uninformative about changes in the evolution of stock market integration over time.

Figure 4 therefore plots the country-specific time-varying indicators of stock market integration FMI_{it} and FMI_{it}^c . The cross-sectional averages of FMI_{it} and FMI_{it}^c over all countries in the sample are presented in Figure 5. Note that this figure contains four vertical bars indicating the moment at which countries are added to the sample. As explained in Section 3, the panel is unbalanced as data for Finland are only available from 1982:1 onward (first vertical bar), data for Greece, Ireland and Portugal are only available from 1988:1 onward (second vertical bar), data for Poland are only available from 1993:1 onward (third vertical bar), and data for Czech Republic and Hungary are only available from 1995:1 onward (fourth vertical bar). These bars are added to the figure because, given the relatively small cross-sectional dimension N of our sample, adding countries to the sample causes - in the period of addition - a small shift in \overline{FMI}_t and particularly in the smoother \overline{FMI}_t^c .

From Figures 4 and 5 we observe that there are clear differences between the uncorrected FMI_{it} measures and the FMI_{it}^c measures which are corrected for temporary volatility fluctuations. The higher volatility of the former indicators may lead to erroneous conclusions about stock market integration. Consider, for instance, the period of the financial crisis, the Great Recession and the euro area debt crisis. Based on the graph for \overline{FMI}_t in Figure 5, one could argue that there has been a significant increase

Table 2: *FMI*, country averages over balanced subsamples

Countries	Start period - 2015				
	1970	1982	1988	1993	1995
Austria	0.49	0.54	0.58	0.62	0.64
Belgium	0.62	0.61	0.61	0.62	0.63
Finland		0.43	0.46	0.48	0.49
France	0.69	0.74	0.77	0.81	0.83
Germany	0.66	0.70	0.72	0.75	0.76
Greece			0.45	0.48	0.49
Ireland			0.52	0.53	0.53
Italy	0.50	0.57	0.61	0.65	0.68
Netherlands	0.70	0.71	0.72	0.75	0.76
Portugal			0.56	0.59	0.60
Spain	0.52	0.60	0.64	0.67	0.69
Denmark	0.49	0.54	0.58	0.61	0.62
UK	0.58	0.64	0.67	0.70	0.71
Sweden	0.54	0.61	0.64	0.67	0.68
Czech Republic					0.47
Poland				0.50	0.52
Hungary					0.57
Norway	0.53	0.58	0.61	0.63	0.64
Switzerland	0.62	0.61	0.61	0.61	0.62
Average over countries	0.58	0.61	0.61	0.63	0.63

Notes: We report the mean of the posterior distribution (over the 5000 Gibbs draws) of the time averages of the FMI^c measure over balanced subsamples with starting dates according to data availability of the individual countries in our sample. In particular, for Finland, the sample starts in 1982:1, for Greece, Ireland and Portugal, the sample starts in 1988:1, for Poland, the sample starts in 1993:1, and for Czech Republic and Hungary, the sample starts in 1995:1.

in average stock market integration in Europe over the period 2008 – 2012. Of course, this measured increase stems from the drastic rise in the volatility of the European risk factor observed during this period (see Figure 1) and cannot be interpreted as a structural increase in integration. Rather, as we argue below, stock market integration in Europe seems to have stagnated and even fallen after 2010. To draw valid conclusions about time-varying structural stock market integration one should therefore focus on FMI_{it}^c rather than on FMI_{it} which is what we do in the remainder of the paper.

The graphs for the country-specific FMI_{it}^c measures reported in Figure 4 show that no country is fully integrated at any moment in time, i.e., the FMI_{it}^c measures are smaller than 1 for all countries in all periods. Additionally, in almost all countries FMI_{it}^c is (often substantially) larger in the last year of the sample period (2015) compared to the first year of the sample (which is 1970 for most countries) so that we can conclude that stock market integration has structurally increased in most European countries under consideration. These results confirm earlier findings for European countries by Bekaert et al. (2009), Pukthuanthong and Roll (2009), and Eiling and Gerard (2011). For some countries the

degree of stock market integration was already quite high in 1970 and shows a rather modest increase afterwards (e.g., Switzerland, Germany). Other countries start from a relatively low degree of integration after which integration rises rapidly (e.g., Austria, Italy) and sometimes very rapidly (e.g., Poland). Still other countries start from a low degree of integration and have experienced a rather modest subsequent increase (e.g., Greece). Hence, the evolution of stock market integration over the sample period was markedly different across countries. Of particular relevance in the light of the recent economic events is that for almost all countries the increasing trend in stock market integration seems to have come to an end after 2010. For many countries the trend now even appears to be falling. After the financial crisis and the euro debt crisis, European countries have implemented new banking rules and have experienced higher sovereign risk and political uncertainty which may be responsible for this (potential) trend reversal in stock market integration. It is interesting to note from Figure 4 that European countries have not experienced reversals in integration before 2010 (at least not over the available sample period). This observation stands in sharp contrast to what has been observed for emerging markets where reversals in integration have been quite frequent (see e.g., Bekaert and Harvey, 1995; Carrieri et al., 2007).

The conclusions drawn for individual countries are confirmed by the graph for the evolution of the cross-sectional average \overline{FMI}_t^c presented in Figure 5. Average stock market integration in Europe shows a steady increase starting in the mid 1980s until 2010 after which the increase halts and the trend starts to slightly fall.

Figure 4: Country-specific FMI measures

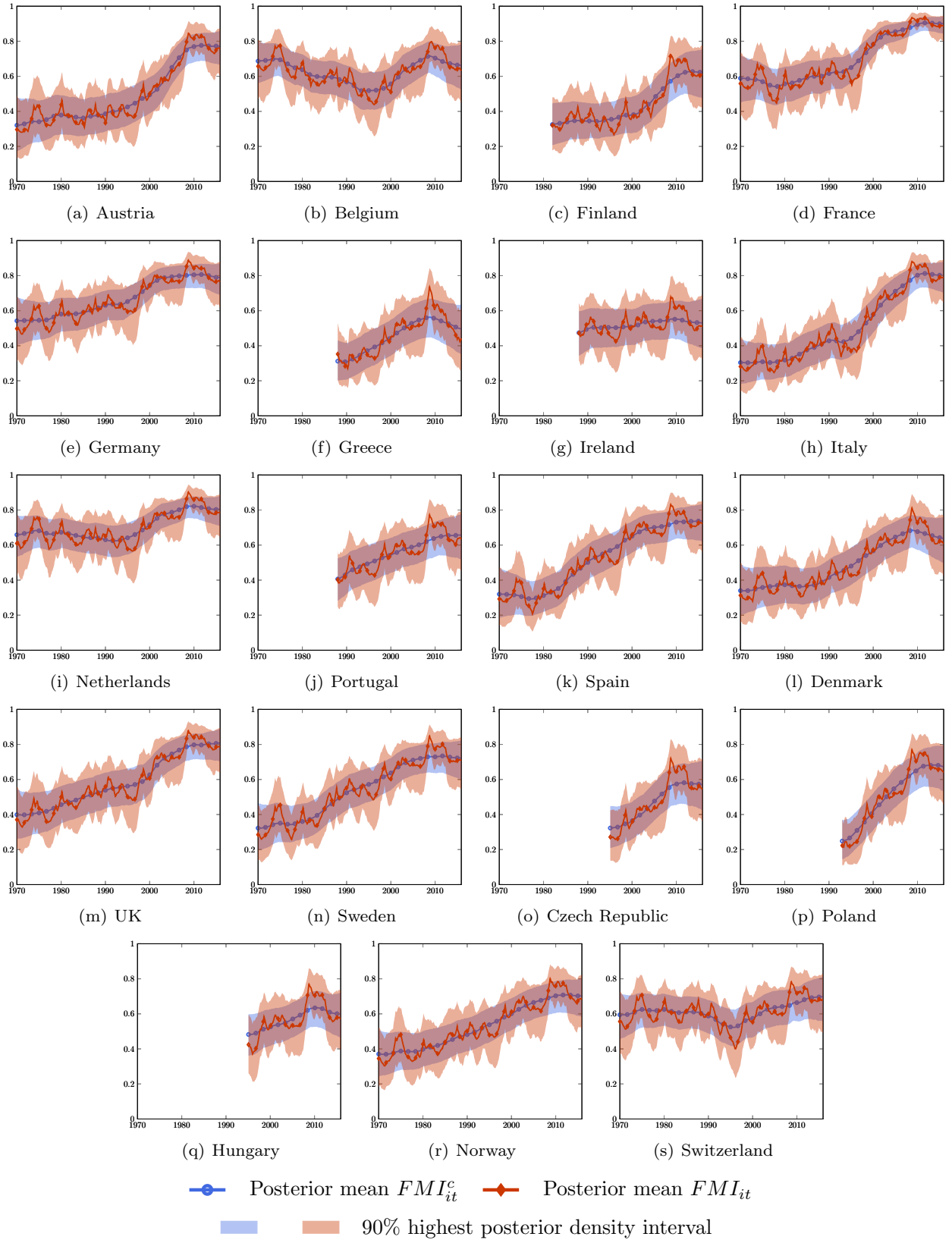
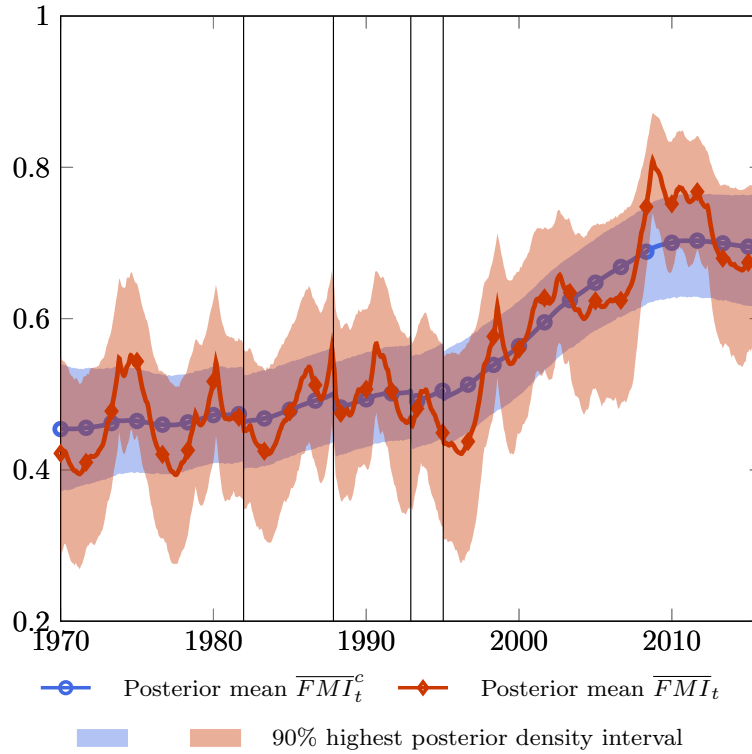


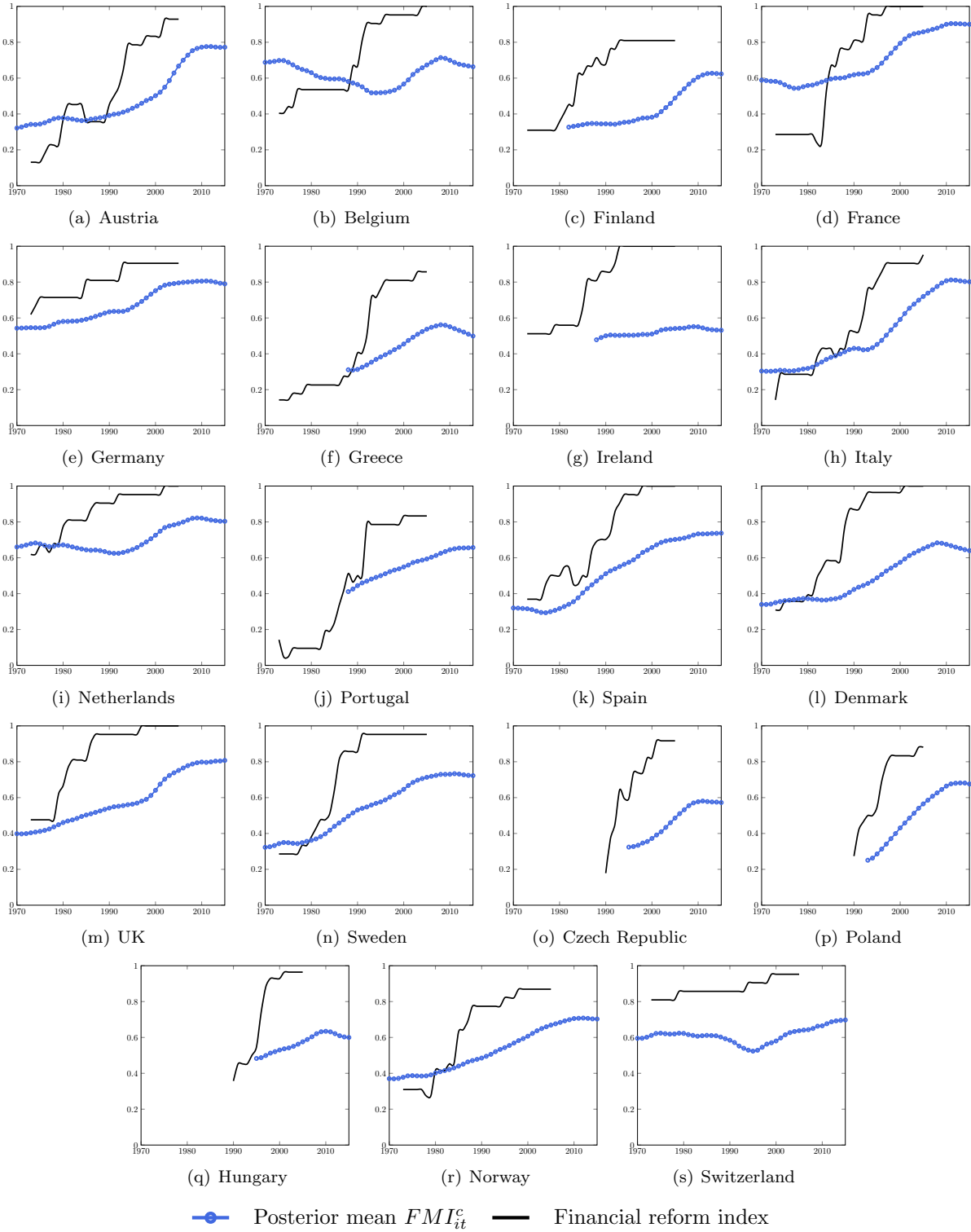
Figure 5: Average FMI measure, all countries



Note: The vertical bars indicate the addition of countries to the sample: (i) Finland in 1982:1, (ii) Greece, Ireland and Portugal in 1988:1, (iii) Poland in 1993:1, (iv) Czech Republic and Hungary in 1995:1.

One of the main explanations given to the process of stock market integration in the literature is financial liberalization (see e.g., Bekaert et al., 2013, for European countries or Bekaert and Harvey, 1995, for emerging markets). Successive financial reforms have loosened investment impediments encountered by foreign investors on European stock markets and these looser investment restrictions may have increased stock market integration. In Figure 6 we compare our corrected FMI measure FMI_{it}^c to the financial reform indicator constructed by Abiad et al. (2008). This indicator is available for all countries in our sample on an annual basis over the period 1973-2005 (and normalized to lie between 0 and 1). It includes reforms on capital controls and reforms of securities markets (among which are stock markets). From the figure we note that, for many countries, both stock market integration and financial liberalization show an increasing trend, with the trend in stock market integration lagging the trend in financial reforms (see also Bekaert et al., 2002, who show for emerging economies that integration tends to lag liberalization). For example, Switzerland which has not experienced a large increase in financial liberalization - the reform indicator equals 0.8 already in the early 1970s - has also experienced a stable and relatively high degree of stock market integration over the sample period. Poland, on the other hand, has experienced a steep increase in both financial market liberalization and in stock market integration over a relatively brief period.

Figure 6: Financial liberalization and FMI



Note: The financial reform index is taken from Abiad et al. (2008). The monthly FMI_{it}^c measure is annualized by taking averages over the 12 months of each year.

While in most countries (almost) full financial liberalization has been achieved by the end of the 1990s, the same is not true for stock market integration. At the end of the sample period average FMI across Europe equals ‘only’ 0.7 (see Figure 5) with - as noted above - the trend increase seemingly halted and

reversed after 2010. Of course, full financial liberalization need not necessarily imply full stock market integration because, for instance, even with fully liberalized financial markets certain investors may still favor to invest at home rather than abroad (i.e., the home bias puzzle).

4.2.2 Country groups and subperiods

While the previous section documents an increase in stock market integration over the sample period in almost all European countries but also shows that the evolution was sometimes quite different across countries, this section focusses on the possibility that the evolution of integration was different for different groups of countries. Since one of the goals of the establishment of the EU and the euro area was the increase of the integration of financial markets of the member states, the country groups that we consider are, first and foremost, the European Union and the euro area. In particular, we investigate whether stock market integration is higher for EU and euro area countries compared to other European economies. We also investigate whether stock market integration is higher for EU core countries - i.e., the initial member states of the EEC (European Economic Community) and EU (i.e., Belgium, France, Germany, Italy, Netherlands) - and for the euro core countries (i.e., Austria, Belgium, France, Germany, Netherlands, Finland).¹²

Table 3 presents the means and 5th and 95th percentiles of the posterior distributions of the average FMI^c measures over countries belonging to the different country groups reported in the table. The construction of the country groups is detailed in the notes to the table. It should be noted that the construction of the country groups takes into account the successive (i.e., staggered) accession dates of countries to the EU and to the euro area. In the same table we also report the means and 5th and 95th percentiles of the posterior distributions of the differences in these statistics between country groups, i.e., we compare EU to non-EU, euro to EU non-euro,...

From the table we note that, over the full sample period, EU countries do have a higher degree of stock market integration compared to non-EU countries. This difference however can be completely attributed to the higher degree of integration of EU core countries (i.e., the member states belonging to the EU from the beginning of the sample) versus non-EU countries. This difference is as large as the difference in integration between EU core countries and EU non-core countries so that the difference in integration between EU non-core countries and non-EU countries is in fact zero. From the table we also note that, over the period 1999-2015, euro countries do have a slightly higher degree of stock market integration compared to non-euro countries. Again, however, this difference can be attributed to the higher degree of

¹²Unreported cross-sectional dependence tests conducted on the country-specific factor μ_{it} after estimation of the dynamic factor model given by equations (1)-(8) suggest that neither of these country groups (the EU, the euro area, the EU core, the euro core) commands an additional common risk factor in the stock excess returns of their member countries.

Table 3: Average FMI for country groups

Country groups	mean			percentiles		Differences	mean		
	5%	95%	5%	95%	5%		95%		
(c1) all	0.55	0.51	0.58						
(c2) EU	0.57	0.53	0.61	(d1)	EU - non-EU	0.07	0.05	0.09	
(c3) non-EU	0.50	0.46	0.54						
(c4) EU core	0.63	0.60	0.67	(d2)	EU core - EU non-core	0.13	0.10	0.15	
				(d3)	EU core - non-EU	0.13	0.11	0.16	
(c5) EU non-core	0.51	0.47	0.55	(d4)	EU non-core - non-EU	0.00	-0.02	0.03	
(c6) euro	0.67	0.61	0.71	(d5)	euro - EU non-euro	0.01	-0.02	0.04	
				(d6)	euro - all non-euro	0.03	0.01	0.06	
(c7) EU non-euro	0.66	0.59	0.71						
(c8) all non-euro	0.63	0.57	0.68						
(c9) euro core	0.71	0.65	0.75	(d7)	euro core - euro non-core	0.09	0.06	0.12	
				(d8)	euro core - EU non-euro	0.05	0.02	0.08	
				(d9)	euro core - all non-euro	0.08	0.05	0.10	
(c10) euro non-core	0.62	0.55	0.67	(d10)	euro non-core - EU non-euro	-0.04	-0.07	-0.01	
				(d11)	euro non-core - all non-euro	-0.02	-0.05	0.01	

Notes: We report the mean and the 5th and 95th percentiles of the posterior distribution (over the 5000 Gibbs draws) of the FMI_{it}^c measure averaged over countries belonging to the country groups mentioned.

Country group ‘all’ consists of the 19 European countries over the full sample period (depending on data availability at a given point in time).

Country group ‘EU’ consists of all countries that are members of the EU taking into account staggered accession dates. Hence Belgium, France, Germany, Italy and the Netherlands belong to the EU group from the beginning of the sample onwards while the following countries enter the EU group at a later stage: Denmark, Ireland and the UK in 1973:1; Greece in 1982:1; Spain and Portugal in 1986:1; Austria, Finland and Sweden in 1995; the Czech Republic, Poland and Hungary in 2004:5. Together with Norway and Switzerland, the 12 countries entering at a later stage belong to the ‘non-EU’ group prior to their EU accession dates (and depending on data availability at a given point in time). Country group ‘EU core’ consists of Belgium, France, Germany, Netherlands and Italy (from the beginning of the sample) while ‘EU non-core’ are all other EU countries.

The average FMI measure for the ‘euro’ group is calculated from 1999:1 onwards and consists of the 10 countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain) that introduced the euro in 1999:1 with Greece being added to the group from 2001:1 onwards. Country group ‘EU non-euro’ consists of Denmark, Sweden and the UK from 1999:1 onwards, Greece between 1999:1 and 2000:12, and Czech Republic, Poland and Hungary from 2004:5 onward. Country group ‘all non-euro’ includes Denmark, Sweden, UK, Czech Republic, Poland, Hungary, Norway and Switzerland from 1999:1 onwards and Greece between 1999:1 and 2000:12. Similarly, the average FMI measure for the ‘euro core’ group is calculated from 1999:1 onwards and consists of Austria, Belgium, France, Germany, Netherlands, Finland. The ‘euro non-core’ group consists of Greece, Ireland, Italy, Portugal, Spain.

stock market integration of the euro core countries versus all other countries in the sample. The peripheral euro area countries do not show higher degrees of stock market integration compared to countries that have not (yet) adopted the euro. In fact, they seem to be somewhat less integrated than the non-euro economies.

In Table 4 we focus in more detail on EU accession and its relation to stock market integration by investigating the evolution in stock market integration over subperiods. Hence, in this table average FMI^c measures are reported both over countries that belong to EU related country groups (i.e., the previously defined groups EU, non-EU, EU core, and EU non-core) and over subperiods which are delineated by the accession dates of countries to the EU. We refer to the notes to Table 3 for the countries accessing at every date and for the composition of the country groups EU, non-EU, EU core, and EU non-core. Again, the table also reports the differences in the FMI^c measures between country groups.

The top part of the table compares stock market integration between the EU and the non-EU countries

Table 4: Average FMI for EU country groups and subperiods

Subperiods	mean		percentiles		
			5%	95%	
	EU	non-EU	EU - non-EU		
(1) 1970.1-1972.12	0.56	0.39	0.17	0.11	0.23
(2) 1973.1-1981.12	0.51	0.41	0.10	0.05	0.14
(3) 1982.1-1985.12	0.51	0.42	0.09	0.05	0.13
(4) 1986.1-1994.12	0.51	0.46	0.06	0.02	0.09
(5) 1995.1-2004.4	0.59	0.49	0.10	0.06	0.13
(6) 2004.5-2015.12	0.68	0.67	0.01	-0.03	0.05
	EU core	non-EU	EU core - non-EU		
(1) 1970.1-1972.12	0.56	0.39	0.17	0.11	0.23
(2) 1973.1-1981.12	0.55	0.41	0.14	0.09	0.18
(3) 1982.1-1985.12	0.55	0.42	0.13	0.08	0.17
(4) 1986.1-1994.12	0.57	0.46	0.11	0.07	0.15
(5) 1995.1-2004.4	0.66	0.49	0.18	0.14	0.21
(6) 2004.5-2015.12	0.78	0.67	0.11	0.07	0.16
	EU non-core	non-EU	EU non-core - non-EU		
(1) 1970.1-1972.12		0.39			
(2) 1973.1-1981.12	0.40	0.41	-0.01	-0.08	0.05
(3) 1982.1-1985.12	0.43	0.42	0.01	-0.05	0.07
(4) 1986.1-1994.12	0.46	0.46	0.01	-0.03	0.05
(5) 1995.1-2004.4	0.54	0.49	0.05	0.02	0.09
(6) 2004.5-2015.12	0.64	0.67	-0.03	-0.07	0.01

Notes: We report the mean and the 5th and 95th percentiles of the posterior distribution (over the 5000 Gibbs draws) of the FMI_{it}^c measure averaged over country groups and subperiods. The subperiods correspond to the staggered accession dates of countries to the EU. See the notes to Table 3 for the countries accessing at every date and for the composition of the country groups EU, non-EU, EU core, and EU non-core.

over the six reported subperiods. The EU countries were on average clearly more integrated than non-EU countries during the 1970s, 1980s and 1990s but this difference has gradually vanished. Over the last subperiod 2004:5-2015:12 the difference in stock market integration between both country groups was essentially zero. While this result seems to suggest that EU membership leads to earlier and faster stock market integration, this conclusion would be premature. The middle part of the table compares stock market integration between EU core countries (i.e., the initial EU member states) and non-EU countries over the 6 reported subperiods. The EU core countries have experienced consistently higher degrees of stock market integration compared to the non-EU countries. The same cannot be said for the EU non-core countries however. The lower part of Table 4 compares stock market integration between EU non-core countries and non-EU countries over 5 subperiods (i.e., there are no EU non-core countries for the period 1970:1-1972:12 so that this subperiod drops out in the lower part of the table). Here, we note that EU non-core countries and non-EU countries show very similar degrees of stock market integration and a rather similar evolution of integration over the subperiods. These results seem to indicate that,

in line with our findings for the EU reported in Table 3, stock market integration in Europe was not EU-driven. All country groups (EU core, EU non-core, non-EU) have experienced a considerable increase in stock market integration over the sample period and while the degree of integration was clearly higher for the initial EU members, the countries subsequently accessing the EU have experienced neither earlier nor faster integration when compared to countries that accessed at a later date or not at all. The speed at which both EU non-core members and non-EU countries caught up with the EU core countries is very similar.

Table 5: Average FMI for euro area country groups and subperiods

Subperiods	mean		percentiles		
			5%	95%	
	euro	all non-euro	euro - all non-euro		
(1) 1992.2-1998.12	0.52	0.49	0.03	-0.01	0.06
(2) 1999.1-2010.3	0.65	0.61	0.04	0.02	0.07
(3) 2010.4-2015.12	0.71	0.67	0.03	0.00	0.07
	euro core	all non-euro	euro core - all non-euro		
(1) 1992.2-1998.12	0.55	0.47	0.07	0.03	0.12
(2) 1999.1-2010.3	0.69	0.60	0.09	0.06	0.12
(3) 2010.4-2015.12	0.76	0.67	0.09	0.05	0.13
	euro non-core	all non-euro	euro non-core - all non-euro		
(1) 1992.2-1998.12	0.49	0.47	0.01	-0.03	0.06
(2) 1999.1-2010.3	0.60	0.60	0.00	-0.03	0.04
(3) 2010.4-2015.12	0.65	0.67	-0.02	-0.07	0.02

Notes: We report the mean and the 5th and 95th percentiles of the posterior distribution (over the 5000 Gibbs draws) of the FMI_{it}^c measure averaged over country groups and subperiods. Countries are assigned to the same group across all subperiods (i.e., we do not use staggered accession dates for this table). The ‘euro’ group consists of the 11 countries that introduced the euro (Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Greece), while the ‘all non-euro’ group includes the other 8 countries in the sample (Denmark, Sweden, UK, Czech Republic, Poland, Hungary, Norway and Switzerland). The ‘euro core’ group consists of Austria, Belgium, Finland, France, Germany and the Netherlands while the ‘euro non-core’ group holds Greece, Ireland, Italy, Portugal and Spain.

In Table 5 we investigate the role played by the introduction of the euro in the evolution of stock market integration. Average FMI^c measures are reported over countries that belong to euro area related country groups and over euro related subperiods. The table also reports the differences in the FMI^c measures between country groups. The country groups contain the same countries in every subperiod (i.e., we do not use staggered accession dates for this table). The ‘euro’ group consists of the 11 countries in the sample that have adopted the euro while the ‘all non-euro’ group consists of the remaining 8 countries in the sample. The ‘euro core’ and ‘euro non-core’ groups are as defined previously. We refer to the notes to Table 5 for the exact composition of the groups. The subperiods considered are delineated by three important euro area related events, namely the signing of the Maastricht Treaty in February

1992 (1992:2) which can be considered the starting point of the monetary unification process in Europe, the introduction of the euro in January 1999 (1999:1), and the downgrading of Greek debt to junk status in April 2010 (2010:4) which marked the beginning of the euro area debt crisis.

The top part of the table compares stock market integration between euro and non-euro countries over the three reported subperiods. The euro countries are only slightly more integrated over all three subperiods with the positive difference remaining constant over time. The difference is only substantial in a statistical sense (i.e., in the sense that the 5% percentile of the distribution of the difference in integration is also positive) during the period 1999:1-2010:3. In the middle part of the table we compare stock market integration between euro core and non-euro countries over the three reported subperiods. We note that, similar to our findings for the EU core economies, the euro core countries are substantially more integrated than the non-euro countries. This is true for the period after the introduction of the euro but also during the run-up to the euro, albeit to a lesser extent. In the lower part of Table 5 we investigate the difference in stock market integration between euro non-core countries (i.e., the peripheral euro countries) and non-euro countries over all subperiods and find that there are no substantial differences in integration between both country groups.¹³ Hence, similar to our findings for the EU, the slightly higher degrees of integration for euro area countries reported in the top part of the table are due to the higher degrees of integration experienced by the euro core countries and are not representative of the euro area as a whole.

To summarize, we find no evidence that countries belonging to the EU or to the euro area have experienced higher levels of stock market integration or have integrated substantially faster than countries that are not members of these institutions. The core members of the EU and the euro area however show consistently higher degrees of stock market integration compared to non-core EU or euro countries. Previous studies that suggest that membership of either the EU or the euro increased European stock market integration may therefore be picking up EU core or euro core effects instead of true EU-wide or euro area-wide effects.

5 Conclusions

We investigate time-varying European stock market integration for 19 European countries over the period 1970-2015 focussing on the role played by institutions, i.e., EU and euro area membership. To this end we estimate a dynamic factor model with time-varying factor loadings and stochastic volatilities using MCMC methods. The empirical specification can be linked to existing asset pricing models such as the international CAPM. From a time-varying variance decomposition applied to the dynamic factor model,

¹³If anything, as we have noted also when discussing the results for the period 1999-2015 reported in Table 3, during the last subperiod (2014:4-2015:12) the euro non-core countries have become slightly less integrated than the non-euro countries.

bias-corrected time-varying stock market integration measures are calculated for every country.

To the best of our knowledge, the Bayesian state space methods employed in this paper have not yet been applied in the context of the measurement of financial market integration. These methods provide a number of useful properties that are of particular interest to the analysis of stock market integration. First, dynamic factor models allow for the estimation of common factors for which country weights are implicitly derived as part of the estimation process. This is important in the analysis of stock market integration as the country weights in the common factor are most likely endogenous to the degree of stock market integration. Second, a state space approach is particularly useful when using variance ratios as measures of time-varying stock market integration. These variance ratios are constructed from the factor loadings and the factor volatilities of our dynamic factor model which can be modelled as time-varying stochastic processes. Moreover, the Gibbs sampler used to estimate the Bayesian dynamic factor model provides the full empirical distributions of the time-varying variance ratios which can be used in statistical tests. Third, the approach allows for a correction of the stock market integration measure for a potential volatility bias so that it is not contaminated by temporary volatility shocks to the country-specific and common risk factors.

Our results suggest that stock market integration has structurally increased in most European countries over the sample period, particularly from the late 1980s and early 1990s onward. Nonetheless, the evolution was sometimes quite different across countries with some countries experiencing modest increases and others integrating more rapidly. In many European economies the evolution of stock market integration clearly lags the increasing trend in financial liberalization. From 2010 onward - i.e., after the global financial crisis, the ensuing Great Recession and the euro area debt crisis - the trend increase in stock market integration seems to have come to an end in all countries. With respect to the impact of institutions, we find no evidence that members of the EU and the euro area have experienced higher levels of stock market integration or have integrated faster than countries that are not members of these institutions. Hence, despite the efforts of political leaders to improve the integration of European markets through European economic and monetary unification, our results suggest that the increase in European stock market integration has occurred largely independently of countries' participation in institutions like the EU or the euro area.

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Appendix A Detailed outline of the blocks in the Gibbs sampler

In this appendix we outline the Gibbs approach to jointly sample the states $(r_p, \mu, \beta, \bar{h}, \bar{g}, \tilde{h}, \tilde{g})$, and the hyperparameters (ϕ) . In the first 3 blocks, we use a forward-filtering-backward-sampling approach for the states based on a general state space model of the form

$$y_t = Z_t \alpha_t + \varepsilon_t, \quad \varepsilon_t \sim iid\mathcal{N}(0, H_t), \quad (\text{B-1})$$

$$\alpha_{t+1} = T_t \alpha_t + K_t \eta_t, \quad \eta_t \sim iid\mathcal{N}(0, Q_t), \quad t = \tau, \dots, T \quad (\text{B-2})$$

$$\alpha_\tau \sim iid\mathcal{N}(a_\tau, P_\tau), \quad (\text{B-3})$$

where y_t is a $p \times 1$ vector of observations and α_t an unobserved $m \times 1$ state vector. The matrices Z_t , T_t , K_t , H_t , Q_t and the expected value a_τ and variance P_τ of the initial state vector α_τ are assumed to be known (conditioned upon) and the error terms ε_t and η_t are assumed to be serially uncorrelated and independent of each other at all points in time. As eqs.(B-1)-(B-3) constitute a linear Gaussian state space model, the unknown state variables in α_t can be filtered using the standard Kalman filter. Sampling $\alpha = [\alpha_\tau, \dots, \alpha_T]$ from its conditional distribution can then be done using the multimove Gibbs sampler of Carter and Kohn (1994).

A.1 Block 1: filtering and sampling the common factor r_p

In this step of the Gibbs sampler, we simultaneously filter and sample the common factor r_p conditioning on the idiosyncratic components μ and β , the stochastic volatilities \bar{g} and \tilde{g} and the hyperparameters ρ , σ_e^2 and σ_ξ^2 . The state space representation for the conditional model in this block is given by:

$$\underbrace{\begin{bmatrix} y_t \\ r_{1t} - \mu_{1t} \\ \vdots \\ r_{Nt} - \mu_{Nt} \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} Z_t \\ \beta_{1t} \\ \vdots \\ \beta_{Nt} \end{bmatrix}}_{Z_t} \underbrace{\begin{bmatrix} \alpha_t \\ r_{pt} \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} \varepsilon_t \\ e_{1t} \\ \vdots \\ e_{Nt} \end{bmatrix}}_{\varepsilon_t}, \quad (\text{B-4})$$

$$\underbrace{\begin{bmatrix} r_{p,t+1} \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} \rho \end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix} r_{pt} \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} e^{\bar{g}_t + \tilde{g}_t} \sigma_\xi \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \xi_t \end{bmatrix}}_{\eta_t}, \quad (\text{B-5})$$

and $H_t = \begin{bmatrix} \sigma_{e_1}^2 & & & 0 \\ & \ddots & & \\ & & & 0 \\ 0 & & & \sigma_{e_N}^2 \end{bmatrix}$, $Q_t = 1$, $a_1 = [0]$, $P_1 = \left[(e^{\bar{g}_1 + \tilde{g}_1})^2 \sigma_\xi^2 / (1 - \rho^2) \right]$, for $t = 1, \dots, T$.

Instead of taking the entire observational vectors y_t as the items for analysis, we follow the univariate

treatment of multivariate series approach of Koopman and Durbin (2000) in which each of the elements y_{it} in y_t is brought into the analysis one at a time. This not only offers significant computational gains, it also avoids the risk that the prediction error variance matrix becomes nonsingular. Moreover, it allows to take into account the unbalancedness of the panel by varying the dimension of y_t over time, i.e., if no data are available for country i at time t the element $r_{it} - \mu_{it}$ is dropped from the vector y_t (also dropping the appropriate elements in Z_t , α_t and ε_t).

A.2 Block 2: filtering and sampling μ and β

In this step of the Gibbs sampler, we filter and sample the idiosyncratic components μ and β conditioning on the common factor r_p , the stochastic volatilities \bar{h} and \tilde{h} and the hyperparameters θ , σ_e^2 , σ_ψ^2 and σ_ω^2 . As these components are cross-sectionally independent, this can be done country-by-country. The state space representation of the model for country i in this block is given by:

$$\underbrace{\begin{bmatrix} y_t \\ r_{it} \end{bmatrix}} = \underbrace{\begin{bmatrix} Z_t \\ 1 & r_{pt} \end{bmatrix}} \underbrace{\begin{bmatrix} \alpha_t \\ \mu_{it} \\ \beta_{it} \end{bmatrix}} + \underbrace{\begin{bmatrix} \varepsilon_t \\ e_{it} \end{bmatrix}}, \quad (\text{B-6})$$

$$\underbrace{\begin{bmatrix} \mu_{i,t+1} \\ \beta_{i,t+1} \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} \theta_i & 0 \\ 0 & 1 \end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix} \mu_{it} \\ \beta_{it} \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} e^{\bar{h}_{it} + \tilde{h}_{it}} \sigma_{\psi_i} & 0 \\ 0 & \sigma_{\omega_i} \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \psi_{it} \\ \omega_{it} \end{bmatrix}}_{\eta_t}, \quad (\text{B-7})$$

$$\text{and } H_t = \begin{bmatrix} \sigma_{e_i}^2 \end{bmatrix}, Q_t = I_2, a_{\tau_i} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, P_{\tau_i} = \begin{bmatrix} \left(e^{\bar{h}_{i\tau_i} + \tilde{h}_{i\tau_i}} \right)^2 \sigma_{\psi_i}^2 / (1 - \theta_i^2) & 0 \\ 0 & 1000 \end{bmatrix}, \text{ for } t = \tau_i, \dots, T.$$

After drawing μ_i and β_i for all countries, we divide β_{it} by a normalizing constant. In order to leave the product $\beta_{it} r_{pt}$ unaltered, we multiply r_{pt} by the same normalizing constant. As a result, the average of the factor loadings over both t and i equals $\frac{1}{N} \sum_{i=1}^N \frac{1}{T - \tau_i + 1} \sum_{t=\tau_i}^T \beta_{it} = 1$.

A.3 Block 3: filtering and sampling \bar{h} , \tilde{h} , \bar{g} and \tilde{g}

A key feature of the stochastic volatility components $e^{\bar{h}_{it} + \tilde{h}_{it}} \sigma_{\psi_i} \psi_{it}$ and $e^{\bar{g}_t + \tilde{g}_t} \sigma_\xi \xi_t$ is that they are nonlinear but can be transformed into linear components by taking the logarithm of their squares

$$\log \left(e^{\bar{h}_{it} + \tilde{h}_{it}} \sigma_{\psi_i} \psi_{it} \right)^2 = 2\bar{h}_{it} + 2\tilde{h}_{it} + \log \sigma_{\psi_i}^2 + \log \psi_{it}^2, \quad (\text{B-8a})$$

$$\log \left(e^{\bar{g}_t + \tilde{g}_t} \sigma_\xi \xi_t \right)^2 = 2\bar{g}_t + 2\tilde{g}_t + \log \sigma_\xi^2 + \log \xi_t^2, \quad (\text{B-8b})$$

where $\log \psi_{it}^2$ and $\log \xi_t^2$ are log-chi-square distributed with expected value -1.2704 and variance 4.93 . Following Kim et al. (1998), we approximate the linear models in (B-8) by an offset mixture time series model as

$$h_{it}^* = 2\bar{h}_{it} + 2\tilde{h}_{it} + \log \sigma_{\psi_i}^2 + \psi_{it}^*, \quad (\text{B-9a})$$

$$g_t^* = 2\bar{g}_t + 2\tilde{g}_t + \log \sigma_{\xi}^2 + \xi_t^*, \quad (\text{B-9b})$$

where $h_{it}^* = \log \left(\left(e^{\bar{h}_{it} + \tilde{h}_{it}} \sigma_{\psi_i} \psi_{it} \right)^2 + c \right)$, $g_t^* = \log \left(\left(e^{\bar{g}_t + \tilde{g}_t} \sigma_{\xi} \xi_t \right)^2 + c \right)$, with $c = .001$ being an offset constant, and the distributions of ψ_{it}^* and ξ_t^* being the following mixtures of normals

$$f(\psi_{it}^*) = \sum_{j=1}^M q_j f_N(\psi_{it}^* | m_j - 1.2704, \nu_j^2), \quad (\text{B-10a})$$

$$f(\xi_t^*) = \sum_{j=1}^M q_j f_N(\xi_t^* | m_j - 1.2704, \nu_j^2), \quad (\text{B-10b})$$

with component probabilities q_j , means $m_j - 1.2704$ and variances ν_j^2 . Equivalently, these mixture densities can be written in terms of the component indicator variables s_{it} and w_t as

$$\psi_{it}^* | (s_{it} = j) \sim \mathcal{N}(m_j - 1.2704, \nu_j^2), \quad \text{with} \quad Pr(s_{it} = j) = q_j, \quad (\text{B-11a})$$

$$\xi_t^* | (w_t = j) \sim \mathcal{N}(m_j - 1.2704, \nu_j^2), \quad \text{with} \quad Pr(w_t = j) = q_j. \quad (\text{B-11b})$$

We follow Kim et al. (1998) by selecting $M = 7$ and using the parameters $\{q_j, m_j, \nu_j^2\}$ in their Table 4 to make the approximation of the mixture distributions to the log-chi-square distribution sufficiently good. The conditional probability mass functions for s_{it} and w_t are given by

$$Pr(s_{it} = j | \bar{h}_{it}, \tilde{h}_{it}, \psi_{it}^*) \propto q_j f_N(\psi_{it}^* | 2\bar{h}_{it} + 2\tilde{h}_{it} + \log \sigma_{\psi_i}^2 + m_j - 1.2704, \nu_j^2), \quad (\text{B-12a})$$

$$Pr(w_t = j | \bar{g}_t, \tilde{g}_t, \xi_t^*) \propto q_j f_N(\xi_t^* | 2\bar{g}_t + 2\tilde{g}_t + \log \sigma_{\xi}^2 + m_j - 1.2704, \nu_j^2). \quad (\text{B-12b})$$

Below we use the notation $s_i = \{s_{it}\}_{t=\tau_i}^T$ and $w = \{w_t\}_{t=1}^T$.

Following Del Negro and Primiceri (2013), in this block we first sample the mixture indicators s_{it} and w_t from their conditional probability mass functions (B-12a) and (B-12b), where s_{it} is only sampled over the period for which data for country i are available while w_t is sampled over the full sample period.

Next, we filter and sample the stochastic volatilities \bar{h}_{it} , \tilde{h}_{it} , \bar{g}_t and \tilde{g}_t conditioning on the transformed states $h_{it}^* = \log \left((\mu_{i,t+1} - \theta_i \mu_{it})^2 + 0.001 \right)$ and $g_t^* = \log \left((r_{p,t+1} - \rho r_{pt})^2 + 0.001 \right)$, on the mixture indicators s_{it} and w_t and on the hyperparameters $\sigma_{\psi_i}^2$, σ_{ξ}^2 , $\sigma_{\bar{\gamma}_i}^2$, $\sigma_{\tilde{\gamma}_i}^2$, σ_{λ}^2 and σ_{λ}^2 .

The state space representation of the model for \bar{h}_{it} and \tilde{h}_{it} is given by:

$$\overbrace{\left[h_{it}^* - \left(\log \sigma_{\psi_i}^2 + m_{s_{it}} - 1, 2704 \right) \right]}^{y_t} = \overbrace{\begin{bmatrix} 2 & 2 \end{bmatrix}}^{Z_t} \overbrace{\begin{bmatrix} \bar{h}_{it} \\ \tilde{h}_{it} \end{bmatrix}}^{\alpha_t} + \overbrace{\left[\tilde{\psi}_{it}^* \right]}^{\varepsilon_t}, \quad (\text{B-13})$$

$$\underbrace{\begin{bmatrix} \bar{h}_{i,t+1} \\ \tilde{h}_{i,t+1} \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & \pi_i \end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix} \bar{h}_{it} \\ \tilde{h}_{it} \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} \sigma_{\bar{\gamma}_i} & 0 \\ 0 & \sigma_{\tilde{\gamma}_i} \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \bar{\gamma}_{it} \\ \tilde{\gamma}_{it} \end{bmatrix}}_{\eta_t}, \quad (\text{B-14})$$

and $H_t = [\nu_{s_{it}}^2]$, $Q_t = I_2$, $a_{\tau_i} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, $P_{\tau_i} = \begin{bmatrix} 1000 & 0 \\ 0 & \sigma_{\tilde{\gamma}_i}^2 / (1 - \pi_i^2) \end{bmatrix}$ for $t = \tau_i, \dots, T$. For given values of s_{it} , the values for $m_{s_{it}}$ and $\nu_{s_{it}}^2$ are taken from Table 4 in Kim et al. (1998) and $\tilde{\psi}_{it}^* = \psi_{it}^* - (m_{s_{it}} - 1, 2704)$ is ψ_{it}^* recentered around zero. After drawing \bar{h}_{it} we normalize $\frac{1}{T - \tau_i + 1} \sum_{t=\tau_i}^T e^{\bar{h}_{it}} = 1$ for each i .

Similarly, the state space representation of the model for \bar{g}_t and \tilde{g}_t is given by:

$$\overbrace{\left[g_t^* - \left(\log \sigma_{\xi}^2 + m_{w_t} - 1, 2704 \right) \right]}^{y_t} = \overbrace{\begin{bmatrix} 2 & 2 \end{bmatrix}}^{Z_t} \overbrace{\begin{bmatrix} \bar{g}_t \\ \tilde{g}_t \end{bmatrix}}^{\alpha_t} + \overbrace{\left[\tilde{\xi}_t^* \right]}^{\varepsilon_t}, \quad (\text{B-15})$$

$$\underbrace{\begin{bmatrix} \bar{g}_{t+1} \\ \tilde{g}_{t+1} \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & \varrho \end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix} \bar{g}_t \\ \tilde{g}_t \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} \sigma_{\bar{\lambda}} & 0 \\ 0 & \sigma_{\tilde{\lambda}} \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \bar{\lambda}_t \\ \tilde{\lambda}_t \end{bmatrix}}_{\eta_t}, \quad (\text{B-16})$$

and $H_t = [\nu_{w_t}^2]$, $Q_t = I_2$, $a_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, $P_1 = \begin{bmatrix} 1000 & 0 \\ 0 & \sigma_{\tilde{\lambda}}^2 / (1 - \varrho^2) \end{bmatrix}$ for $t = 1, \dots, T$. For given values of w_t , the values for m_{w_t} and $\nu_{w_t}^2$ are again taken from Table 4 in Kim et al. (1998) and $\tilde{\xi}_t^* = \xi_t^* - (m_{w_t} - 1, 2704)$ is ξ_t^* recentered around zero. After drawing \bar{g}_t we normalize $\frac{1}{T} \sum_{t=1}^T e^{\bar{g}_t} = 1$.

A.4 Block 4: estimating and sampling the hyperparameters ϕ

In the final block of the Gibbs sampler we estimate and draw the hyperparameters ϕ . Conditioning on the idiosyncratic components μ and β , the common factor R_p and the stochastic volatilities \bar{h} , \tilde{h} , \bar{g} and \tilde{g} , these are all unknown parameters in the standard static linear regression model

$$y_t = b' x_t + u_t, \quad u_t \sim \mathcal{N}(0, \sigma^2), \quad (\text{B-17})$$

where x_t and b are $(\ell \times 1)$ vectors. The matrix version of (B-17) is $y = Xb + u$ with obvious notations X ($T \times \ell$ matrix), y and u ($T \times 1$ vectors). We follow the approach outlined in Bauwens et al. (1999)

(pages 56-61). Prior information is represented through the following normal-inverted gamma-2 density

$$\varphi(b, \sigma^2) = f_{NIg}(b, \sigma^2 | b_0, M_0, s_0, S_0), \quad (\text{B-18})$$

with the prior information being summarized by the hyperparameters $(b_0, V_0, \sigma_0^2, v_0)$. First, b_0 is the prior belief about the coefficient vector b with prior variance V_0 such that the prior precision $M_0 = V_0^{-1}$. Second, σ_0^2 is the prior belief about the error variance σ^2 , such that $s_0 = \sigma_0^2 S_0$ is the prior belief about the residual sum of squares $s = u'u$ with S_0 being the corresponding prior strength defined as $S_0 = v_0 T$ where v_0 is the prior degrees of freedom proportional to the sample size T .

The posterior density of b and σ^2 in the linear regression model (B-17) with prior density (B-18) is a normal-inverted gamma-2 distribution

$$\varphi(b, \sigma^2 | y, X) = f_{NIg}(b, \sigma^2 | b_*, M_*, s_*, S_*), \quad (\text{B-19})$$

with hyperparameters defined by

$$\begin{aligned} b_* &= M_*^{-1} (M_0 b_0 + X' X \hat{b}), & M_* &= M_0 + X' X, \\ s_* &= s_0 + s + (b_0 - \hat{b})' (M_0^{-1} + (X' X)^{-1})^{-1} (b_0 - \hat{b}), & S_* &= S_0 + T, \end{aligned}$$

with \hat{b} the LS estimator for b in (B-17). Sampling b and σ^2 from the posterior distribution (B-19) can then be done separately from

$$b \sim \mathcal{N}\left(b_*, \frac{S_*}{S_* - 2} M_*^{-1}\right), \quad (\text{B-20})$$

$$\sigma^2 \sim IG_2(S_*, s_*). \quad (\text{B-21})$$

If $X = [.]$, the posterior density in (B-19) reduces to

$$\varphi(\sigma^2 | y, X) = f_{Ig}(\sigma^2 | s_*, S_*), \quad (\text{B-22})$$

with $s_* = s_0 + s$ and S_* as defined above.

The hyperparameters ϕ can now be sampled as:

- Obtain the posterior distribution of $\sigma_{e_i}^2$ in (1) for each country i separately conditioning on μ_{it} , β_{it} and r_{pt} by using (B-22) setting $y_t = r_{it} - \mu_{it} - \beta_{it} r_{pt}$ and $x_t = [.]$ in (B-17). Next, sample $\sigma_{e_i}^2$ from (B-21).
- Obtain the posterior distribution of θ_i and $\sigma_{\psi_i}^2$ in (2) for each country i separately conditioning on

μ_{it} , \bar{h}_{it} and \tilde{h}_{it} by using (B-19) setting $y_t = \mu_{i,t+1} / e^{\bar{h}_{it} + \tilde{h}_{it}}$ and $x_t = \mu_{it} / e^{\bar{h}_{it} + \tilde{h}_{it}}$ in (B-17) such that this becomes a GLS-type regression model. Next, sample θ_i and $\sigma_{\psi_i}^2$ from (B-20) and (B-21).

- Obtain the posterior distribution of $\sigma_{\tilde{\gamma}_i}^2$ in (3) for each country i separately conditioning on \bar{h}_{it} by using (B-22) setting $y_t = \bar{h}_{i,t+1} - \bar{h}_{it}$ and $x_t = [.]$ in (B-17). Next, sample $\sigma_{\tilde{\gamma}_i}^2$ from (B-21).
- Obtain the posterior distribution of π_i and $\sigma_{\tilde{\gamma}_i}^2$ in (4) for each country i separately conditioning on \tilde{h}_{it} by using (B-19) setting $y_t = \tilde{h}_{i,t+1}$ and $x_t = \tilde{h}_{it}$ in (B-17). Next, sample π_i and $\sigma_{\tilde{\gamma}_i}^2$ from (B-20) and (B-21).
- Obtain the posterior distribution of ρ and σ_{ξ}^2 in (5) conditioning on r_{pt} , \bar{g}_t and \tilde{g}_t by using (B-19) setting $y_t = r_{p,t+1} / e^{\bar{g}_t + \tilde{g}_t}$ and $x_t = r_{pt} / e^{\bar{g}_t + \tilde{g}_t}$ in (B-17) such that this becomes a GLS-type regression model. Next, sample ρ and σ_{ξ}^2 from (B-20) and (B-21).
- Obtain the posterior distribution of σ_{λ}^2 in (6) conditioning on \bar{g}_t by using (B-22) setting $y_t = \bar{g}_{t+1} - \bar{g}_t$ and $x_t = [.]$ in (B-17). Next, sample σ_{λ}^2 from (B-21).
- Obtain the posterior distribution of ϱ and σ_{λ}^2 in (7) conditioning on \tilde{g}_t by using (B-19) setting $y_t = \tilde{g}_{t+1}$ and $x_t = \tilde{g}_t$ in (B-17). Next, sample ϱ and σ_{λ}^2 from (B-20) and (B-21).
- Obtain the posterior distribution of $\sigma_{\omega_i}^2$ in (8) for each country i separately conditioning on β_{it} by using (B-22) setting $y_t = \beta_{i,t+1} - \beta_{it}$ and $x_t = [.]$ in (B-17). Next, sample $\sigma_{\omega_i}^2$ from (B-21).