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WORKING PAPER

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The dynamics of European financial market integration*

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Abstract

This paper investigates financial market integration using a panel of monthly stock market returns for 16 European countries over the period 1970:01-2012:10. Based on an international CAPM with local investment impediments, equity risk premiums are decomposed into a country-specific and a common European component. The CAPM is estimated as a Bayesian dynamic factor model with stochastic factor loadings and stochastic volatilities for the factor error terms. This approach avoids the use of proxy's for the unobserved risk premium components. A time-varying measure for the degree of integration is obtained that is corrected for the bias induced by temporary volatility shocks to the risk premium components. The results suggest that integration has increased in all countries from the 1980s onward until the Great Recession and that countries belonging to the EU and the euro area have not experienced higher integration than other European economies.

JEL Classification: G15, C32

Keywords: Financial Markets, Stock Markets, CAPM, Integration, Dynamic Factor Model, Unobserved Components, State Space, Stochastic Volatility

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1 Introduction

The environment in which European financial markets operate has changed drastically in recent decades. From the 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., **?**). 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. Accurate knowledge of the degree and evolution of financial market integration is important for different reasons. On the upside, financial integration, by reducing the portfolio home bias of investors (i.e., the tendency of investors to overweight domestic assets in their portfolios), may increase market efficiency. On the downside, financial market integration may increase the spill-over of shocks between countries and may therefore increase contagion risk.

A large part of the research on European financial market integration has focused on stock market integration. In general there is 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). 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. Unsurprisingly, many recent studies have studied 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). In general, these studies document an increase in stock market integration of countries joining the euro. Berben and Jos Jansen (2005) however argue that stock market integration evolved largely independent of monetary unification while 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. (2011) 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 investigates European stock market integration for 16 European countries over the period

1970-2012 using a new empirical approach. The methodology is based on a theoretical framework in which a standard international CAPM (see Harvey, 1991), which assumes full international integration of the national stock markets, is nested into an international CAPM that incorporates impediments faced by investors to invest in national stock markets (see Pozzi and Wolswijk, 2012). Examples of such impediments are regulations (e.g., ownership restrictions, capital controls), taxation, transaction costs, lack of liquidity, etc. As such, countries in the model can be (partially) segmented from international financial markets. This feature of the model allows for the measurement of financial market integration. The econometric approach consists of the estimation of this international CAPM as a dynamic *unobserved* factor model in a non-linear state space framework. From the theory, the equity excess returns of a country are decomposed into a country-specific risk premium and a common European risk premium. We then model these premiums as unobserved factors that follow AR(1) processes with innovation variances that follow stochastic volatility processes. In particular, the log standard deviations of the shocks are modeled as the sum of a transitory (stationary) component (i.e., an AR(1) process) *and* a trend component (i.e., a driftless random walk process). The country-specific exposures to the common European risk premium (i.e., the beta's) constitute the time-varying factor loadings of the factor model and are modeled as driftless random walks. Estimates for the distributions of the unobserved factors, factor loadings, stochastic volatilities and parameters in the non-linear state space model are obtained through Markov chain Monte Carlo (MCMC) methods. From a time-varying variance decomposition, applied to the dynamic factor model, time-varying financial integration measures, i.e., variance ratios, are calculated for every country. While variance ratios have been used before to estimate financial market integration (see e.g., Errunza and Losq, 1985; Baele et al., 2004; Carrieri et al., 2007), the method used in the paper to estimate them is new.

Our methodological approach 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., **?**Del Negro and Otrok, 2008; **?**). To the best of our knowledge, these Bayesian state space methods have not yet been applied in the context of the estimation of (international) CAPM models and the measurement of financial market integration.[1] Besides the obvious advantages of these methods such as the possibility of a simultaneous analysis of a large number of countries (i.e., in a data rich environment), it is our contention that these methods provide a number of clear-cut advantages that are of particular interest to the analysis of financial market integration.

[1]While state space methods have been used previously to estimate the CAPM, they have *not* been used to filter out both factors and factor loadings simultaneously. 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)

First, by filtering out the country-specific and common risk premiums in equity excess returns data, our approach avoids the use of - potentially low-quality - proxy's, instruments and conditioning variables in the estimation of these premiums. With respect to the common factor for instance, it is common practice in the literature to use "world" equity indices or "European" equity indices. These indices may give the wrong weight to certain countries, thereby causing biased financial market integration results.[2]

Second, our approach allows for a focus on *time-varying* financial market integration. This is of particular importance as many papers have explicitly emphasized the time-varying nature of financial integration (see e.g., Bekaert and Harvey, 1995, and Carrieri et al., 2007, who provide evidence for emerging economies or Fratzscher, 2002, and Cappiello et al., 2006, who provide evidence for European economies). Structural changes in financial market integration in Europe might have occurred because of increased globalization and financial liberalization, as a result of the process of European economic and monetary unification, but also as a result of crises such as the Great Recession (2008-2009) and the euro area debt crisis (2010-2012). To this end, the factor loadings and the factor volatilities are modeled as time-varying stochastic processes and used in the construction of our time-varying measures of financial market integration. Modeling factor loadings as time-varying processes is especially useful as the time-varying loadings are an immediate implication of the theoretical international CAPM put forward in the paper (i.e., the beta's are time-varying). By 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).

Third, the decomposition of the stochastic volatility of the factor innovations into a stationary component and a non-stationary trend component makes it possible to correct our financial market integration measure for a potential volatility or heteroskedasticity bias (see e.g., Forbes and Rigobon, 2002). There is a volatility bias in the measure of financial market integration when measured integration is high (low) because the volatility of the common factor is *temporarily* high (low). Likewise, there is a volatility bias when measured integration is high (low) because the volatility of the country-specific factor is *temporarily* low (high). The bias-corrected measure of financial market integration calculated in this paper avoids these problems since only the trend components of the volatilities are used in its construction.

Our results suggest that financial market integration has structurally increased in all European countries over the sample period, particularly from the 1980s 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 financial market integration has

[2] Harvey (1991) e.g., notes that the MSCI world index gives too much weight to Japanese stocks because of the large amount of cross-corporate ownership.

followed the increasing trend in financial liberalization. From 2007 onward - i.e., after the global financial crisis and the ensuing Great Recession - the trend increase in financial market integration seems to have come to an end in almost all countries. At the end of the sample period the degree of stock market integration was below 100% in all countries (with an average degree of about 65% 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 1990*s*. Additionally, we find no direct evidence that countries belonging to the EU or to the euro area have experienced higher levels and/or higher increases in financial market integration compared to 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 countries that would eventually constitute the core members of the euro area *did* however experience consistently (i.e., over the full sample period) higher degrees of stock market integration compared to countries that do not belong to either the EU or the euro core. This suggests that geographical proximity and similarity of economic conditions might have been more important catalysts of financial market integration than the process of European economic and monetary unification.

The remainder of the paper is organized as follows. Section 2 presents an international CAPM that allows for investment impediments on the local stock markets. In Section 3 we discuss the state space representation of this international CAPM. We then discuss the proposed measure of time-varying financial market integration within the context of the existing literature. The section ends with a description of the econometric approach followed to estimate the state space system. Section 4 discusses the data used. Section 5 then presents and discusses the results obtained from the estimation of the full dynamic factor model. The focus is on the estimated time-varying financial market integration measures. Section 6 concludes.

2 An international CAPM with local investment impediments

Consider a representative international investor who maximizes expected utility by choosing a consumption path over an infinite lifetime. Following Pozzi and Wolswijk (2012), we assume that this investor invests in the imperfectly integrated equity markets of N different countries, in a risk-free asset and in an international equity portfolio, with period t returns denoted by respectively R_{it} $(i = 1, ..., N)$, R_{ft}, and R_{pt}. Since stock markets are imperfectly integrated, when investing in the stock market of country i the investor takes into account the costs of local impediments denoted by U_{it}. These country-specific costs reflect the compensation the investor asks when encountering impediments to invest in the stock market of country i such as certain regulations, taxation, transaction costs, lack of liquidity, etc. For the risk-free asset and for the stock portfolio we assume, without loss of generality, that these costs are zero. The period t utility function for the international investor is denoted by $u(c_t)$ where c_t is period t real consumption. The subjective rate of time preference of the investor is captured by the discount factor δ (with $0 < \delta < 1$). The stochastic discount factor m_t used to discount the future returns of the individual stocks and of the international stock portfolio is defined by $m_t \equiv \delta \frac{u'(c_t)}{u'(c_{t-1})}$.[3]

These assumptions lead to the following first-order conditions,

$$E_{t-1}[m_t(R_{it} - U_{it})] = 1 \quad \forall i, \tag{1}$$

$$E_{t-1}[m_t]R_{ft} = 1, \tag{2}$$

$$E_{t-1}[m_t R_{pt}] = 1, \tag{3}$$

where E_{t-1} is the expectations operator conditional on the period $t-1$ information set. Each of the first-order conditions reflects the fact that, in the optimum, the investor is indifferent between consuming an amount of 1 at time $t-1$ or investing this amount in the country-specific stock markets, in the risk-free asset or in the international equity portfolio and consuming respectively $R_{it} - U_{it}$, R_{ft}, or R_{pt} in period t. The expected discounted marginal utility of these decisions is equal. When $U_{it} = 0$, eq.(1) equals the Euler equation of a standard international CAPM (see Harvey, 1991). We thus nest a standard international CAPM, which assumes full international integration of the national economies, into an international CAPM that incorporates impediments to invest in the national stock markets which implies that countries can be (partially) segmented from international financial markets.

Rewriting eq.(1) as

$$E_{t-1}(m_t)E_{t-1}(R_{it} - U_{it}) + cov_{t-1}(m_t, R_{it} - U_{it}) = 1, \tag{4}$$

and using $E_{t-1}(m_t) = 1/R_{ft}$ from eq.(2) yields

$$E_{t-1}(R_{it}) - R_{ft} = E_{t-1}(U_{it}) - cov_{t-1}(m_t, R_{it} - U_{it})R_{ft}. \tag{5}$$

Similarly, eq.(3) can be rewritten as

$$E_{t-1}(R_{pt}) - R_{ft} = -cov_{t-1}(m_t, R_{pt})R_{ft}. \tag{6}$$

[3]Through the consumption levels c_t and c_{t-1} of the representative international investor, m_t reflects the international economic environment.

Combining eqs.(5) and (6) we obtain,

$$E_{t-1}[R_{it}] - R_{ft} = E_{t-1}[U_{it}] + \beta_{it}(E_{t-1}[R_{pt}] - R_{ft}), \tag{7}$$

where $\beta_{it} = \frac{cov_{t-1}(m_t, R_{it} - U_{it})}{cov_{t-1}(m_t, R_{pt})}$. Eq.(7) states that the expected return of the stock of country i over the risk-free asset's return - i.e. country i's excess return or risk premium - depends on the expected cost of investment impediments U_{it} encountered on market i, on the expected excess return of the international equity portfolio $R_{pt} - R_{ft}$, and on β_{it} which depends on the conditional covariance of both the country-specific stock return and the stock portfolio return with the stochastic discount factor. As the stock portfolio consists of individual stocks, the returns R_{it} and R_{pt} are driven by the same stochastic discount factor m_t and R_{pt} is some unspecified weighted average of R_{it}.[4] Both covariances in β_{it} are expected to have the same sign so that in general β_{it} will be positive. For a given value of U_{it}, if the stock market return of country i is more (respectively less or equally) sensitive to the stochastic discount factor than the international stock portfolio return, country i's stock market commands a risk premium larger than (respectively smaller than or equal to) the international risk premium, i.e., $\beta_{it} > 1$ (respectively $\beta_{it} < 1$ or $\beta_{it} = 1$).

3 Empirical set-up

In this section, we first discuss the state space representation of the international CAPM in Section 3.1. Next we present our measure for financial market integration in Section 3.2. The econometric approach followed to estimate the state space system is discussed in Section 3.3.

3.1 State-space representation of the international CAPM

The relationship in terms of expected returns in eq.(7) can be rewritten in terms of realized returns as

$$R_{it} - R_{ft} = U_{it} + \beta_{it}(R_{pt} - R_{ft}) + e_{it}, \qquad i = 1, \ldots, N, \quad t = \tau_i, \ldots, T, \tag{8}$$

where $(R_{it} - R_{ft})$ is the excess return on the stock market of country i, U_{it} is the country-specific risk factor and $(R_{pt} - R_{ft})$ is the common international risk factor. The error term e_{it} is given by $e_{it} = (R_{it} - E_{t-1}[R_{it}]) - (U_{it} - E_{t-1}[U_{it}]) - \beta_{it}(R_{pt} - E_{t-1}[R_{pt}])$. It is straightforward to show that $E_{t-1}[e_{it}] = 0$, $cov_{t-1}(R_{pt}, e_{it}) = 0$ and $cov_{t-1}(U_{it}, e_{it}) = 0$. Hence e_{it} can be interpreted as pure

[4] Note that it is straightforward to obtain the more familiar expression for β_{it}, namely $\beta_{it} = cov_{t-1}(R_{pt}, R_{it} - U_{it})/V_{t-1}(R_{pt})$, by imposing more structure on the relationship between the stochastic discount factor, the individual stock returns and the international portfolio return (see Pozzi and Wolswijk, 2012). For the methodological approach of this paper these further steps are unnecessary and are left out of the analysis.

measurement error. Note that, as for a number of countries data are missing for the first years of the sample period (see Section 4 below), τ_i denotes the first available observation for country i.

Defining r_{it} as the excess return $(R_{it} - R_{ft})$ in deviation from its country-specific mean[5], eq.(8) can be rewritten as

$$r_{it} = \mu_{it} + \beta_{it} r_{pt} + e_{it}. \tag{9}$$

Note that demeaning excess returns implies that the unobserved idiosyncratic risk factor U_{it} and the unobserved international risk factor $(R_{pt} - R_{ft})$ in eq.(8) are now zero-mean processes, denoted by the lower case factors μ_{it} and r_{pt} respectively.

Eq.(9) 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 international risk factor r_{pt} and the additive noise e_{it}, which we assume to be generated as $e_{it} \sim iid\mathcal{N}\left(0, \sigma_{e_i}^2\right)$. 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* (10)-(16) below.

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

$$\mu_{i,t+1} = \theta_i \mu_{it} + e^{h_{it}} \sigma_{\psi_i} \psi_{it}, \qquad \psi_{it} \sim iid\mathcal{N}(0,1), \tag{10}$$

for $i = 1, \ldots, N$ and $t = \tau_i, \ldots, T$. 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., $e^{h_{it}} = e^{\overline{h}_{it} + \widetilde{h}_{it}}$ where $\overline{h}_{it}$ is a permanent trend component modeled as a driftless random walk process

$$\overline{h}_{i,t+1} = \overline{h}_{it} + \sigma_{\overline{\gamma}_i} \overline{\gamma}_{it}, \qquad \overline{\gamma}_{it} \sim iid\mathcal{N}(0,1), \tag{11}$$

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

$$\widetilde{h}_{i,t+1} = \pi_i \widetilde{h}_{it} + \sigma_{\widetilde{\gamma}_i} \widetilde{\gamma}_{it}, \quad |\pi_i| < 1, \qquad \widetilde{\gamma}_{it} \sim iid\mathcal{N}(0,1). \tag{12}$$

The innovations ψ_{it}, $\overline{\gamma}_{it}$ and $\widetilde{\gamma}_{it}$ 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

[5]The 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.

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

$$r_{p,t+1} = \rho r_{pt} + e^{g_t}\sigma_\xi \xi_t, \qquad \xi_t \sim iid\mathcal{N}(0,1), \tag{13}$$

for $t = 1, \ldots, T$. The stochastic volatility e^{g_t} is again modeled as consisting of two distinct components, i.e., $e^{g_t} = e^{\overline{g}_t + \widetilde{g}_t}$ where $\overline{g}_t$ is a permanent trend component modeled as a driftless random walk

$$\overline{g}_{t+1} = \overline{g}_t + \sigma_{\overline{\lambda}}\overline{\lambda}_t, \qquad \overline{\lambda}_t \sim iid\mathcal{N}(0,1), \tag{14}$$

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

$$\widetilde{g}_{t+1} = \varrho \widetilde{g}_t + \sigma_{\widetilde{\lambda}}\widetilde{\lambda}_t, \quad |\varrho| < 1, \qquad \widetilde{\lambda}_t \sim iid\mathcal{N}(0,1). \tag{15}$$

The innovations ξ_t, $\overline{\lambda}_t$ and $\widetilde{\lambda}_t$ 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

$$\beta_{i,t+1} = \beta_{it} + \sigma_{\omega_i}\omega_{it}, \qquad \omega_{it} \sim iid\mathcal{N}(0,1), \tag{16}$$

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

3.2 Measuring financial market integration

Following the literature (see e.g., Errunza and Losq, 1985; Baele et al., 2004; Carrieri et al., 2007) we measure time-varying financial market integration using a variance ratio, i.e., the proportion of a country's excess returns that can be explained by the common risk factor.[6] From eq.(9), a time-varying measure for the degree of financial market integration of country i in period t is therefore given by

$$FMI_{it} = \frac{V_t(\beta_{it} r_{pt})}{V_t(r_{it} - e_{it})} = \frac{V_t(\beta_{it} r_{pt})}{V_t(\mu_{it} + \beta_{it} r_{pt})}, \tag{17}$$

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 important investment impediments are encountered on market i such that $V_t(\mu_{it})$ is high and, as a result, $V_t(\beta_{it} r_{pt}) \ll V_t(\mu_{it} + \beta_{it} r_{pt})$. If $FMI_{it} = 1$ there

[6] A variance ratio is preferred over the use of simple cross-country correlations because a correlation is a measure of comovement between two countries only and thus is not necessarily informative about the integration of all markets.

is full international integration of country i. This is the case if investment impediments on market i are negligible such that $V_t(\mu_{it}) \approx 0$ and, as a result, $V_t(\beta_{it} r_{pt}) \approx V_t(\mu_{it} + \beta_{it} r_{pt})$. Using the state space model in eqs.(9)-(16), the variance ratio based FMI measure proposed in eq.(17) can be calculated as

$$FMI_{it} = \frac{\beta_{it}^2 \left(e^{g_{t-1}}\right)^2 \sigma_\xi^2 / \left(1-\rho^2\right)}{\left(e^{h_{i,t-1}}\right)^2 \sigma_{\psi_i}^2 / (1-\theta_i^2) + \beta_{it}^2 \left(e^{g_{t-1}}\right)^2 \sigma_\xi^2 / (1-\rho^2)}. \tag{18}$$

A potentially important limitation of using the variance ratio in eq.(17) or (18) as a measure for financial market integration - or against the use of simple cross-country correlations for that matter (see e.g., Longin and Solnik, 1995) - is that it can be contaminated by a heteroskedasticity or volatility bias. Forbes and Rigobon (2002) argue that in periods when the volatility of the common factor is temporarily high, measured integration could be erroneously high.[7] Likewise, when the volatility of the idiosyncratic factor is temporarily high, integration measured with a variance ratio could be erroneously low. For this reason some authors prefer to measure financial market integration directly via the factor loading on the common factor (i.e., the β's in our model) rather than via a variance ratio like eq.(17) (see e.g., Fratzscher, 2002). It is our contention however that this approach to measure financial market integration is only justified if shocks to the variances of both the common and the idiosyncratic risk premiums r_{pt} and μ_{it} are purely transitory, i.e., if the volatilities of r_{pt} and μ_{it} show no long-run trend. If the factor volatilities are hit by persistent shocks, then part of the long-run structural evolution that constitutes integration is caused by the evolution of these volatilities and this should be incorporated into a measure of integration.[8] A mere focus on the time-variation of the β's will then result in a poor measurement of stock market integration.

In the empirical set-up in section 3.1, we explicitly take this issue into account by disentangling the transitory and permanent components from the volatilities of the common and idiosyncratic risk premiums r_{pt} and μ_{it}. As such we can correct the variance ratio of the type given by eq.(17) for a potential heteroskedasticity or volatility bias. More specifically, our bias-corrected measure of financial market integration

$$FMI_{it}^c = \frac{\beta_{it}^2 \left(e^{\overline{g}_{t-1}}\right)^2 \sigma_\xi^2 / \left(1-\rho^2\right)}{\left(e^{\overline{h}_{i,t-1}}\right)^2 \sigma_{\psi_i}^2 / (1-\theta_i^2) + \beta_{it}^2 \left(e^{\overline{g}_{t-1}}\right)^2 \sigma_\xi^2 / (1-\rho^2)}, \tag{19}$$

is constructed using only the permanent trend components $\overline{h}_{it}$ and $\overline{g}_t$ of the stochastic volatilities of the

[7] King et al. (1994) for instance 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.

[8] Note from eq.(17) that stock market integration as measured by FMI_{it} increases when the loading on the common factor β_{it} increases, when the volatility of the common factor r_{pt} increases, and when the volatility of the country-specific factor μ_{it} falls.

factors μ_{it} and r_{pt}.

3.3 Estimation method

3.3.1 Identification and normalization

As it stands, the model in eqs.(9)-(16) 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 $e^{\overline{h}_{it}+\widetilde{h}_{it}}\sigma_{\psi_i}\psi_{it}$ and $e^{\overline{g}_t+\widetilde{g}_t}\sigma_{\xi}\xi_t$, where the level of $\overline{h}_{it}$ and $\overline{g}_t$ and the scale of the variances $\sigma^2_{\psi_i}$ and σ^2_{ξ} are not separately identified[9], e.g., $e^{\overline{h}_{it}+\widetilde{h}_{it}}\sigma_{\psi_i}=e^{(a+\overline{h}_{it})+\widetilde{h}_{it}}(\sigma_{\psi_i}/e^{a})$. Therefore, we impose the normalizations $\frac{1}{T-\tau_i+1}\sum_{t=\tau_i}^{T}e^{\overline{h}_{it}}=1$ for each i and $\frac{1}{T}\sum_{t=1}^{T}e^{\overline{g}_t}=1$. As such, $\sigma^2_{\psi_i}/\left(1-\theta_i^2\right)$ and $\sigma^2_{\xi}/\left(1-\rho^2\right)$ represent the unconditional variances of μ_{it} and r_{pt} respectively.

3.3.2 Gibbs sampling algorithm

For notational convenience, 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, $\overline{h}$, $\widetilde{h}$, $\overline{g}$ and $\widetilde{g}$. 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 common factors from the data and to 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 nonlinear such that the standard Kalman filter is inapplicable and the exact likelihood function is hard to evaluate. Although approximate filters for the unobserved states and maximum likelihood estimates for the unknown parameters $\phi=[\theta,\rho,\pi,\varrho,\sigma^2_e,\sigma^2_{\overline{\gamma}},\sigma^2_{\widetilde{\gamma}},\sigma^2_{\overline{\lambda}},\sigma^2_{\widetilde{\lambda}},\sigma^2_{\omega},\sigma^2_{\psi},\sigma^2_{\xi}]$ 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.

[9]The level of $\overline{h}_{it}$ and $\overline{g}_t$ is not identified as these are random walk processes. The level of $\widetilde{h}_{it}$ and $\widetilde{g}_t$ in contrast is identified as these are zero-mean AR(1) processes.

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 $f\left(r_p, \mu, \beta, \overline{h}, \widetilde{h}, \overline{g}, \widetilde{g}, \phi | r\right)$. Given an arbitrary set of starting values $\left(r_p^0, \mu^0, \beta^0, \overline{h}^0, \widetilde{h}^0, \overline{g}^0, \widetilde{g}^0, \phi^0\right)$:

1. sample r_p^1 from $f\left(r_p | r, \mu^0, \beta^0, \overline{g}^0, \widetilde{g}^0, \phi^0\right)$
2. sample $\left(\mu_i^1, \beta_i^1\right)$ from $f\left(\mu_i, \beta_i | r, r_p^1, \overline{h}^0, \widetilde{h}^0, \phi^0\right)$ for $i = 1, ..., N$
3. (a) sample $\overline{h}_i^1$ and $\widetilde{h}_i^1$ from $f\left(\overline{h}_i, \widetilde{h}_i | \mu_i^1, \phi^0\right)$ for $i = 1, ..., N$

   (b) sample $\overline{g}^1$ and $\widetilde{g}^1$from $f\left(\overline{g}, \widetilde{g} | r_p^1, \phi^0\right)$
4. sample ϕ^1 from $f\left(\phi | r, r_p^1, \mu^1, \beta^1, \overline{h}^1, \widetilde{h}^1, \overline{g}^1, \widetilde{g}^1\right)$

Sampling from these blocks can then be iterated J times and, after a sufficiently long burn-in period B, the sequence of draws $(B + 1, ..., J)$ approximates a sample from the virtual posterior distribution $f\left(r_p, \mu, \beta, \overline{h}, \widetilde{h}, \overline{g}, \widetilde{g}, \phi | r\right)$. Details on the exact implementation of each of the blocks can be found in Appendix A. The FMI measure defined in eq.(18) is calculated in each sweep of the Gibbs sampler such that we obtain its 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 5.3 below. Note that the results reported in the paper are based on 15000 draws (i.e., $J = 15000$) of which the first 10000 are used as burn-in draws (i.e., $B = 10000$) and of which the last 5000 are draws that are actually used to construct the posterior distributions of states, hyperparameters, statistics and FMI measures.

3.3.3 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[10]. Details on 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, $\widetilde{h}_{it}$ and $\widetilde{g}_t$, 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

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

to the variances of the factors is about 3 months or a quarter. We set relatively uninformative priors for all 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	$\sigma_{\overline{\gamma}}$	0.01	0.10	0.0086	0.0120
Transitory shock to SV common factor	$\sigma_{\widetilde{\gamma}}$	0.05	0.10	0.0432	0.0595
Permanent shock to SV idiosyncratic factor	$\sigma_{\overline{\lambda}}$	0.01	0.10	0.0086	0.0120
Transitory shock to SV idiosyncratic factor	$\sigma_{\widetilde{\lambda}}$	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 $\sigma^2_{e_i}$ $(\forall i)$ embodies the belief that measurement error in eq.(9) is small and is therefore set to 0.01^2. Our prior beliefs for the random walk error variances $\sigma^2_{\overline{\gamma}_i}$ $(\forall i)$, $\sigma^2_{\overline{\lambda}}$ and $\sigma^2_{\omega_i}$ $(\forall i)$ are also set to the relatively low value of 0.01^2, which embodies the belief that the permanent components of the stochastic volatilities, $\overline{h}_{it}$ and $\overline{g}_t$, 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, $\widetilde{h}_{it}$ and $\widetilde{g}_t$, the prior beliefs for the variances $\sigma^2_{\widetilde{\gamma}_i}$ $(\forall i)$ and $\sigma^2_{\widetilde{\lambda}}$ are set to a somewhat higher value, namely 0.05^2. The prior beliefs for the variances $\sigma^2_{\psi_i}$ $(\forall i)$ and σ^2_ξ are set to 9 and 1 respectively.[11] The reason for the smaller prior on the variance of the shock to the common factor σ^2_ξ is that we do not want to put too much prior weight on financial market integration. Robustness checks with smaller values for $\sigma^2_{\psi_i}$ and larger values for σ^2_ξ do not show any marked differences compared to the results of the baseline simulation. 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 factor as we do not want to be informative on the relative importance of these two factors.

[11] Note that the unconditional variances of the actual equity excess returns (expressed in percentage terms) over the sample period $1970:1-2012:10$ lie between 20.6 and 101.4.

4 Data

We use monthly data over the period 1970:1-2012:10 on the excess returns for 16 European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. The maximum number of observations per country is 514. For some countries we have fewer observations. This makes the panel unbalanced. Those countries are Finland, for which the sample starts in 1982:1 (370 observations), and Greece, Ireland and Portugal, for which the sample starts in 1988:1 (298 observations). To calculate monthly excess returns in % we calculate continuously compounded returns from a stock market index and subtract the risk free rate, i.e.,

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

where S_{it} is the value of the stock market index in country i at time t and B_{it} is the value of the treasury bills index in country i at time t. As a measure for S_{it} we use the country-specific MSCI equity return index in USD provided by Morgan Stanley taken from Datastream. It covers 90-95% of the investable market capitalization. On a monthly basis these data are available from 1969 onward. Note that the MSCI country indices are value weighted and are calculated with dividend reinvestment. As a measure for B_{it} we use the total return bill index in USD as reported by *Global Financial Data* which is based upon the yields on 3-month treasury bills. For countries that do not issue treasury bills, either the central bank discount rate or commercial paper yields have been used as a substitute for the yields on treasury bills. The MSCI index as well as the treasury bills index as calculated by *Global Financial Data* are widely used in the literature. The estimations have also been conducted with local currency returns but the differences are negligible.[12] These alternative results are not reported but are available from the authors upon request. Note finally that the excess returns are expressed in real terms because the inflation components in the stock returns are canceled out by the inflation components in the short-term interest rates (see e.g., Harvey, 1991).

5 Estimation results

In this section we discuss the results of the estimation of the international CAPM in state space form as given by equations (9)-(16). First, we discuss the estimated states of which those that drive financial market integration (i.e., the factor loadings and the stochastic volatilities) receive particular attention. Second, we investigate whether our international CAPM is well-specified and does not contain more than

[12] To 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). Here we opt for the USD but any common currency would do.

one common risk factor. Third, we discuss the estimated measures of time-varying financial market integration. The discussion tackles the country-specific FMI measures as well as cross-country and time averages of the FMI measures.

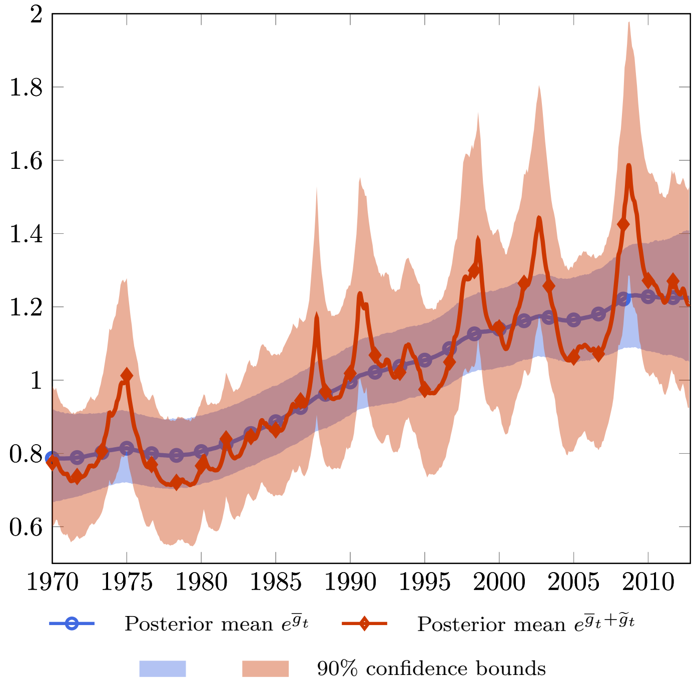
5.1 Estimation of the states and hyperparameters

The estimation of the international CAPM in state space form given by equations (9)-(16) provides estimates for the country-specific factors μ_{it}, the common 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.(17)-(19), are expected to drive financial market integration are presented in Figures 1-3 while figures for the factors μ_{it} and r_{pt} are presented in Appendix B. Histograms for the posterior parameter distributions are also presented in Appendix B.

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 global episodes of financial turmoil that have impacted the European stock markets are 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 of 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 and the ensuing Great Recession of $2008-2009$. It should be noted that no similar spike in the volatility of the common European risk factor can be observed during the $2010-2012$ euro area debt crisis. This observation stands in sharp contrast to the high turmoil that was observed in euro area government bonds markets during the same period.[13]

[13]We argue in the next section that there is no evidence to suggest that there is an additional EU-wide or euro area-wide common factor in the data that instead may have captured the $2010-2012$ euro area debt crisis. Additionally, at the country level the only country where higher turmoil is clearly visible during the $2010-2012$ period is, unsurprisingly, Greece (see Figure 2).

Figure 1: Stochastic volatility in the common European risk factor



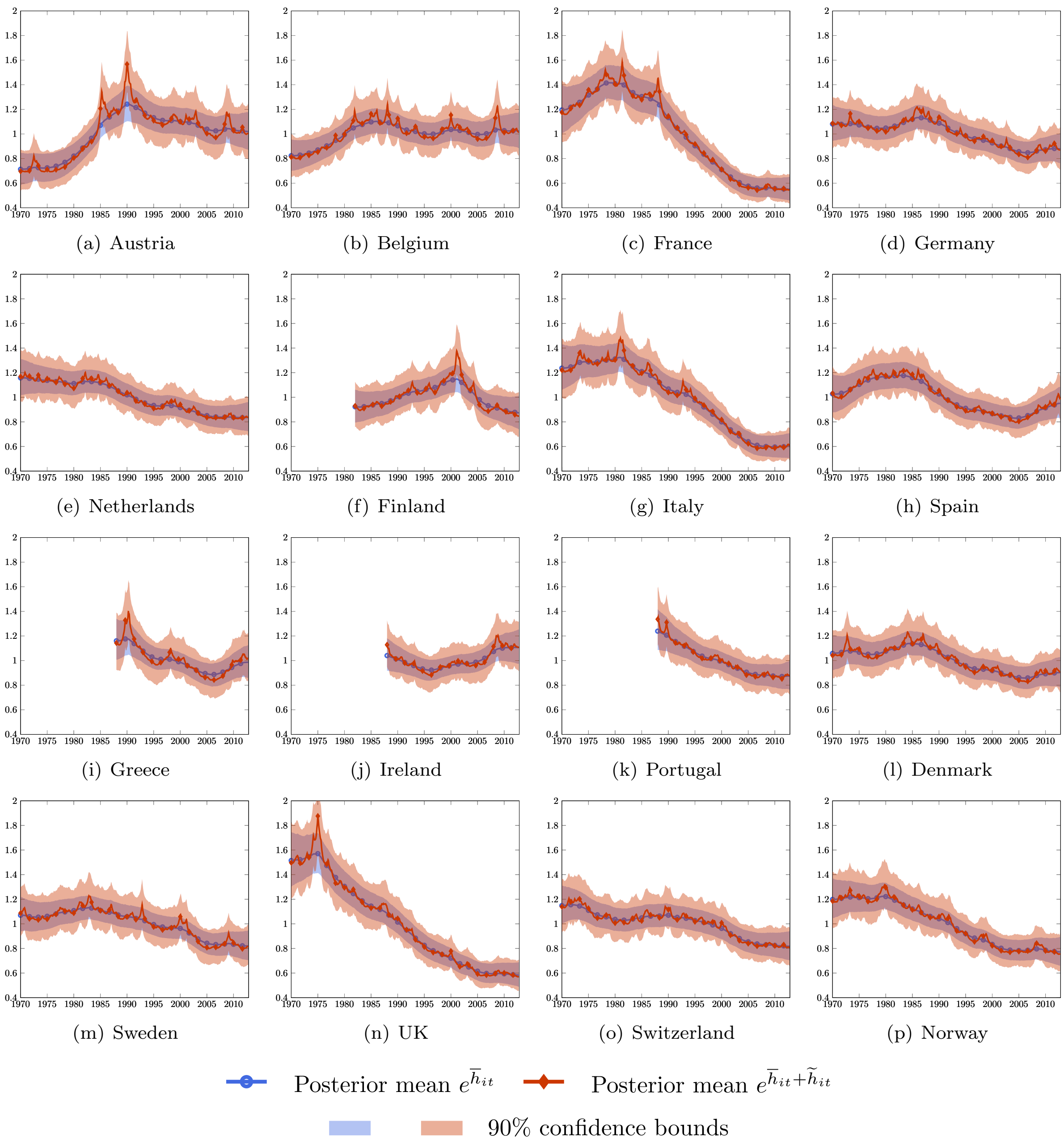
As we note in Section 3.2 however, the measurement of financial market integration should not depend on such transitory episodes. In Figure 1 we also report the estimated trend component of the volatility of the common factor, i.e., $e^{\bar{g}_t}$. From the figure it is clear that there has been a significant structural increase in the volatility of the common factor, especially from the 1980s onward. This observed structural increase in the importance of common shocks for European economies points towards increased financial market integration in Europe, a result that we confirm in Section 5.3 when discussing our estimated integration measures.

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 16 countries in our sample. In this graph, 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 financial market integration. To measure financial market integration, it is the structural evolution in the stochastic volatility of the idiosyncratic factors that matters. The estimated trend components of the idiosyncratic 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 decreased significantly in almost all countries suggesting that lower country-specific investment impediments encountered on European stock markets have been an important driving force of integration.

In Figure 3 we present the time-varying loadings β_{it} on the common factor for each of the 16 countries in our sample. From the figure we note that the country-specific exposures to the common European risk factor have remained rather stable over the sample period for most countries. The exceptions are Austria which shows a significant increase in β_{it} and the UK and Switzerland which show a (modest) decline in β_{it}.

These findings suggest that changes in European financial market integration have been driven more by structural volatility changes of the risk factors (both common and country-specific) and less by a structural evolution in the exposures to common risk. This conclusion reemphasizes the inadequacy of using only factor loadings as measures of financial market integration, a conclusion already mentioned in our discussion on the measurement of financial market integration in Section 3.2.

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



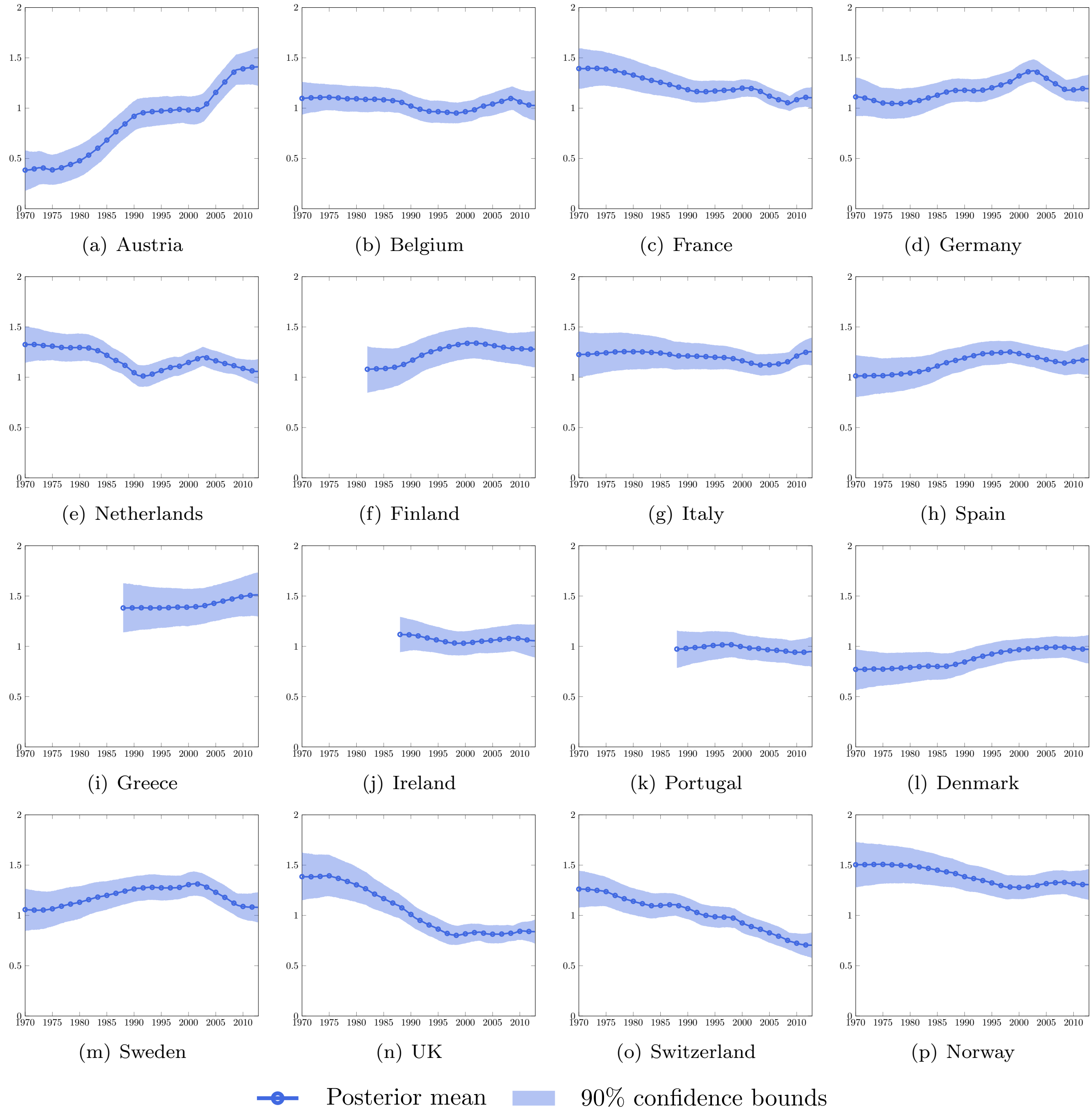
(a) Austria (b) Belgium (c) France (d) Germany

(e) Netherlands (f) Finland (g) Italy (h) Spain

(i) Greece (j) Ireland (k) Portugal (l) Denmark

(m) Sweden (n) UK (o) Switzerland (p) Norway

Figure 3: Factor loadings on the common European risk factor



5.2 Determining the number of common factors

The international CAPM presented above assumes that European stock market excess returns are driven by one common European-wide risk factor r_{pt}. It is conceivable however that there are multiple common factors. In particular, as financial market integration may have been affected by the process of European economic and monetary unification, countries belonging to the EU (i.e., all the countries in our sample minus Norway and Switzerland) or to the euro area (i.e., all EU countries minus Denmark, Sweden and the UK) could possibly load on an additional EU-wide or euro-wide common factor. Alternatively or additionally, countries belonging to the core of the EU (i.e., the original EU member states Belgium, France, Germany, Netherlands and Italy) or to the core - as opposed to the periphery - of the euro area (i.e., Austria, Belgium, France, Germany, Netherlands, Finland) could possibly load on a common EU-core factor or a common euro-core factor. In all these cases our model with only one common factor would be misspecified. To test whether there are additional common factors in the data that have not been accounted for when estimating the state space system given by equations (9)-(16), we calculate cross-sectional dependence measures from the estimated idiosyncratic factor μ_{it}. In particular, to test whether an EU factor, a euro factor or a (EU or euro) core factor is present in the data, we calculate average pairwise correlations in μ_{it} between countries belonging to the EU, countries belonging to the euro area and countries belonging to the EU and euro core. The results are reported in Table 2 where the means and the 5% and 95% percentiles of the posterior distributions of these average correlations are reported for the different country groups. From the table it is clear that these correlations tend to be very small (in absolute value) and are mostly negative so that there is little evidence to suggest that there are additional common factors in μ_{it} after one common factor has been filtered out of the excess returns r_{it}.

Table 2: Average correlation in μ_{it} over country groups

		mean	percentiles	
Country groups	(sample)		5%	95%
(1) all	$(1970:1-2012:10)$	-0.052	-0.055	-0.050
(2) EU	$(1970:1-2012:10)$	-0.055	-0.057	-0.053
(3) euro	$(1970:1-2012:10)$	-0.054	-0.057	-0.052
(4) euro	$(1999:1-2012:10)$	-0.017	-0.023	-0.013
(5) EU core	$(1970:1-2012:10)$	0.030	0.026	0.033
(6) euro core	$(1970:1-2012:10)$	-0.015	-0.018	-0.012
(7) euro core	$(1999:1-2012:10)$	-0.026	-0.033	-0.015

Notes: We report the mean and the 5th and 95th percentiles of the posterior distribution (over the 5000 Gibbs draws) of the average correlation in μ_{it} over different country groups. Country group 'all' consists of the 16 European countries in the sample. Country group 'EU' consists of all countries minus Norway and Switzerland. Country group 'euro' consists of the 14 EU countries minus Denmark, Sweden and the UK. Country group 'EU core' consists of Belgium, France, Germany, Netherlands, Italy. Country group 'euro core' consists of Austria, Belgium, France, Germany, Netherlands, Finland.

5.3 Measures of time-varying financial market integration

5.3.1 Individual country results and average over all countries

In Table 3 we report the estimated average measures of financial market integration over the full sample period for every country in the sample, i.e., $\overline{FMI}_i^c = \frac{1}{T-\tau_i+1}\sum_{t=\tau_i}^{T} FMI_{it}^c$. 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 $\overline{FMI}^c = \frac{1}{N}\sum_{i=1}^{N}\overline{FMI}_i^c$. The numbers presented in Table 3 show the mean and the 5% and 95% percentiles of the posterior distributions of these statistics. From the table we note that the average degree of stock market integration over the full sample period across the 16 European countries that we consider is about 0.5. Of course, while indicative of the average degree of integration of European countries in recent decades, this number may hide important differences in the degree of financial market integration across countries. Indeed, the numbers in the table show full period integration measures that vary between low values of about 0.35 for Austria and Greece and high values of about 0.65 for France, Germany and the Netherlands. Again, these numbers, while indicative of the average degree of stock market integration of particular European countries during recent decades, may hide important changes in the evolution of financial market integration over time.

Table 3: Full period FMI, country averages

	mean	percentiles	
Countries		5%	95%
Austria	0.37	0.31	0.42
Belgium	0.57	0.51	0.62
France	0.64	0.60	0.69
Germany	0.60	0.55	0.65
Netherlands	0.70	0.65	0.74
Finland	0.40	0.33	0.46
Italy	0.48	0.43	0.53
Spain	0.49	0.44	0.55
Greece	0.38	0.30	0.46
Ireland	0.52	0.44	0.59
Portugal	0.48	0.40	0.55
Denmark	0.41	0.35	0.46
Sweden	0.50	0.44	0.55
UK	0.56	0.51	0.62
Switzerland	0.60	0.55	0.65
Norway	0.51	0.45	0.56
Average over countries	0.51	0.47	0.54

Notes: We report the mean and the 5th and 95th percentiles of the posterior distribution (over the 5000 Gibbs draws) of the full period time averages of the FMI^c measure.

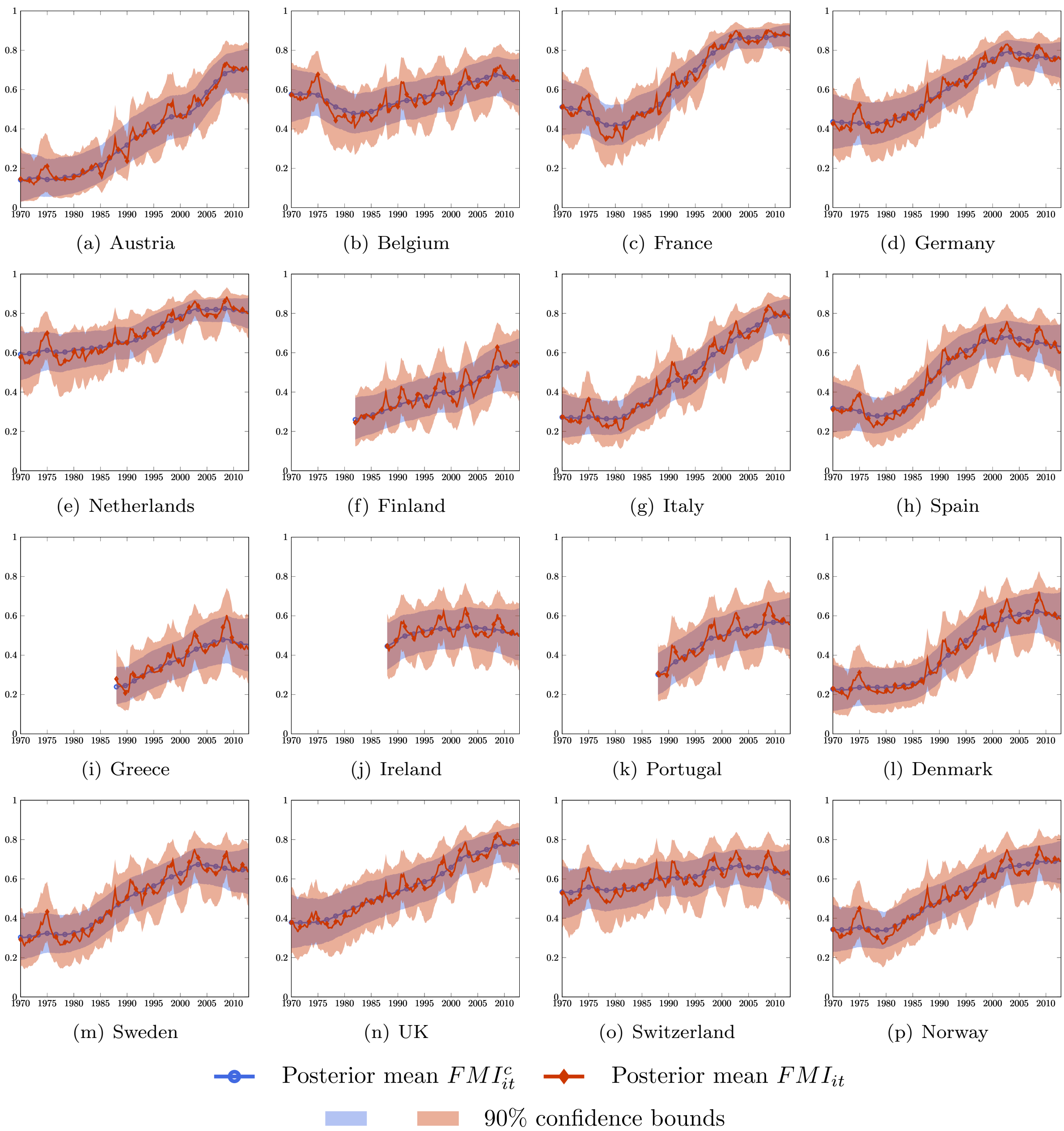
We therefore focus instead on the country-specific time-varying indicators of financial market integration, i.e., FMI_{it} and FMI_{it}^c. These indicators are presented in Figure 4. The cross-sectional averages of FMI_{it} and FMI_{it}^c over all countries in the sample, i.e., $\overline{FMI}_t = \frac{1}{N}\sum_{i=1}^{N} FMI_{it}$ and $\overline{FMI}_t^c = \frac{1}{N}\sum_{i=1}^{N} FMI_{it}^c$, are presented in Figure 5. Note that the latter figure contains two vertical bars that indicate the moment when countries are added to the sample. As explained in Section 4, the panel is unbalanced as data for Finland are only available from 1982 onward and data for Greece, Ireland and Portugal are only available from 1988 onward. Hence, the first vertical bar indicates the addition of Finland to the sample while the second vertical bar indicates the addition of Greece, Ireland and Portugal to the sample. 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 - induces 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 short-run volatility fluctuations. The higher volatility of the former indicators may lead to erroneous conclusions about financial market integration. Consider, for instance, the period of the financial crisis and the Great Recession. Based on the graph for $\overline{FMI}_t$ in Figure 5 one could argue that there has been a significant increase in average financial market integration in Europe over the period $2007 - 2010$. Of course, this measured increase stems from the drastic rise in the volatility of the international risk factor observed during this period (see Figure 1) and cannot be interpreted as an increase in integration. Rather, as we argue below, stock market integration in Europe seems to have stagnated or even fallen after 2007. To draw valid conclusions about time-varying structural financial 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 all countries FMI_{it}^c is (often substantially) larger in the last year of the sample period (2012) compared to the first year of the sample (which is 1970 for most countries) so that we can conclude that financial market integration has structurally increased in all European countries under consideration. These results confirm earlier findings for European countries by Pukthuanthong and Roll (2009) and Eiling and Gerard (2011). For some countries the degree of total financial market integration was already quite high in 1970 and shows a rather modest increase. This is the case, for example, for Switzerland which was characterized by a high degree of financial market liberalization already in the early $1970s$ (see Figure 6 below). Other countries start from a relatively low degree of integration in 1970 after which integration rises rather rapidly, especially from the $1980s$ onward. Examples are Austria and Italy. Still other countries start from a low degree of integration and have experienced a rather modest subsequent increase. This, for instance, is the case for Greece. Hence, even though from Table 3 one could argue that on average over the period $1970 - 2012$ Greece and Austria are equally integrated, the evolution of stock market integration over the sample period was markedly different for both countries. Of particular relevance in light of the recent economic events is that for almost all countries this increasing trend seems to have come to an end at the onset of or during the financial crisis and the Great Recession of $2007 - 2010$. For some countries the trend now even appears to be falling (e.g., Spain, Ireland). Since 2007 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 previously, i.e., since the beginning of the sample period until 2007. 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 financial market integration in Europe shows a steady increase starting in the early to mid 1980s until 2007 after which the increase halts and the trend starts to slightly fall.

Figure 4: Country-specific FMI measures



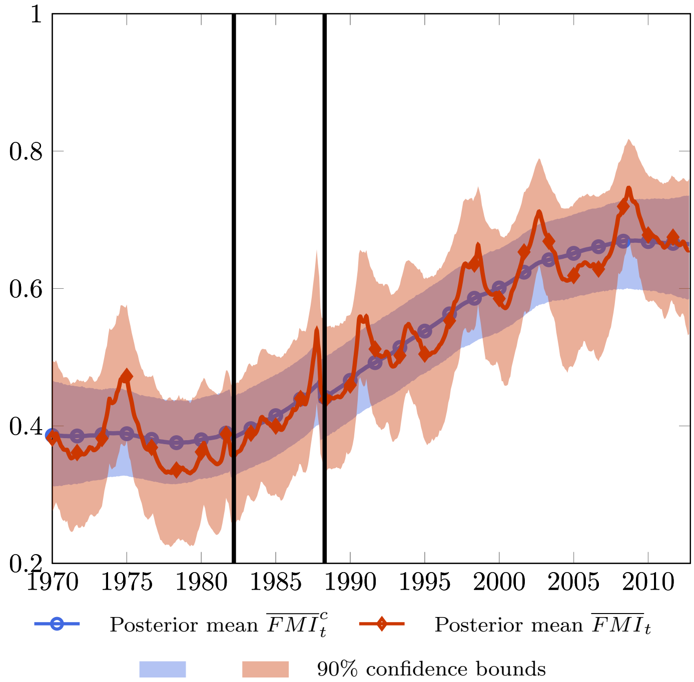
(a) Austria (b) Belgium (c) France (d) Germany

(e) Netherlands (f) Finland (g) Italy (h) Spain

(i) Greece (j) Ireland (k) Portugal (l) Denmark

(m) Sweden (n) UK (o) Switzerland (p) Norway

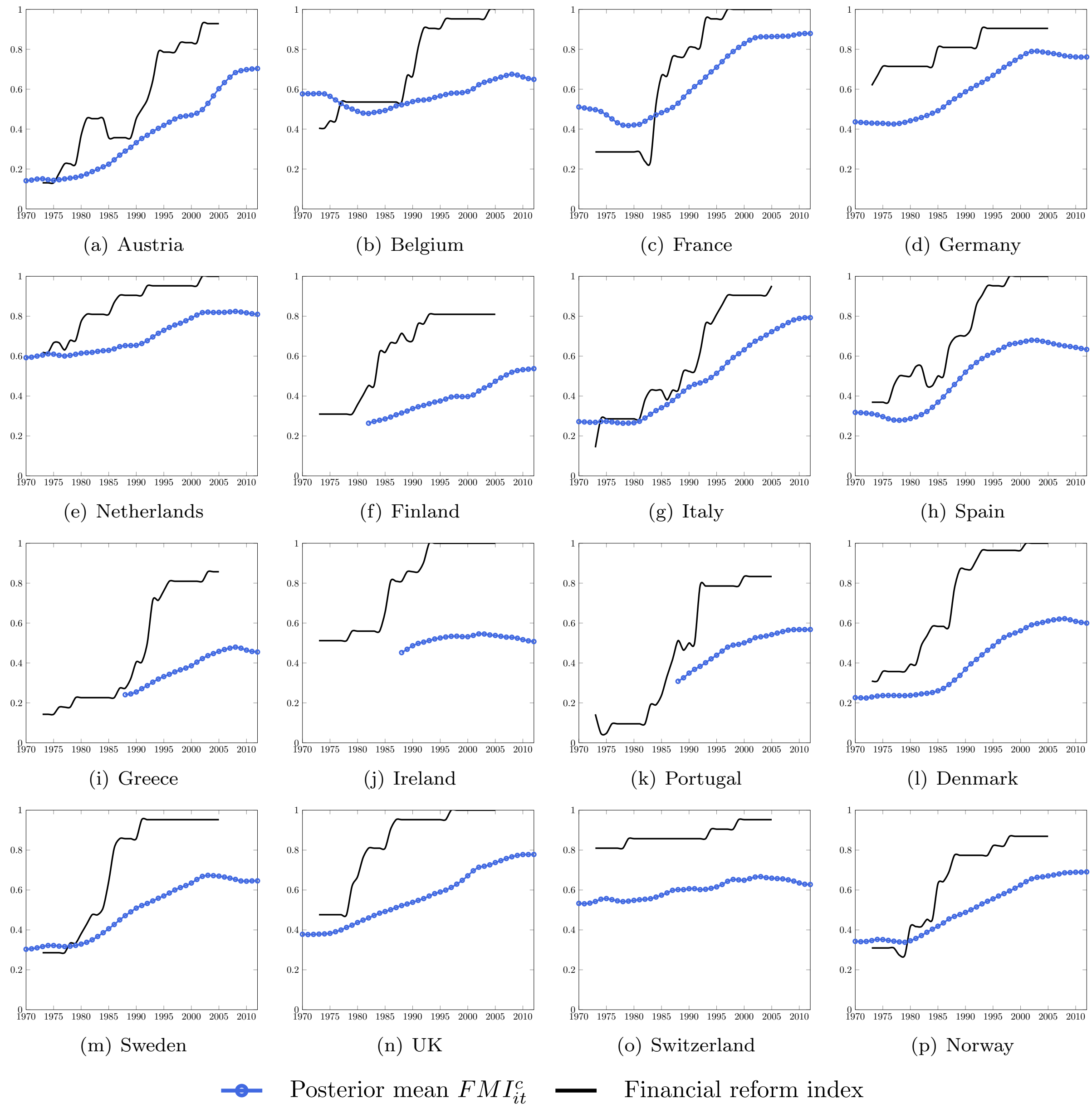
Figure 5: Average FMI measure, all countries



Note: The first vertical bar indicates the addition of Finland to the sample in 1982 : 1 while the second vertical bar indicates the addition of Greece, Ireland and Portugal to the sample in 1988 : 1.

One of the main explanations given to the process of financial 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 equity market integration. In Figure 6 we compare our corrected FMI measure FMI_{it}^c to the financial reform indicator constructed by **?**. This indicator is available for all countries in our sample on an annual basis for the period $1973 - 2005$ (and normalized to be between 0 and 1). It includes reforms on capital controls and reforms of securities markets (among which are equity markets). From the figure we note that, for many countries, both financial market integration and financial liberalization show an increasing trend, with the trend in financial market integration lagging the trend in financial reforms (see also **?**, who show for emerging economies that integration tends to lag liberalization). 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 financial market integration over the sample period. While in most countries (almost) full financial liberalization has been achieved by the end of the $1990s$, the same is not true for financial market integration. At the end of the sample period (i.e., in 2012) average FMI across Europe still equals 'only' 0.66 (see Figure 5) with - as noted above - the trend increase seemingly halted after 2007. Of course, full financial liberalization need not necessarily imply full financial 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).

Figure 6: Financial liberalization and FMI



(a) Austria (b) Belgium (c) France (d) Germany

(e) Netherlands (f) Finland (g) Italy (h) Spain

(i) Greece (j) Ireland (k) Portugal (l) Denmark

(m) Sweden (n) UK (o) Switzerland (p) Norway

Note: The financial reform index is taken from ?. The quarterly FMI_{it}^{c} measure is annualized by taking averages over the 4 quarters of each year.

5.3.2 Country groups

While the previous section documents an increase in financial market integration over the sample period in 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 across country groups. 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 the level and increase of financial market integration is higher for EU and euro area countries compared to other European economies. We also investigate whether the level and increase of stock market integration is higher for EU-core countries - i.e., the initial member states of the EU or EEC (European Economic Community) - and for the euro-core countries. We already established in Section 5.2 that neither of these country groups (the EU, the euro area, the EU-core, the euro-core) commands an additional common risk premium in the equity excess returns of their member countries. Given the presence of only one common European risk factor and given the FMI measures calculated with respect to this one factor as presented in Section 5.3.1, we compare average FMI^c statistics over countries belonging to the EU, the euro area, the EU-core and the euro-core with average FMI^c statistics over countries that do *not* belong to respectively the EU (i.e., the non-EU countries), the euro area (i.e., the non-euro countries), the EU-core (i.e, the EU non-core countries) and the euro-core (i.e., the euro non-core countries).

Table 4: Full period FMI, average over country groups

	mean	percentiles	
Country groups		5%	95%
(1) all	0.51	0.47	0.54
(2) EU	0.50	0.46	0.53
(3) non-EU	0.55	0.51	0.60
(4) non-EU (excl. Switzerland)	0.51	0.45	0.56
(5)=(2)-(3)	−0.05	−0.08	−0.02
(6)=(2)-(4)	−0.01	−0.05	0.04
(7) euro	0.51	0.47	0.54
(8) non-euro	0.49	0.44	0.53
(9)=(7)-(8)	0.02	−0.01	0.04
(10) EU core	0.60	0.56	0.63
(11) EU non-core	0.43	0.39	0.47
(12)=(10)-(11)	0.17	0.15	0.19
(13) euro core	0.55	0.51	0.58
(14) euro non-core	0.43	0.39	0.47
(15)=(13)-(14)	0.12	0.09	0.15

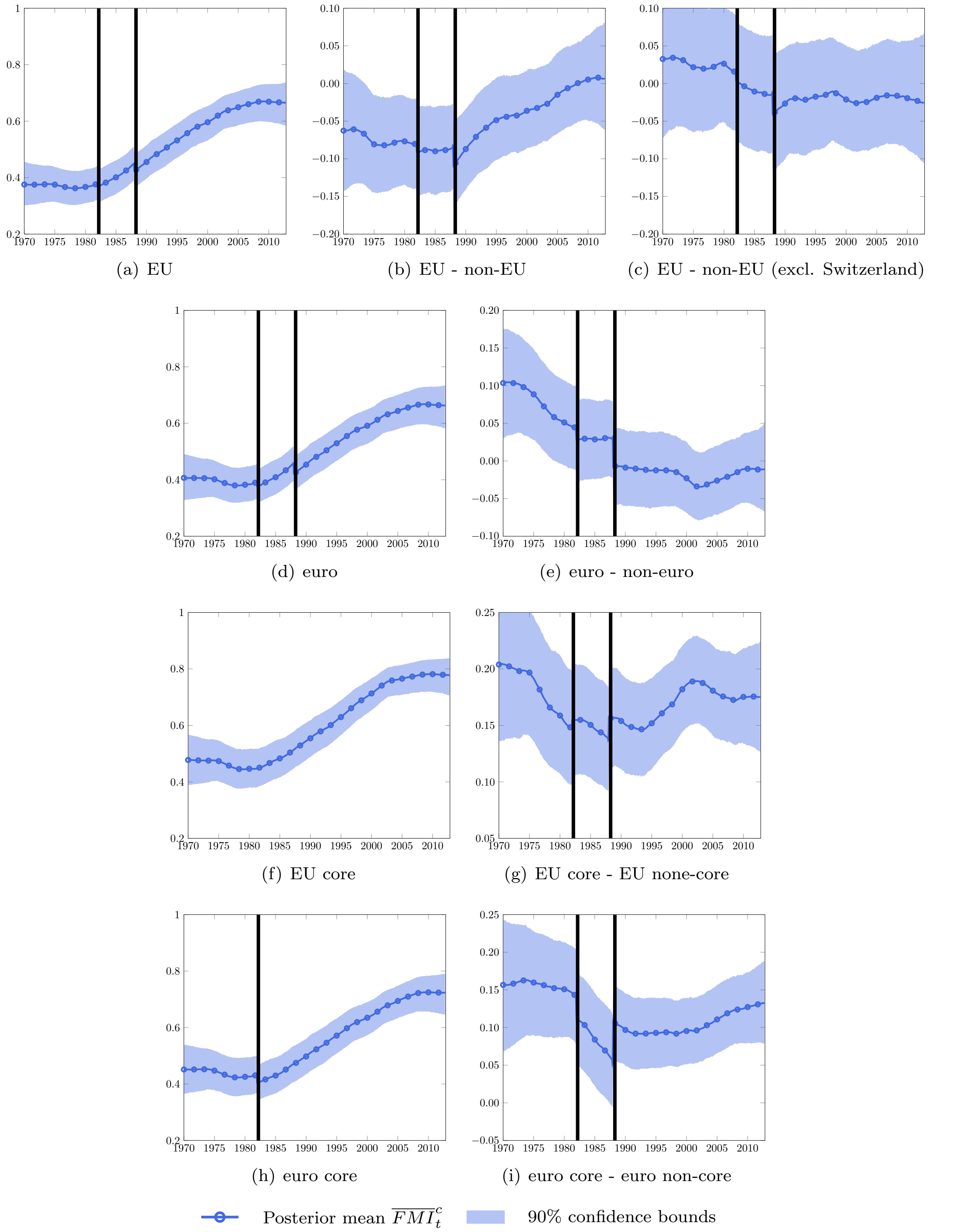
Notes: We report the mean and the 5th and 95th percentiles of the posterior distribution (over the 5000 Gibbs draws) of the average over country groups of the full period $\overline{FMI}_i^c$ measure. The countries belonging to the country groups 'all', 'EU', 'euro', 'EU core' and 'euro core' are reported in the notes to Table 2. Country group 'non-EU' consists of Norway and Switzerland. Country group 'non-euro' consists of Denmark, Sweden and the UK. Country group 'EU non-core' consists of Austria, Finland, Spain, Greece, Ireland, Portugal, Denmark, Sweden, the UK. Country group 'euro non-core' consists of Greece, Ireland, Italy, Portugal, Spain.

Table 4 presents the means and 5th and 95th percentiles of the posterior distributions of the average over the different country groups of the full period $\overline{FMI}_i^c$ measure where $\overline{FMI}_i^c = \frac{1}{T-\tau_i+1} \sum_{t=\tau_i}^{T} FMI_{it}^c$.

We also report the means and 5th and 95th percentiles of the posterior distributions of the *differences* of these statistics between country groups, i.e., we compare EU to non-EU, euro to non-euro, EU core to EU non-core and euro core to euro non-core. From the table we note that over the full sample period EU countries do not have a higher degree of financial market integration compared to non-EU countries. The difference in integration between EU countries and non-EU countries as reported in row (5) of the table is even negative. Since the non-EU group consists of Norway and Switzerland and since, as noted above, Switzerland already had a high degree of integration in the early 1970*s* we also calculate the difference in integration between the EU and Norway only (i.e., the non-EU excluding Switzerland). In this case reported in row (6) we find that the difference, while still negative, is very close to zero. From the table we also note that over the full sample period euro countries do not have a higher degree of financial market integration compared to non-euro countries. The difference in FMI reported in row (9) of Table 4 is only slightly positive. When comparing the EU core countries (i.e., the initial EU member states) and the euro core countries to countries that are not in the EU core respectively the euro core, we *do* find a substantially higher average degree of integration. From Table 4 we note that average FMI is 17 percentage points higher in the EU core compared to the EU non-core and 12 percentage points higher in the euro core compared to the euro non-core or periphery.

Again, time averages may hide important evolutions in financial market integration over time. Therefore, in Figure 7, we also present time series (i.e., the posterior means and the 5th and 95th percentiles) for the cross-country averages of FMI_{it}^{c} over the country groups EU, euro, EU-core and euro-core, as well as time series for the *differences* of these statistics between country groups, i.e., between EU and non-EU, between euro and non-euro, between EU core and EU non-core, and between euro core and euro non-core. From Figure 7(b) we note that the difference in integration between EU and non-EU (i.e., Norway and Switzerland) has increased. This result does not point towards a faster integration process in the EU compared to countries outside of the EU however. The reason is that the non-EU group is strongly driven by Switzerland which is an atypical country as it has been characterized by a consistently stable and high degree of integration over the full sample period. In Figure 7(c) we instead compare the EU with Norway (i.e., the non-EU excluding Switzerland) which has known an evolution in financial liberalization and financial market integration comparable to that observed for most EU countries (see Figure 4). According to this figure, the difference in integration between EU countries and Norway has been stable around zero over the full sample period. In other (unreported) estimations we have included other countries to the non-EU group, in particular EU countries before they accessed the EU (e.g., Spain and Portugal in 1986 and Austria, Sweden and Finland in 1995). Similar to the estimations with only Norway, these estimations - which were necessarily conducted over reduced sample periods (i.e., before

Figure 7: Average FMI measures, country groups



(a) EU (b) EU - non-EU (c) EU - non-EU (excl. Switzerland)

(d) euro (e) euro - non-euro

(f) EU core (g) EU core - EU none-core

(h) euro core (i) euro core - euro non-core

Note: The first vertical bar indicates the addition of Finland to the sample in 1982 : 1 while the second vertical bar indicates the addition of Greece, Ireland and Portugal to the sample in 1988 : 1. No bars are added in (f) as Finland, Greece, Ireland and Portugal do not belong to the EU core. Only one bar is added to (h) as only Finland - which is added to the sample in 1982 : 1 - belongs to the euro core.

the access dates) - did not reveal differences in the level or trend of integration between EU and non-EU countries. With respect to the euro, the difference in integration between euro countries and non-euro countries has also been stable around (and slightly below) zero from the mid 1980s onward until 2012.

This can be seen in Figure 7(e). The process of monetary unification it seems has neither lead to a higher level nor to a larger increase in stock market integration for the (eventual) euro countries compared to the countries that did not adopt the euro. With respect to the core countries of the EU and the euro area, we note from Figures 7(g) and 7(i) that their degrees of integration have been consistently higher than those measured for the countries that do not belong to either the EU or the euro core. This difference has been stable over the sample period. Hence, for the initial member states of the EU and for the economies that eventually would constitute the core of the euro area, integration was already higher in the early 1970s and remained substantially higher over the sample period. The latter result suggests that geographical proximity (which, for instance, facilitates trade) and similarity of economic conditions might have been more important catalysts of financial market integration than the process of European economic and monetary unification. It is possible that studies that suggest that membership of either the EU or the euro increased European stock market integration (see Section 1 for an overview) are picking up core-EU or core-euro effects instead of true EU-wide or euro area-wide effects.

In Appendix C we present a number of tables where the (corrected) degree of financial market integration FMI^c is compared for different country groups (EU, euro, EU core, euro core, non-EU, non-euro, EU non-core, euro non-core) both before and after a number of dates that have been of particular importance to Europe's recent history, i.e., the signing of the Single European Act in February 1986 (Table C-1) which was followed by the relaxation of of capital controls in a number of major EU countries such as France and Italy; the signing of the Maatricht Treaty in February 1992 (Table C-2) which can be considered the starting point of the monetary unification process in Europe; the introduction of the euro in January 1999 (Table C-3); the default of Lehman Brothers in September 2008 which marked the beginning of the global financial crisis and the Great Recession (Table C-4); and the downgrading of Greek debt to junk status in April 2010 which marked the beginning of the European debt crisis (Table C-5). These tables essentially present a difference-in-difference analysis of financial market integration between country groups and subperiods (i.e., country group versus country group and subperiod versus subperiod). If the European economic and monetary unification process has been an important driving force of European financial market integration, we would expect that the signing of the Single European Act, the signing of the Maastricht Treaty and the introduction of the euro have increased financial market integration in EU countries versus non-EU countries and/or in euro countries versus non-euro countries. We do not find evidence for this. Neither do we find evidence that the crises (i.e., the global financial crisis/Great Recession and the European debt crisis) have affected these country groups differently. Finally, neither one of these five events has affected the difference in integration between the core countries (of both the EU and the euro area) and the non-core countries. Financial market integration has been consistently higher in these core countries but the difference has remained stable over the full sample period. All these results basically confirm the conclusions established when analyzing Figure 7.

6 Conclusions

We investigate European stock market integration for 16 European countries over the period 1970-2012 using Bayesian estimation of a dynamic factor model with time-varying factor loadings and stochastic volatilities. The empirical specification is derived from a theoretical framework in which a standard international CAPM is nested into an international CAPM that incorporates impediments faced by investors to invest in national stock markets. From a time-varying variance decomposition, applied to the dynamic factor model, time-varying financial 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 estimation of (international) CAPM models and the measurement of financial market integration. These methods provide a number of clear-cut advantages that are of particular interest to the analysis of financial market integration. First, our approach avoids the use of - potentially low-quality - proxy's, instruments and conditioning variables in the estimation of the country-specific and common risk components in equity excess returns. Second, our approach allows for an explicit focus on time-varying financial market integration in Europe. This is necessary because structural changes in financial market integration in Europe might have occurred during the past decades because of increased globalization and financial liberalization, as a result of the process of European economic and monetary unification, but also as a result of crises such as the Great Recession (2008-2009) and the euro area debt crisis (2010-2012). Third, our approach allows for a correction of the financial market integration measure for a potential volatility bias so that it is not contaminated by temporary volatility shocks to the risk premium components.

The results suggest that stock market integration has structurally increased in all European countries over the sample period, particularly from the 1980s onward. Nonetheless, the evolution was sometimes quite different across countries with some countries experiencing modest increases and other countries integrating more rapidly. In most European countries the evolution of stock market integration has followed the increasing trend in financial liberalization. From 2007 onward - i.e., after the global financial crisis and the ensuing Great Recession - the trend increase in financial market integration seems to have come to an end in almost all countries. The results further suggest that members of the EU and the euro area have neither experienced higher levels nor stronger increases in financial market integration compared to countries that are not members of the EU and the euro area. Hence, despite the efforts of political leaders to improve the integration of European markets through European economic and monetary unification, the increase in financial market integration seems to have occurred mainly globally for all European countries irrespective of their membership of the EU or the euro area. On the other hand, for the initial member states of the EU and for the economies that eventually would constitute the core of the euro area, integration was already higher in the early 1970s and remained substantially higher over the sample period. The latter result suggests that geographical proximity and similarity of economic conditions might have been more important catalysts of financial market integration than the process of European economic and monetary unification.

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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 $(r_p, \mu, \beta, \overline{h}, \overline{g}, \widetilde{h}, \widetilde{g})$, 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

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

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

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

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 $\alpha = [\alpha_\tau, \ldots, \alpha_T]$ from its conditional distribution can then be done using the multimove Gibbs sampler of Shephard (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 $\overline{g}$ and $\widetilde{g}$ 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:

$$\overbrace{\begin{bmatrix} r_{1t} - \mu_{1t} \\ \vdots \\ r_{Nt} - \mu_{Nt} \end{bmatrix}}^{y_t} = \overbrace{\begin{bmatrix} \beta_{1t} \\ \vdots \\ \beta_{Nt} \end{bmatrix}}^{Z_t} \overbrace{\begin{bmatrix} r_{pt} \end{bmatrix}}^{\alpha_t} + \overbrace{\begin{bmatrix} e_{1t} \\ \vdots \\ e_{Nt} \end{bmatrix}}^{\varepsilon_t}, \tag{B-4}$$

$$\underbrace{\begin{bmatrix} r_{p,t+1} \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} \rho \end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix} r_{pt} \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} e^{\overline{g}_t + \widetilde{g}_t} \sigma_\xi \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \xi_t \end{bmatrix}}_{\eta_t}, \tag{B-5}$$

and $H_t = \begin{bmatrix} \sigma^2_{e_1} & & 0 \\ & \ddots & \\ 0 & & \sigma^2_{e_N} \end{bmatrix}$, $Q_t = 1$, $a_1 = \begin{bmatrix} 0 \end{bmatrix}$, $P_1 = \begin{bmatrix} \left(e^{\overline{g}_1+\widetilde{g}_1}\right)^2 \sigma^2_\xi / \left(1-\rho^2\right) \end{bmatrix}$, for $t = 1, \ldots, T$.

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 $\overline{h}$ and $\widetilde{h}$ and the hyperparameters θ, σ^2_e, σ^2_ψ and σ^2_ω. 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:

$$\overbrace{\begin{bmatrix} r_{it} \end{bmatrix}}^{y_t} = \overbrace{\begin{bmatrix} 1 & r_{pt} \end{bmatrix}}^{Z_t} \overbrace{\begin{bmatrix} \mu_{it} \\ \beta_{it} \end{bmatrix}}^{\alpha_t} + \overbrace{\begin{bmatrix} e_{it} \end{bmatrix}}^{\varepsilon_t}, \tag{B-6}$$

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

and $H_t = \begin{bmatrix} \sigma^2_{e_i} \end{bmatrix}$, $Q_t = I_2$, $a_{\tau_i} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, $P_{\tau_i} = \begin{bmatrix} \left(e^{\overline{h}_{i\tau_i}+\widetilde{h}_{i\tau_i}}\right)^2 \sigma^2_{\psi_i} / \left(1-\theta^2_i\right) & 0 \\ 0 & 1000 \end{bmatrix}$, for $t = \tau_i, \ldots, T$.

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 $\overline{h}$, $\widetilde{h}$, $\overline{g}$ and $\widetilde{g}$

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

$$\log\left(e^{\overline{h}_{it}+\widetilde{h}_{it}}\sigma_{\psi_i}\psi_{it}\right)^2 = 2\overline{h}_{it} + 2\widetilde{h}_{it} + \log\sigma^2_{\psi_i} + \log\psi^2_{it}, \tag{B-8a}$$

$$\log\left(e^{\overline{g}_t+\widetilde{g}_t}\sigma_\xi\xi_t\right)^2 = 2\overline{g}_t + 2\widetilde{g}_t + \log\sigma^2_\xi + \log\xi^2_t, \tag{B-8b}$$

where $\log\psi^2_{it}$ and $\log\xi^2_t$ 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

$$h^*_{it} = 2\overline{h}_{it} + 2\widetilde{h}_{it} + \log\sigma^2_{\psi_i} + \psi^*_{it}, \tag{B-9a}$$

$$g^*_t = 2\overline{g}_t + 2\widetilde{g}_t + \log\sigma^2_\xi + \xi^*_t, \tag{B-9b}$$

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

$$f\left(\psi^*_{it}\right) = \sum_{j=1}^{M} q_j f_N\left(\psi^*_{it}|m_j - 1.2704, \nu^2_j\right), \tag{B-10a}$$

$$f\left(\xi^*_t\right) = \sum_{j=1}^{M} q_j f_N\left(\xi^*_t|m_j - 1.2704, \nu^2_j\right), \tag{B-10b}$$

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

$$\psi^*_{it}|\left(s_{it} = j\right) \sim \mathcal{N}\left(m_j - 1.2704, \nu^2_j\right), \qquad \text{with} \qquad Pr\left(s_{it} = j\right) = q_j, \tag{B-11a}$$

$$\xi^*_t|\left(w_t = j\right) \sim \mathcal{N}\left(m_j - 1.2704, \nu^2_j\right), \qquad \text{with} \qquad Pr\left(w_t = j\right) = q_j. \tag{B-11b}$$

We follow Kim et al. (1998) by selecting $M = 7$ and using the parameters $\{q_j, m_j, \nu^2_j\}$ 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

$$Pr\left(s_{it} = j|\overline{h}_{it}, \widetilde{h}_{it}, \psi^*_{it}\right) \propto q_j f_{\mathcal{N}}\left(\psi^*_{it}|2\overline{h}_{it} + 2\widetilde{h}_{it} + \log\sigma^2_{\psi_i} + m_j - 1.2704, \nu^2_j\right), \tag{B-12a}$$

$$Pr\left(w_t = j|\overline{g}_t, \widetilde{g}_t, \xi^*_t\right) \propto q_j f_{\mathcal{N}}\left(\xi^*_t|2\overline{g}_t + 2\widetilde{g}_t + \log\sigma^2_\xi + m_j - 1.2704, \nu^2_j\right). \tag{B-12b}$$

Below we use the notation $s_i = \{s_{it}\}^T_{t=\tau_1}$ and $w = \{w_t\}^T_{t=1}$.

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 $\overline{h}_{it}$, $\widetilde{h}_{it}$, $\overline{g}_t$ and $\widetilde{g}_t$ conditioning on the transformed states $h^*_{it} = \log\Big((\mu_{i,t+1} - \theta_i \mu_{it})^2 + 0.001\Big)$ and $g^*_t = \log\Big((r_{p,t+1} - \rho r_{pt})^2 \;\; +0.001)$, on the mixture indicators s_{it} and w_t and on the hyperparameters $\sigma^2_{\psi_i}$, σ^2_{ξ}, $\sigma^2_{\overline{\gamma}_i}$, $\sigma^2_{\widetilde{\gamma}_i}$, $\sigma^2_{\overline{\lambda}}$ and $\sigma^2_{\widetilde{\lambda}}$.

The state space representation of the model for $\overline{h}_{it}$ and $\widetilde{h}_{it}$ is given by:

$$\overbrace{\begin{bmatrix} h^*_{it} - \Big(\log\sigma^2_{\psi_i} + m_{s_{it}} - 1,2704\Big) \end{bmatrix}}^{y_t} = \overbrace{\begin{bmatrix} 2 & 2 \end{bmatrix}}^{Z_t} \overbrace{\begin{bmatrix} \overline{h}_{it} \\ \widetilde{h}_{it} \end{bmatrix}}^{\alpha_t} + \overbrace{\begin{bmatrix} \widetilde{\psi}^*_{it} \end{bmatrix}}^{\varepsilon_t}, \tag{B-13}$$

$$\underbrace{\begin{bmatrix} \overline{h}_{i,t+1} \\ \widetilde{h}_{i,t+1} \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & \pi_i \end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix} \overline{h}_{it} \\ \widetilde{h}_{it} \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} \sigma_{\overline{\gamma}_i} & 0 \\ 0 & \sigma_{\widetilde{\gamma}_i} \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \overline{\gamma}_{it} \\ \widetilde{\gamma}_{it} \end{bmatrix}}_{\eta_t}, \tag{B-14}$$

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

Similarly, the state space representation of the model for $\overline{g}_t$ and $\widetilde{g}_t$ is given by:

$$\overbrace{\begin{bmatrix} g^*_{t} - \Big(\log\sigma^2_{\xi} + m_{w_t} - 1,2704\Big) \end{bmatrix}}^{y_t} = \overbrace{\begin{bmatrix} 2 & 2 \end{bmatrix}}^{Z_t} \overbrace{\begin{bmatrix} \overline{g}_{t} \\ \widetilde{g}_{t} \end{bmatrix}}^{\alpha_t} + \overbrace{\begin{bmatrix} \widetilde{\xi}^*_{t} \end{bmatrix}}^{\varepsilon_t}, \tag{B-15}$$

$$\underbrace{\begin{bmatrix} \overline{g}_{t+1} \\ \widetilde{g}_{t+1} \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & \varrho \end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix} \overline{g}_{t} \\ \widetilde{g}_{t} \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} \sigma_{\overline{\lambda}} & 0 \\ 0 & \sigma_{\widetilde{\lambda}} \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \overline{\lambda}_{t} \\ \widetilde{\lambda}_{t} \end{bmatrix}}_{\eta_t}, \tag{B-16}$$

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

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 $\overline{h}$, $\widetilde{h}$, $\overline{g}$ and

$\widetilde{g}$, these are all unknown parameters in the standard static linear regression model

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

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

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

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

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

with hyperparameters defined by

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

with $\widehat{b}$ 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

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

$$\sigma^2 \sim IG_2\left(S_*, s_*\right). \tag{B-21}$$

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

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

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

The hyperparameters ϕ can now be sampled as:

- Obtain the posterior distribution of $\sigma^2_{e_i}$ in (9) 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 $\sigma^2_{e_i}$ from (B-21).
- Obtain the posterior distribution of θ_i and $\sigma^2_{\psi_i}$ in (10) for each country i separately conditioning on μ_{it}, $\overline{h}_{it}$ and $\widetilde{h}_{it}$ by using (B-19) setting $y_t = \mu_{i,t+1} \Big/ e^{\overline{h}_{it}+\widetilde{h}_{it}}$ and $x_t = \mu_{it} \Big/ e^{\overline{h}_{it}+\widetilde{h}_{it}}$ in (B-17) such that this becomes a GLS-type regression model. Next, sample θ_i and $\sigma^2_{\psi_i}$ from (B-20) and (B-21).
- Obtain the posterior distribution of $\sigma^2_{\overline{\gamma}_i}$ in (11) for each country i separately conditioning on $\overline{h}_{it}$ by using (B-22) setting $y_t = \overline{h}_{i,t+1} - \overline{h}_{it}$ and $x_t = [.]$ in (B-17). Next, sample $\sigma^2_{\overline{\gamma}_i}$ from (B-21).
- Obtain the posterior distribution of π_i and $\sigma^2_{\widetilde{\gamma}_i}$ in (12) for each country i separately conditioning on $\widetilde{h}_{it}$ by using (B-19) setting $y_t = \widetilde{h}_{i,t+1}$ and $x_t = \widetilde{h}_{it}$ in (B-17). Next, sample π_i and $\sigma^2_{\widetilde{\gamma}_i}$ from (B-20) and (B-21).
- Obtain the posterior distribution of ρ and σ^2_{ξ} in (13) conditioning on r_{pt}, $\overline{g}_t$ and $\widetilde{g}_t$ by using (B-19) setting $y_t = r_{p,t+1} \big/ e^{\overline{g}_t+\widetilde{g}_t}$ and $x_t = r_{pt} \big/ e^{\overline{g}_t+\widetilde{g}_t}$ in (B-17) such that this becomes a GLS-type regression model. Next, sample ρ and σ^2_{ξ} from (B-20) and (B-21).
- Obtain the posterior distribution of $\sigma^2_{\overline{\lambda}}$ in (14) conditioning on $\overline{g}_t$ by using (B-22) setting $y_t = \overline{g}_{t+1} - \overline{g}_t$ and $x_t = [.]$ in (B-17). Next, sample $\sigma^2_{\overline{\lambda}}$ from (B-21).
- Obtain the posterior distribution of ϱ and $\sigma^2_{\widetilde{\lambda}}$ in (15) conditioning on $\widetilde{g}_t$ by using (B-19) setting $y_t = \widetilde{g}_{t+1}$ and $x_t = \widetilde{g}_t$ in (B-17). Next, sample ϱ and $\sigma^2_{\widetilde{\lambda}}$ from (B-20) and (B-21).
- Obtain the posterior distribution of $\sigma^2_{\omega_i}$ in (16) 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 $\sigma^2_{\omega_i}$ from (B-21).

Appendix B Figures

Figure B-1: The common European risk factor (posterior mean)

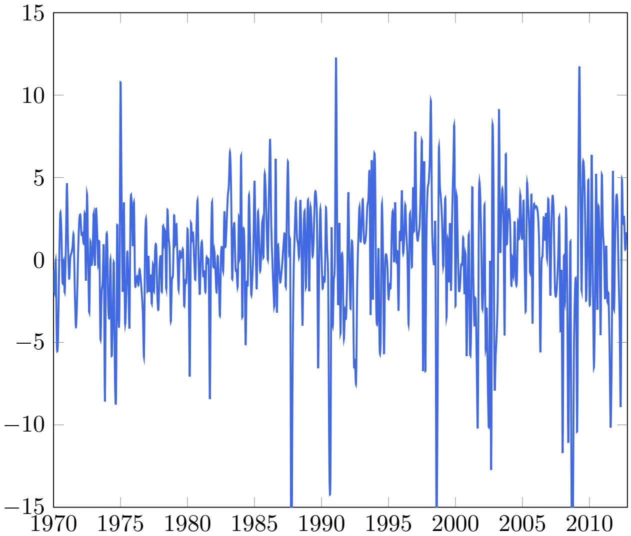
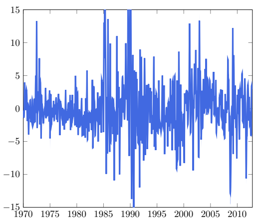
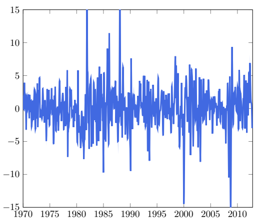
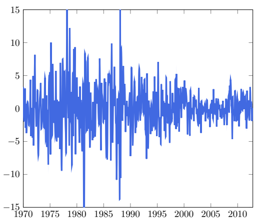
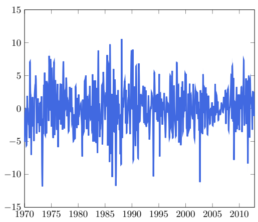


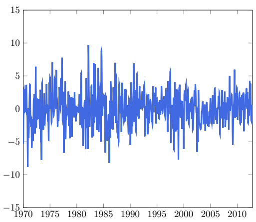
Figure B-2: Country-specific risk factors (posterior means)

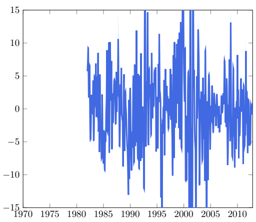

(a) Austria

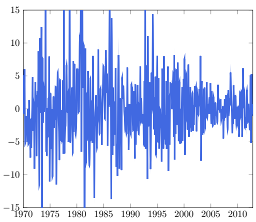

(b) Belgium

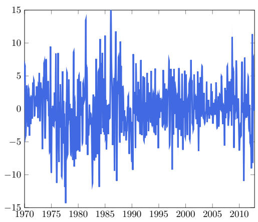

(c) France

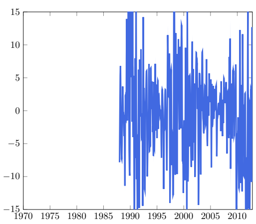

(d) Germany

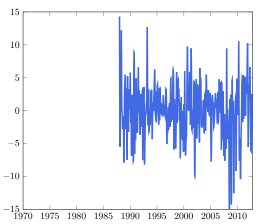

(e) Netherlands

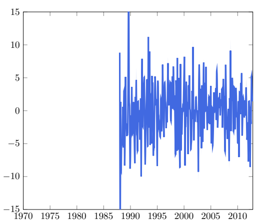

(f) Finland

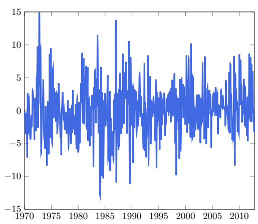

(g) Italy

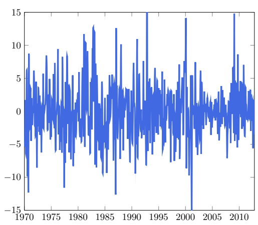

(h) Spain

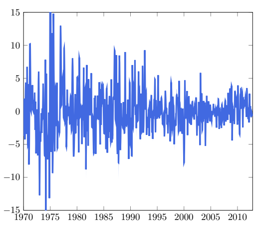

(i) Greece

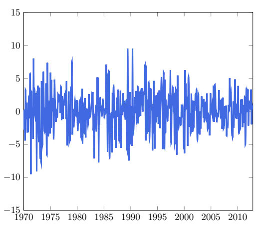

(j) Ireland


(k) Portugal


(l) Denmark


(m) Sweden


(n) UK


(o) Switzerland

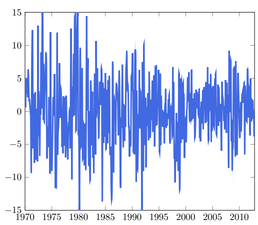
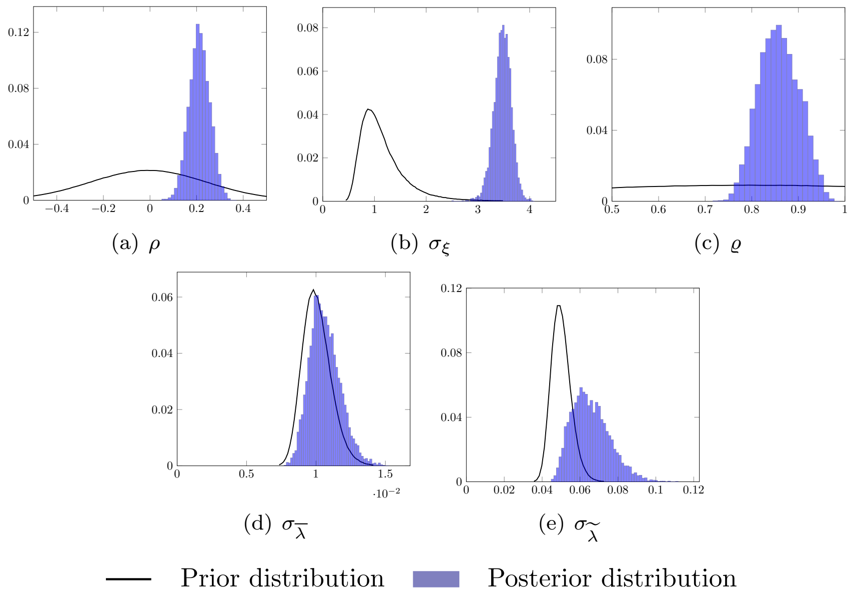

(p) Norway

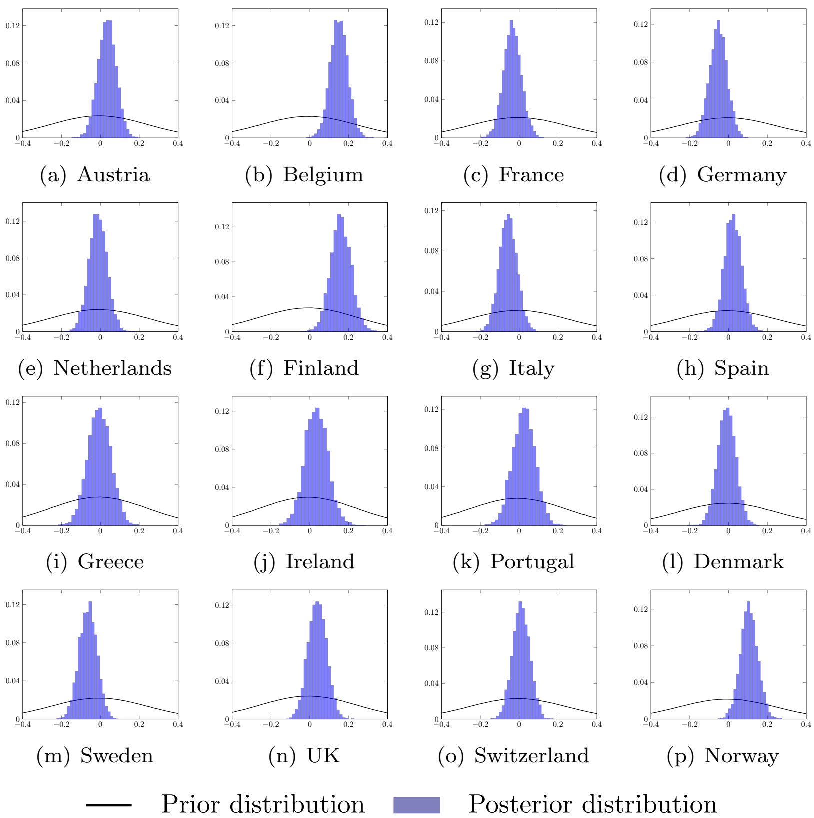
Figure B-3: Prior and posterior distributions ρ, σ_ξ, ϱ, $\sigma_{\overline{\lambda}}$ and $\sigma_{\widetilde{\lambda}}$



(a) ρ (b) σ_ξ (c) ϱ

(d) $\sigma_{\overline{\lambda}}$ (e) $\sigma_{\widetilde{\lambda}}$

Figure B-4: Prior and posterior distributions θ_i



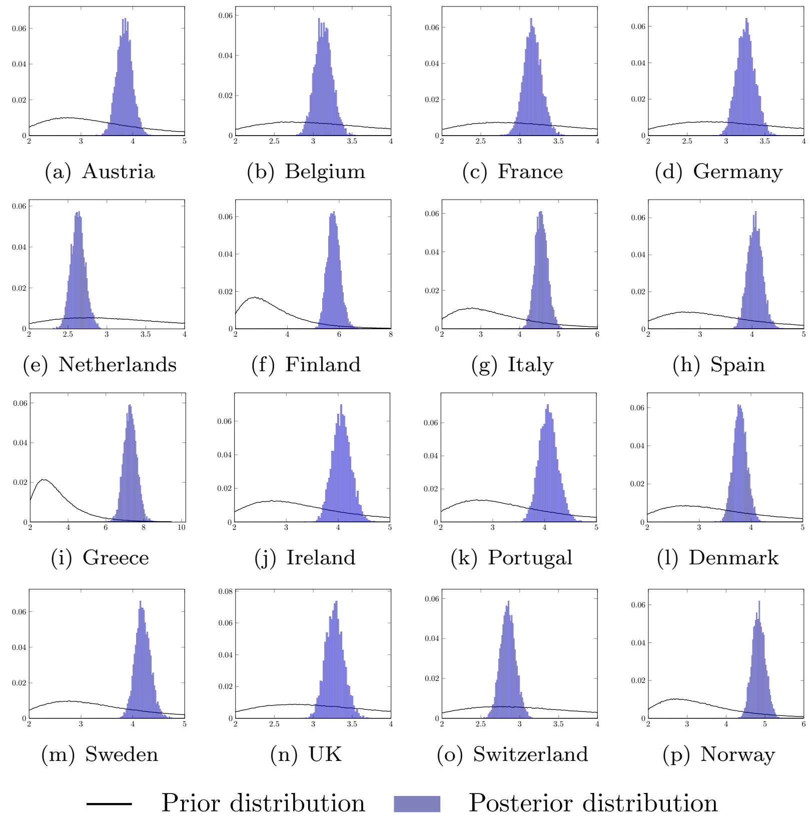
(a) Austria (b) Belgium (c) France (d) Germany

(e) Netherlands (f) Finland (g) Italy (h) Spain

(i) Greece (j) Ireland (k) Portugal (l) Denmark

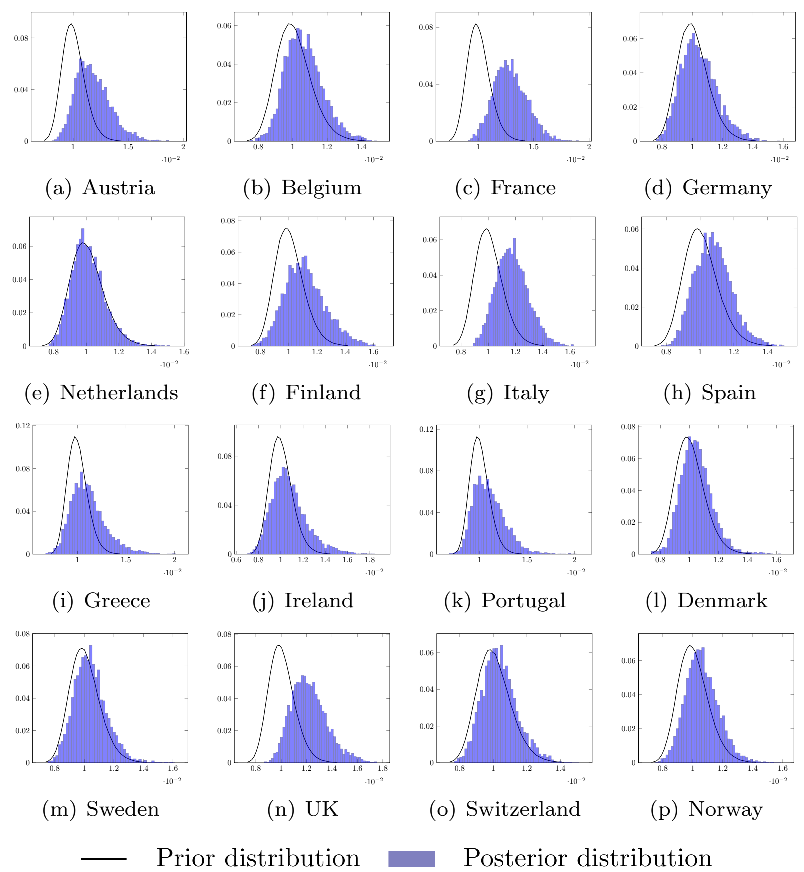
(m) Sweden (n) UK (o) Switzerland (p) Norway

Figure B-5: Prior and posterior distributions σ_{ψ_i}



(a) Austria (b) Belgium (c) France (d) Germany (e) Netherlands (f) Finland (g) Italy (h) Spain (i) Greece (j) Ireland (k) Portugal (l) Denmark (m) Sweden (n) UK (o) Switzerland (p) Norway

Figure B-6: Prior and posterior distributions $\sigma_{\overline{\gamma}_i}$



(a) Austria (b) Belgium (c) France (d) Germany (e) Netherlands (f) Finland (g) Italy (h) Spain (i) Greece (j) Ireland (k) Portugal (l) Denmark (m) Sweden (n) UK (o) Switzerland (p) Norway

Figure B-7: Prior and posterior distributions $\sigma_{\tilde{\gamma}_i}$

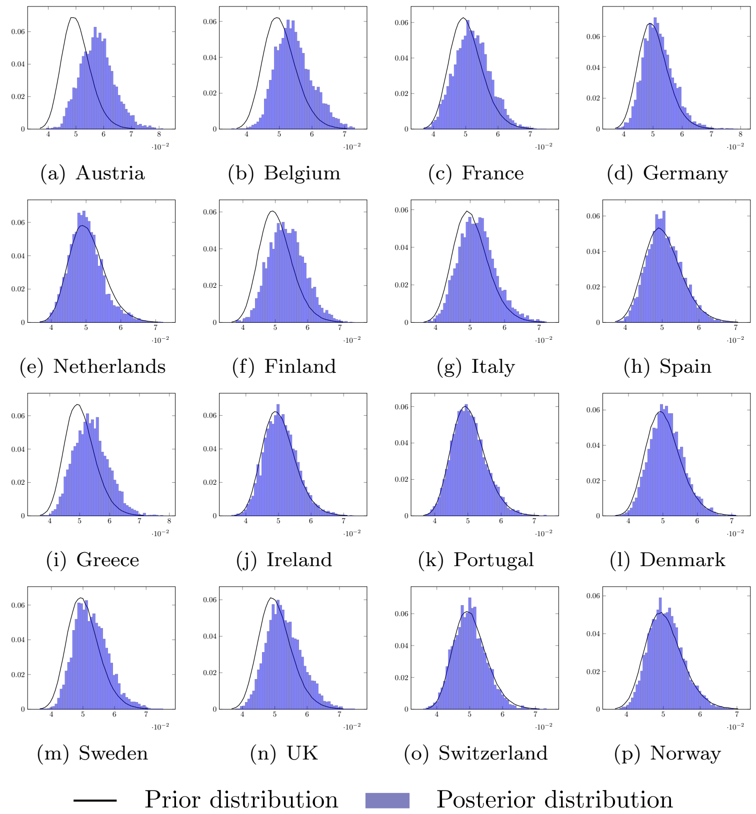


Figure B-8: Prior and posterior distributions σ_{ω_i}

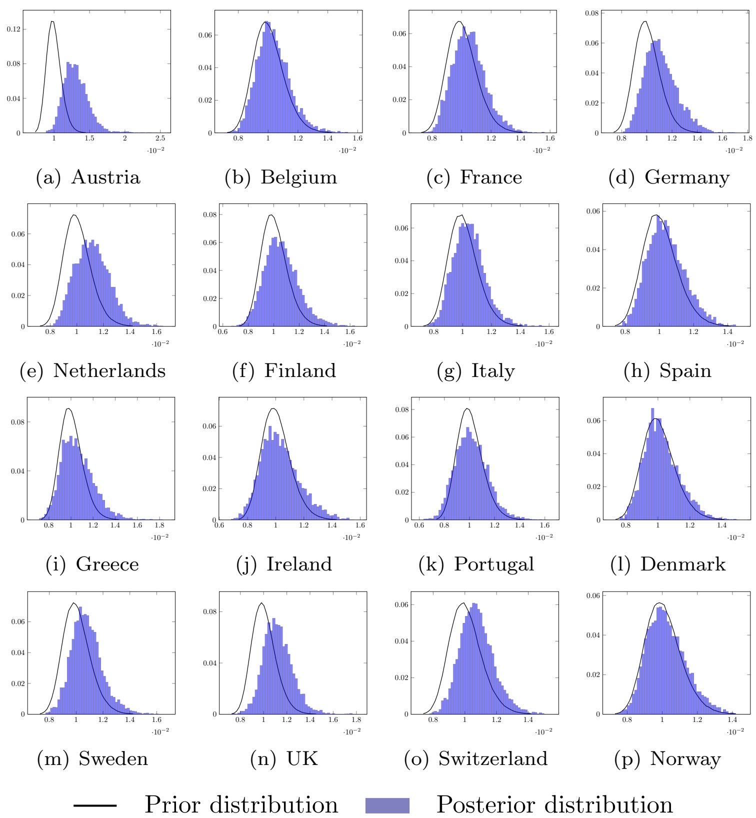
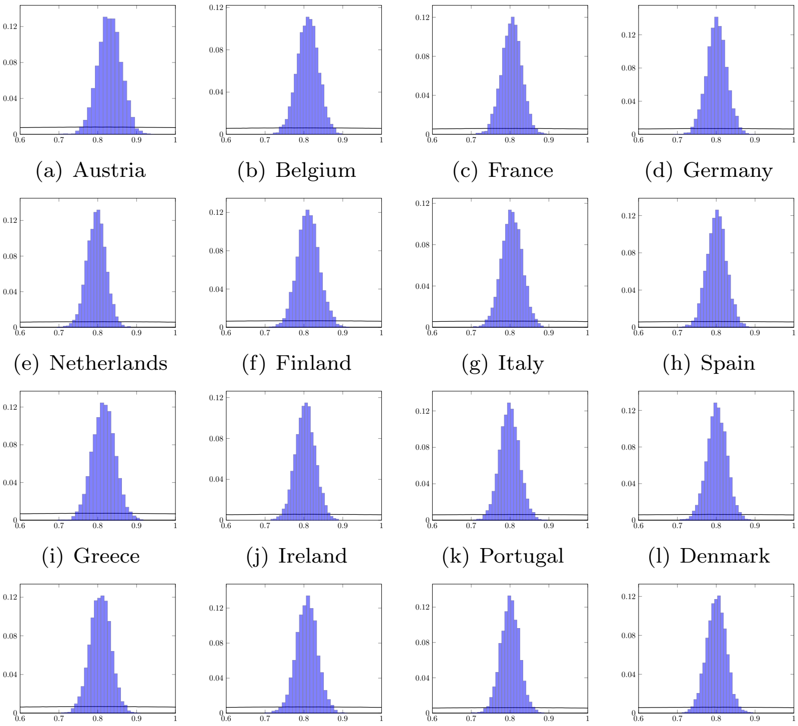


Figure B-9: Prior and posterior distributions π_i



(a) Austria (b) Belgium (c) France (d) Germany

(e) Netherlands (f) Finland (g) Italy (h) Spain

(i) Greece (j) Ireland (k) Portugal (l) Denmark

(m) Sweden (n) UK (o) Switzerland (p) Norway

Prior distribution Posterior distribution

Appendix C FMI over country groups and subperiods

Table C-1: Pre and post Single European Act period FMI, average over country groups

	(a) 1970:1-1986:1			(b) 1986:2-1992:1			(c)=(b)-(a)		
	mean	percentiles		mean	percentiles		mean	percentiles	
Country groups		5%	95%		5%	95%		5%	95%
(1) all	0.39	0.34	0.44	0.46	0.41	0.51	0.07	0.02	0.12
(2) EU	0.38	0.33	0.42	0.45	0.40	0.50	0.07	0.02	0.13
(3) non-EU	0.45	0.39	0.52	0.54	0.47	0.60	0.08	0.01	0.15
(4) non-EU (excl. Switz.)	0.36	0.28	0.44	0.47	0.39	0.55	0.11	0.03	0.20
(5)=(2)-(3)	−0.08	−0.13	−0.03	−0.09	−0.13	−0.04	−0.01	−0.06	0.04
(6)=(2)-(4)	0.02	−0.05	0.08	−0.02	−0.09	0.04	−0.04	−0.11	0.03
(7) euro	0.40	0.35	0.45	0.45	0.40	0.50	0.05	−0.00	0.11
(8) non-euro	0.33	0.27	0.39	0.45	0.38	0.51	0.12	0.05	0.18
(9)=(7)-(8)	0.07	0.02	0.11	0.00	−0.04	0.05	−0.06	−0.11	−0.01
(10) EU core	0.46	0.41	0.52	0.54	0.48	0.60	0.08	0.01	0.14
(11) EU non-core	0.29	0.24	0.34	0.39	0.34	0.44	0.10	0.04	0.15
(12)=(10)-(11)	0.17	0.13	0.22	0.15	0.11	0.19	−0.02	−0.07	0.02
(13) euro core	0.43	0.38	0.49	0.49	0.43	0.54	0.05	−0.01	0.11
(14) euro non-core	0.29	0.24	0.36	0.40	0.34	0.46	0.10	0.04	0.17
(15)=(13)-(14)	0.14	0.09	0.19	0.09	0.04	0.13	−0.05	−0.11	0.00

Notes: We report the mean and the 5th and 95th percentiles of the posterior distribution (over the 5000 Gibbs draws) of the average over country groups of the $\overline{FMI}^c_{i,s}$ measure where $\overline{FMI}^c_{i,s}$ is a time average of FMI^c_{it} over the reported subperiod s. The countries belonging to the different country groups are reported in the notes to Table 2 and Table 4.

Table C-2: Pre and post Maastricht Treaty period FMI, average over country groups

	(a) 1986:2-1992:1			(b) 1992:2-1998:12			(c)=(b)-(a)		
	mean	percentiles		mean	percentiles		mean	percentiles	
Country groups		5%	95%		5%	95%		5%	95%
(1) all	0.46	0.41	0.51	0.55	0.49	0.60	0.09	0.04	0.13
(2) EU	0.45	0.40	0.50	0.54	0.48	0.59	0.09	0.04	0.14
(3) non-EU	0.54	0.47	0.60	0.59	0.52	0.65	0.05	−0.01	0.11
(4) non-EU (excl. Switz.)	0.47	0.39	0.55	0.56	0.47	0.63	0.08	0.01	0.16
(5)=(2)-(3)	−0.09	−0.13	−0.04	−0.05	−0.09	−0.00	0.04	−0.01	0.08
(6)=(2)-(4)	−0.02	−0.09	0.04	−0.02	−0.08	0.05	0.01	−0.05	0.07
(7) euro	0.45	0.40	0.50	0.54	0.48	0.59	0.09	0.04	0.13
(8) non-euro	0.45	0.38	0.51	0.55	0.48	0.61	0.10	0.04	0.16
(9)=(7)-(8)	0.00	−0.04	0.05	−0.01	−0.05	0.03	−0.02	−0.06	0.02
(10) EU core	0.54	0.48	0.60	0.64	0.58	0.69	0.10	0.05	0.15
(11) EU non-core	0.39	0.34	0.44	0.48	0.42	0.54	0.09	0.04	0.14
(12)=(10)-(11)	0.15	0.11	0.19	0.16	0.12	0.19	0.01	−0.03	0.04
(13) euro core	0.49	0.43	0.54	0.58	0.52	0.63	0.09	0.04	0.14
(14) euro non-core	0.40	0.34	0.46	0.49	0.42	0.54	0.09	0.04	0.14
(15)=(13)-(14)	0.09	0.04	0.13	0.09	0.05	0.13	0.00	−0.03	0.04

Notes: see Table C-1.

Table C-3: Pre and post euro period FMI, average over country groups

	(a) 1992:2-1998:12			(b) 1999:1-2008:8			(c)=(b)-(a)		
	mean	percentiles		mean	percentiles		mean	percentiles	
Country groups		5%	95%		5%	95%		5%	95%
(1) all	0.55	0.49	0.60	0.64	0.58	0.69	0.09	0.05	0.14
(2) EU	0.54	0.48	0.59	0.64	0.58	0.68	0.10	0.05	0.14
(3) non-EU	0.59	0.52	0.65	0.66	0.59	0.72	0.07	0.00	0.13
(4) non-EU (excl. Switz.)	0.56	0.47	0.63	0.66	0.57	0.73	0.10	0.02	0.17
(5)=(2)-(3)	−0.05	−0.09	−0.00	−0.02	−0.06	0.02	0.03	−0.02	0.07
(6)=(2)-(4)	−0.02	−0.08	0.05	−0.02	−0.07	0.04	−0.00	−0.06	0.06
(7) euro	0.54	0.48	0.59	0.63	0.57	0.68	0.09	0.05	0.14
(8) non-euro	0.55	0.48	0.61	0.66	0.59	0.71	0.11	0.05	0.16
(9)=(7)-(8)	−0.01	−0.05	0.03	−0.03	−0.06	0.01	−0.01	−0.05	0.03
(10) EU core	0.64	0.58	0.69	0.75	0.70	0.80	0.11	0.07	0.16
(11) EU non-core	0.48	0.42	0.54	0.57	0.51	0.63	0.09	0.04	0.14
(12)=(10)-(11)	0.16	0.12	0.19	0.18	0.15	0.21	0.03	−0.01	0.06
(13) euro core	0.58	0.52	0.63	0.68	0.63	0.73	0.10	0.05	0.15
(14) euro non-core	0.49	0.42	0.54	0.57	0.51	0.63	0.09	0.03	0.14
(15)=(13)-(14)	0.09	0.05	0.13	0.11	0.07	0.14	0.01	−0.02	0.05

Notes: see Table C-1.

Table C-4: Pre and post Lehman Brothers crisis period FMI, average over country groups

	(a) 1999:1-2008:8			(b) 2008:9-2010:3			(c)=(b)-(a)		
	mean	percentiles		mean	percentiles		mean	percentiles	
Country groups		5%	95%		5%	95%		5%	95%
(1) all	0.64	0.58	0.69	0.67	0.60	0.73	0.03	−0.01	0.07
(2) EU	0.64	0.58	0.68	0.67	0.60	0.73	0.03	−0.01	0.08
(3) non-EU	0.66	0.59	0.72	0.67	0.58	0.74	0.01	−0.05	0.07
(4) non-EU (excl. Switz.)	0.66	0.57	0.73	0.69	0.59	0.77	0.03	−0.03	0.10
(5)=(2)-(3)	−0.02	−0.06	0.02	0.00	−0.05	0.06	0.02	−0.02	0.07
(6)=(2)-(4)	−0.02	−0.07	0.04	−0.02	−0.08	0.05	0.00	−0.05	0.06
(7) euro	0.63	0.57	0.68	0.67	0.60	0.73	0.04	−0.01	0.08
(8) non-euro	0.66	0.59	0.71	0.68	0.60	0.75	0.02	−0.03	0.07
(9)=(7)-(8)	−0.03	−0.06	0.01	−0.01	−0.05	0.03	0.01	−0.02	0.05
(10) EU core	0.75	0.70	0.80	0.78	0.72	0.83	0.03	−0.01	0.07
(11) EU non-core	0.57	0.51	0.63	0.61	0.53	0.68	0.04	−0.01	0.08
(12)=(10)-(11)	0.18	0.15	0.21	0.17	0.14	0.21	−0.01	−0.04	0.02
(13) euro core	0.68	0.63	0.73	0.72	0.66	0.78	0.05	0.00	0.09
(14) euro non-core	0.57	0.51	0.63	0.60	0.52	0.67	0.03	−0.02	0.08
(15)=(13)-(14)	0.11	0.07	0.14	0.13	0.08	0.17	0.02	−0.01	0.05

Notes: see Table C-1.

Table C-5: Pre and post European debt crisis period FMI, average over country groups

	(a) 2008:9-2010:3			(b) 2010:4-2012:10			(c)=(b)-(a)		
	mean	percentiles		mean	percentiles		mean	percentiles	
Country groups		5%	95%		5%	95%		5%	95%
(1) all	0.67	0.60	0.73	0.67	0.59	0.73	−0.00	−0.03	0.03
(2) EU	0.67	0.60	0.73	0.67	0.59	0.73	−0.00	−0.03	0.03
(3) non-EU	0.67	0.58	0.74	0.66	0.57	0.75	−0.01	−0.05	0.04
(4) non-EU (excl. Switz.)	0.69	0.59	0.77	0.69	0.58	0.78	0.00	−0.05	0.05
(5)=(2)-(3)	0.00	−0.05	0.06	0.01	−0.05	0.07	0.00	−0.03	0.04
(6)=(2)-(4)	−0.02	−0.08	0.05	−0.02	−0.09	0.06	−0.00	−0.04	0.03
(7) euro	0.67	0.60	0.73	0.66	0.59	0.73	−0.00	−0.03	0.03
(8) non-euro	0.68	0.60	0.75	0.68	0.59	0.75	−0.00	−0.04	0.03
(9)=(7)-(8)	−0.01	−0.05	0.03	−0.01	−0.06	0.04	0.00	−0.03	0.03
(10) EU core	0.78	0.72	0.83	0.78	0.72	0.83	−0.00	−0.03	0.02
(11) EU non-core	0.61	0.53	0.68	0.60	0.52	0.68	−0.00	−0.04	0.03
(12)=(10)-(11)	0.17	0.14	0.21	0.18	0.13	0.22	0.00	−0.02	0.02
(13) euro core	0.72	0.66	0.78	0.72	0.65	0.78	−0.00	−0.03	0.03
(14) euro non-core	0.60	0.52	0.67	0.59	0.51	0.67	−0.01	−0.04	0.03
(15)=(13)-(14)	0.13	0.08	0.17	0.13	0.08	0.18	0.00	−0.02	0.03

Notes: see Table C-1.