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Financial market interdependence, contagion and jumpy risk exposure

This paper measures the degree of common movements across European stock markets and aims to understand possible contagion effects when shocks occur.

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Keywords: Bayesian analysis, factor model, regime switching, stock markets

JEL codes: C11, C58, G15

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We develop a factor model to jointly measure financial market interdependence and contagion effects. Countries' exposure to the common factor is composed of a slow-moving trend, measuring cross-market linkages during 'normal times', and a regime-switching component, measuring excess sensitivity often indicative of contagion. When estimating the model using daily excess returns for 19 European stock markets over the period 1995–2025, we find a decreasing degree of interdependence after the Great Recession. Moreover, we identify contagion days in multiple countries, often linked to well-known market events. Finally, allowing for regime changes in the factor loadings can help improve forecasts of downside risk.

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1 Introduction

The question as to what extent observed comovement of financial markets reflects interdependence due to structural factors such as globalisation, or a contagious transmission of shocks, has concerned both researchers and policymakers for decades. Since no unanimously accepted definition of financial contagion exists (see, e.g., Claessens et al., 2001; Pericoli and Sbracia, 2003; Forbes, 2012; Dungey and Gajurel, 2014), and various methods have been used to study comovement in different financial markets, the findings range from 'only interdependence' to 'significant presence of contagion'. Contributing to this debate, we propose a new approach to jointly measure financial market interdependence and contagion effects and analyse both for the case of European stock markets.

Starting from King and Wadhwani (1990), numerous papers have studied interdependence and contagion by looking at whether cross-market correlations have increased significantly during times of crisis compared to non-crisis periods (e.g. Lee and Kim, 1993; Calvo and Reinhart, 1996). In a seminal paper, Forbes and Rigobon (2002) show that correlation coefficients are always conditional on market volatility, which tends to be higher during crises. As a result, this simple measure is biased towards finding evidence of contagion. Alternatively, they suggest a heteroscedasticity-adjusted correlation coefficient and find almost no evidence of contagion during the 1987 U.S. stock market crash, the 1994 Mexican peso devaluation, and the 1997 East Asian crisis when using daily stock market data for a large number of countries. However, the adjustment of Forbes and Rigobon (2002) has been criticised due to its restrictive assumptions on the variance ratio of common and country-specific shocks (Billio and Pelizzon, 2003; Corsetti et al., 2005; Dungey and Renault, 2018) and its lack of robustness, e.g. with respect to the dating of crisis periods (Billio and Pelizzon, 2003).

Partly based on some of this criticism, Bekaert et al. (2005) have argued that market integration and financial contagion should be studied in a factor model framework where all sources of changing cross-market correlations can be properly modeled.[1] Bekaert et al.

[1] Alternative approaches to analyse contagion exist. Bae et al. (2003) identify contagion through coinciding extreme returns, and find contagion during previous episodes both within and from Latin America and Asia, but being more important in the former case. Ciccarelli and Rebucci (2007) use a time-varying coefficients model for the Chilean FX market during the Argentine crisis. While a non-zero coefficient on another country's characteristics reflects interdependence, sudden changes indicate contagion. Their approach is robust to heteroscedasticity and omitted variables. The authors find interdependence between

(2005) study 22 Asian, European, and Latin American equity markets and assume that a country's (monthly) excess return depends on a U.S. and a regional factor, as well as country-specific shocks. The U.S. and the regional factor are proxied by value-weighted indices while time variation in the factor loadings depends on a country's respective trade shares as well as the importance of trade for the economy. The authors define contagion as correlation of the model residuals, i.e. return comovement that is 'excessive' compared to what would be implied by the underlying factor model. Comparing this residual correlation between crisis and non-crisis periods, the findings suggest no contagion during the Mexican crisis (11/1994–12/1995), but meaningful contagion during the Asian crisis (04/1997–10/1998). Baele and Inghelbrecht (2010) assume that time variation in the factor loadings is determined by fundamentals and, in addition, a two-state regime-switching process that should capture changing integration over the cycle. Analysing 14 European markets and various crisis periods, they show that allowing for such regime switches can impact the results of the contagion test of Bekaert et al. (2005), with little evidence of contagion in the preferred model.[2] Bekaert et al. (2014) extend the model of Bekaert et al. (2005) to study the sources of contagion. The authors allow the factor loadings and the transmission channels through fundamentals to change during crisis periods, reflecting excessive exposure to the common factor, i.e. contagion. Focusing on shock transmission during the Global Financial Crisis (GFC) across a large number of country-industry equity portfolios, their results indicate that "If there is contagion, it must be captured by changing exposures to the factors" (Bekaert et al., 2014, p. 2623). They find little evidence of global contagion but sizable domestic one during the GFC.

The focus of this paper is the measurement of financial market interdependence and contagion – rather than the analysis of its transmission channels. The above-mentioned factor models can have shortcomings in this regard. First, a limited set of observed structural variables might not be sufficient to capture time-varying market interdependence. Second, previous studies typically use weekly or monthly return observations (Bekaert et al., 2005; Baele and Inghelbrecht, 2010; Bekaert et al., 2014). However, since stock market crises and subsequent contagion effects are often short-lived, spanning only a few

Chile and Brazil and some evidence of contagion from Argentina. Lastly, note that many approaches to identify contagion can be linked to a factor structure for returns (Dungey et al., 2005).

[2] Cho et al. (2015) extend the model of Baele and Inghelbrecht (2010) by additionally incorporating crisis dummies in the loadings equation.

days or even less, analysing weekly or monthly data could average out short occurrences of contagion. Finally, previous work has often relied on exogenously defined crisis periods while the results of contagion tests can strongly depend on the windows used to define these periods (Billio and Pelizzon, 2003).[3]

We develop an unobserved factor model with time-varying factor loadings and stochastic volatility to study interdependence and contagion in European stock markets using data at daily frequency.[4] In this framework, the time-varying degree of a market's integration is measured by the excess return variation explained by the ('normal times') common return component (Bekaert and Harvey, 1995; Pukthuanthong and Roll, 2009). By contrast, we consider a situation as indicative of contagion where a country's exposure to a common shock suddenly increases and exceeds what would be implied by time-varying interdependence during 'normal times'. To operationalise this distinction, we model a country's time-varying exposure to the common factor as the sum of a random walk component and a Markov-switching component. The random walk process captures slowly-evolving observed drivers of market interdependence and fundamentals that are inherently unobservable as well as cyclical variation in integration.[5] The regime-switching component identifies days and countries for which the transmission channel of common European shocks suddenly widens, often indicative of contagious shock transmission.[6] Our approach relates to existing factor models that have been applied to study financial market integration and contagion. However, our analysis only uses excess stock returns as input and provides a flexible decomposition into common (European) and idiosyncratic shocks, at the cost of ignoring the economic and financial channels of interdependence and contagion. Therefore, the model can be to some extent viewed as a fully 'unobserved components version' of the models used in Baele and Inghelbrecht (2010) and, somewhat less so, in Bekaert et al. (2014).

[3]Exceptions include Bae et al. (2003), Gravelle et al. (2006) and Ciccarelli and Rebucci (2007), who do not assume an exact crisis period to identify contagion.

[4]The model belongs to the class of factor stochastic volatility models (Pitt and Shephard, 1999; Aguilar and West, 2000; Chib et al., 2006) with time-varying loadings (Lopes and Carvalho, 2007; Del Negro and Otrok, 2008).

[5]Iseringhausen and Vierke (2019) have followed a similar approach for modeling business cycle volatility.

[6]Baele and Inghelbrecht (2010) note that when adding a third regime to their specification, this exhibits spike-like behavior, potentially reflecting non-fundamental events and contagion. Since the random walk process captures slow-moving and cyclical changes, this is how we interpret the regime-switching component in our model. Using a somewhat different idea, Gravelle et al. (2006) apply a factor model with regime-switching loadings and volatilities to study contagion in currency and bond markets.

The approach put forward in this paper to quantify contagious cross-market transmission of shocks can be linked to existing approaches and definitions of contagion. Motivated by the definition of contagion as "...the comovement in excess of that implied by the factor model" (Bekaert et al., 2014, p. 2598), our focus lies on sudden changes in factor exposures, which go beyond both slowly-evolving structural and cyclical dynamics. In our reduced-form model we remain agnostic about whether such shifts are linked to fundamental-based contagion, e.g. due to trade linkages, or non-fundamental contagion, e.g. due to 'wake-up calls' (see Forbes, 2012, for a discussion of different contagion channels). Moreover, a sudden rise in a country's factor exposure increases bilateral return correlations which – on days with sizable common shocks – is consistent with previous work that "...defines contagion as a significant increase in cross-market linkages after a shock to an individual country (or group of countries)" (Forbes and Rigobon, 2001, p. 44). Similarly to other factor-based approaches, we do not identify the shocks' sources. However, combining the timing of increased factor exposure with qualitative information on certain events can support this. Lastly, our model in principle allows large shocks to propagate differently than small shocks. This relates to previous work emphasising the importance of non-linearities and focusing on the (co-)occurrence of extreme returns, rather than return correlations, when studying contagion (Bae et al., 2003).

Our contribution to the literature is threefold. First, by relying on a factor model where both the time-varying loadings and the common factor are unobserved, no choice is required as to which variables drive interdependence and how to proxy common European shocks. Second, we measure events of contagion using daily return data. While this can help to identify short-lived events as opposed to using lower-frequency observations, the computational burden of standard algorithms to estimate factor models involving multiple unobserved states, quickly increases with both the cross-sectional and the time dimension. However, sparse matrix algorithms (see, e.g., Chan and Jeliazkov, 2009; McCausland et al., 2011) allow for fast posterior sampling of most of the model's unobserved states, even when using a large dataset of daily stock returns. Finally, our model does not restrict the occurrence of possible contagion to pre-defined crisis periods but determines days with excessive common shock exposure endogenously. Moreover, in contrast to 'model-free' approaches comparing (adjusted) correlation coefficients over different periods, our approach can quantify the relevance of a possibly contagious shift in a market's common factor exposure for its total return on a given day.

When applying our factor model to daily excess returns of 19 European stock market indices over the period 02/01/1995–30/04/2025, we obtain the following results. First, the proposed model captures most of the cross-market correlation. Second, before 2011/12 the average comovement of European stock markets has been characterised by an increasing trend. However, afterwards there is some evidence of decoupling. Third, we find sudden increases of varying frequency in the exposures of various countries to the common European factor during different periods.[7] The majority of abrupt shifts falls on dates that can be associated with well-known events and in most cases these constitute evidence of contagion. Lastly, to provide further support for our model, we conduct a stylised out-of-sample forecasting exercise for measures of downside risk, Value-at-Risk and expected shortfall. The results show that i) adding a Markov-switching component to the factor loadings generally improves forecasts compared to a nested specification and ii) our model can in several cases improve upon a frequently used time-varying volatility (GARCH) model.

The remainder of the paper is structured as follows: Section 2 introduces the factor model with time-varying and composite loadings and discusses estimation issues as well as prior choices. The results are presented and discussed in Section 3. Section 4 concludes.

2 A factor model with composite loadings

2.1 Empirical specification

Our empirical analysis assumes that excess returns of a country's stock market index are driven by both a common return factor and a country-specific return component. In particular, we specify the excess return y of country i in period t in deviation from its country-specific mean as

$$y_{it} = \beta_{it} f_t + \varepsilon_{it}, \qquad i = 1, ..., N, \quad t = 1, ..., T, \tag{1}$$

[7] Since our Bayesian approach provides (posterior) probabilities to be in a specific regime, the labeling of high factor exposure days in our discussion is always conditional on a probability threshold.

where f_t is the common return factor, β_{it} is the country-specific factor exposure or loading and ε_{it} is the country-specific return factor.[8] Equation (1) is consistent with asset pricing theory, in particular the (international) CAPM (see, e.g., Bekaert and Harvey, 1995; Bekaert et al., 2014), where a market's integration is the larger the higher the variance of the common component $\beta_{it} f_t$ is, relative to the variance of ε_{it}. The common return factor and the idiosyncratic component are assumed to follow stationary AR(1) processes

$$f_t = \rho f_{t-1} + e^{g_t/2} \kappa_t, \qquad \kappa_t \sim t(\nu_\kappa), \qquad |\rho| < 1, \tag{2}$$

$$\varepsilon_{it} = \theta_i \varepsilon_{i,t-1} + e^{h_{it}/2} \epsilon_{it}, \qquad \epsilon_{it} \sim t(\nu_{\epsilon,i}), \qquad |\theta_i| < 1, \tag{3}$$

where the shocks to the country-specific component, ϵ_{it}, are assumed uncorrelated across countries. To allow for 'volatility clustering' (see, e.g., Mandelbrot, 1963), both shocks feature stochastic volatility where the latent volatility processes also follow stationary AR(1) processes

$$g_t = \mu_g + \phi_g (g_{t-1} - \mu_g) + \eta_t, \qquad \eta_t \sim \mathcal{N}(0, \sigma_\eta^2), \qquad |\phi_g| < 1, \tag{4}$$

$$h_{it} = \mu_{h,i} + \phi_{h,i} (h_{i,t-1} - \mu_{h,i}) + \psi_{it}, \qquad \psi_{it} \sim \mathcal{N}(0, \sigma_{\psi,i}^2), \qquad |\phi_{h,i}| < 1. \tag{5}$$

In addition, we allow for excess kurtosis beyond what is implied by the volatility dynamics by relaxing the assumption of Gaussianity (see, e.g., Bai et al., 2003). Instead, we assume that the (standardised) return shocks are t-distributed with ν_κ and $\nu_{\epsilon,i}$ degrees of freedom.

The main methodological contribution of this paper is the introduction of unobserved time-varying factor loadings that account for both slowly-evolving changes and sudden shifts in countries' exposure to the common factor. Specifically, the factor loadings β_{it} are modeled as the sum of two components

$$\beta_{it} = \widetilde{\beta}_{it} + \gamma_{it}, \tag{6}$$

where the first component follows a driftless random walk process

$$\widetilde{\beta}_{it} = \widetilde{\beta}_{i,t-1} + \omega_{it}, \qquad \omega_{it} \sim \mathcal{N}(0, \sigma_{\omega,i}^2). \tag{7}$$

[8] An alternative to subtracting the country-specific mean for each series would be to include a country-specific constant in Equation (1).

The second component follows a two-state, first-order Markov-switching process

$$\gamma_{it} = \gamma_{0,i} + \gamma_{1,i} S_{it}, \qquad S_{it} \in [0, 1], \quad \gamma_{1,i} > 0, \tag{8}$$

where $\gamma_{1,i} > 0 \ \forall \ i = 1, ..., N$ is the standard normalisation to identify the states (see, e.g., Hamilton, 1989) and with transition probabilities q_i and p_i defined as

$$Pr(S_{it} = 0 | S_{i,t-1} = 0) = q_i, \qquad Pr(S_{it} = 1 | S_{i,t-1} = 1) = p_i. \tag{9}$$

A few remarks regarding our model specification are appropriate. First, allowing for fat-tailed (standardised) shocks to both the common and the country-specific factor is crucial to avoid misspecification when estimating our model using daily data of equity returns. Chiu et al. (2017) show that volatility estimates are upward biased when the model innovations, in the presence of larger tails, are erroneously assumed to be Gaussian. Even more importantly, this should at least reduce the chance that regime changes in the exposures to the common factor mistakenly capture data dynamics that are actually due to non-normal idiosyncratic return shocks.[9] Second, while the model could in principle be extended to allow for more than two regimes in the exposures to the common factor, two regimes suffice to illustrate our modeling idea, allow for a straightforward interpretation, and keep the computational burden manageable. We also provide evidence that one common factor in Equation (1) captures most of the cross-sectional dependence in excess returns of European stock indices. Since our sample consists of countries from the same region, the factor captures both region-specific and global return shocks, which have been included separately in other studies (see, for example, Bekaert et al., 2005).

As it stands, the proposed factor stochastic volatility model with composite time-varying loadings is not identified. First, while the product of factor and loadings $\beta_{it} f_t$ is identified, the relative scales and signs of its constituent components are not. Multiplying the loadings by a constant c while dividing the common factor by the same c, would leave the product unchanged, making the two models equivalent. To address this identification issue, we normalise the overall average of the random walk component of the factor loadings to 1, i.e. $\frac{1}{N} \sum_{i=1}^{N} \frac{1}{T} \sum_{t=1}^{T} \widetilde{\beta}_{it} = 1$ (see also Everaert and Pozzi, 2016). Besides identifying the scale of both components, this normalisation also identifies the sign of

[9] Section 3.4 discusses this issue in greater detail.

the factor and the loadings. Moreover, to ensure that $\widetilde{\beta}_{it}$ reflects the exposure of each country to the common factor during 'normal times', i.e. to identify its level, we set $\gamma_{0,i} = 0 \ \forall \ i = 1, ..., N$.

2.2 Bayesian estimation and prior choice

The factor stochastic volatility model with composite time-varying loadings outlined above corresponds to a state space model with the observation equation given by merging Equations (1), (6) and (8), and the state Equations (2)-(3), (4)-(5), (7) and (9) describing the laws of motion for the unobserved components. This paper relies on Markov Chain Monte Carlo (MCMC) methods for estimation. The proposed model is highly nonlinear due to the multiplicative link between the unobserved factor and the loadings and because of the stochastic volatility components, which enter exponentially into Equations (2)-(3). Thus, the standard application of the Kalman filter in combination with the maximum likelihood method is not feasible. Instead, a Gibbs sampling procedure is applied. Specifically, the complex model is split into blocks of parameters and components that are linear conditional on the other blocks. By sampling repeatedly from these blocks, we obtain parameter draws from the joint posterior distribution. We iterate the Gibbs steps 1,100,000 times and drop the first 100,000 draws as a 'burn in' period. This ensures convergence to the ergodic distribution. From the remaining 1,000,000 draws we save every 100th draw.[10] The results presented in Section 3 are thus based on 10,000 draws. Our dataset at daily frequency is larger than those of other papers using factor models of similar complexity and computation becomes feasible due to fast matrix algorithms for sampling most of the unobserved states (Chan and Jeliazkov, 2009; McCausland et al., 2011; Chan and Hsiao, 2014).[11] A detailed description of the MCMC algorithm can be found in Appendix A.

Table 1 contains the prior distributions for the model parameters. The prior values can be considered almost uninformative for the majority of parameters. However, we set somewhat more informative priors on the transition probabilities to support a clear-cut differentiation between regimes (see Bianchi et al., 2017, for a similar approach). The

[10] We apply this so-called 'thinning' purely for computational reasons to deal with memory limits when working with a large number of daily observations (see also Gelman et al., 2011).

[11] From a computational perspective, sampling the regime indicators S remains a bottleneck.

transition probabilities account for our belief that elevated exposure to common shocks is a rare event and stock markets are likely to be in the 'normal regime' most of the days. The prior means for q and p imply an unconditional probability to be in the tranquil regime of around 83%. Our prior configuration for γ_1 reflects a loose expectation that the total common factor exposure β_{it} for $S_{it} = 1$ is twice as large as the grand mean of $\widetilde{\beta}$, which is normalised to 1 (see Section 2.1). Finally, the upper bound of the uniform priors for the degrees of freedom parameters ν_κ and ν_ϵ is based on the consideration that for $\nu > 50$ the t-distribution becomes indistinguishable from the standard normal distribution.

Table 1: Prior distributions

Para.	Description	Density	Specification	
			a_0	$\sqrt{A_0}$
μ_g	Intercept common volatility	$\mathcal{N}(a_0, A_0)$	0.00	$\sqrt{5}$
μ_h	Intercept idiosyncratic volatility	$\mathcal{N}(a_0, A_0)$	0.00	$\sqrt{5}$
ϕ_g	AR parameter common volatility	$\mathcal{N}(a_0, A_0)\mathcal{I}(\vert\phi_g\vert < 1)$	0.95	1.0
ϕ_h	AR parameter idiosyncratic volatility	$\mathcal{N}(a_0, A_0)\mathcal{I}(\vert\phi_h\vert < 1)$	0.95	1.0
ρ	AR parameter common factor	$\mathcal{N}(a_0, A_0)\mathcal{I}(\vert\rho\vert < 1)$	0.00	1.0
θ	AR parameter idiosyncratic factor	$\mathcal{N}(a_0, A_0)\mathcal{I}(\vert\theta\vert < 1)$	0.00	1.0
γ_1	Factor loading shift if $S_t = 1$	$\mathcal{N}(a_0, A_0)\mathcal{I}(\gamma_1 > 0)$	1.00	1.0
			Mean	S.D.
q	$Pr(S_t = 0 \vert S_{t-1} = 0)$	beta(u_{00}, u_{01})	0.9	0.1
p	$Pr(S_t = 1 \vert S_{t-1} = 1)$	beta(u_{11}, u_{10})	0.5	0.1
			Mean	S.D.
σ^2_κ	Shock variance of common volatility	$\mathcal{IG}(c_0, C_0)$	0.05	0.10
σ^2_ψ	Shock variance of idiosyncratic volatility	$\mathcal{IG}(c_0, C_0)$	0.05	0.10
σ^2_ω	Shock variance of random walk loadings	$\mathcal{IG}(c_0, C_0)$	0.01	0.10
			$\underline{\nu}$	$\bar{\nu}$
ν_κ	d.f. of common factor	$\mathcal{U}(\underline{\nu}, \bar{\nu})$	0	50
ν_ϵ	d.f. of idiosyncratic factor	$\mathcal{U}(\underline{\nu}, \bar{\nu})$	0	50

Note: The underlying parameters of the inverse-gamma prior distributions for the volatility (loadings) shocks are $c_0 = 2.25$ (2.01) and $C_0 = 0.0625$ (0.0101). The beta prior hyperparameters are $u_{00} = 7.2$, $u_{01} = 0.8$, $u_{11} = 12$ and $u_{10} = 12$.

3 Results

After a short description of the data, we start by presenting the (in-sample) common and country-specific parameter estimates. We discuss the model's ability to capture the correlation structure of European stock markets and the evolution of markets' integration. Next, the occurrence of regime shifts in the factor exposures is discussed in detail. We end with a stylised out-of-sample forecasting exercise and a number of robustness checks.

3.1 Data

Our dataset contains daily excess returns for the period 02/01/1995–30/04/2025 ($T = 7,852$) for 19 European countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. Excess returns are computed as log-differences ($\times 100$) of the country-specific MSCI equity price index denominated in U.S. dollars minus the 3-month U.S. Treasury-bill rate (see, e.g., Bekaert et al., 2009).[12] The MSCI price index is a value-weighted equity index that covers a market's large and mid cap segments (around 85% of the investable market capitalisation) and does not include dividends.[13] The MSCI data from Morgan Stanley is obtained through Refinitiv Datastream. Appendix B contains time series plots and summary statistics.

3.2 Parameter estimates and unobserved components

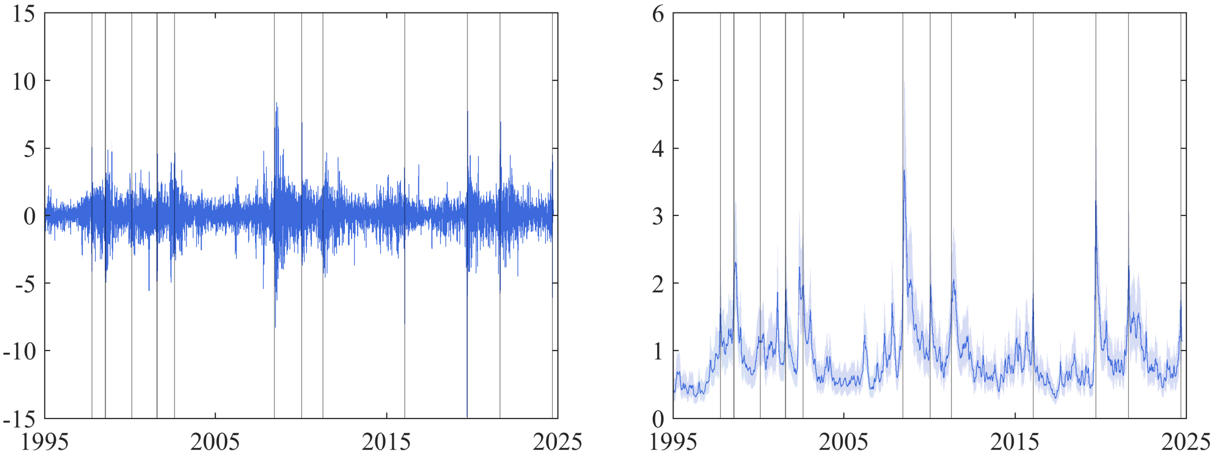
Figure 1 plots the posterior mean and 95% highest density interval (HDI) of the common European return factor along with its time-varying volatility. The size of common shocks clearly varies over time and the identified peaks in volatility correspond to well-known events that had a significant impact on European stock markets. We clearly identify as common shocks, for example, the Russian financial crisis in 1998, the September 11 attacks in 2001, the financial crisis leading to the failure of large banks in the U.S., the

[12]The Treasury-bill rates are provided by the U.S. Federal Reserve in annualised percentage terms and obtained from the Federal Reserve Economic Data (FRED) database. We convert the rates to daily numbers as follows: $r_t^{\text{daily}} = \left((1 + r_t^{\text{yearly}}/100)^{1/360} - 1\right) \times 100$. Moreover, we linearly interpolate the treasury rates on non-trading days in the United States.

[13]Daily MSCI total return indices (including reinvested dividends) for our sample are only available from 2001. However, the average correlation across countries between the returns of both indices is 0.998.

European sovereign debt crisis in 2010, the 'Brexit' vote in June 2016, the onset of the Covid-19 pandemic in Europe in March 2020, Russia's invasion of Ukraine in February 2022, as well as the announcement of sizable tariffs by the U.S. government in April 2025.

Figure 1: Common factor and volatility of common shocks



(a) Common factor: f_t

(b) Volatility of common shocks: $e^{g_t/2}$

Posterior mean   95% Highest density interval (HDI)   Event dates

Notes: The grey lines refer to particular market shocks. These are in chronological order: 27/10/1997 (crash after Asian economic crisis), 17/08/1998 (Russian financial crisis), 10/03/2000 (Dot-com bubble), 11/09/2001 (September 11 attacks), 09/10/2002 (stock market downturn), 16/09/2008 (GFC), 27/04/2010 (European sovereign debt crisis), 01/08/2011 (stock markets fall), 24/06/2016 ('Brexit' vote), 16/03/2020 (Covid-19), 24/02/2022 (Russian invasion of Ukraine), and 03/04/2025 (U.S. tariffs announcement).

Table 2 contains the posterior estimates of the parameters driving the unobserved processes of the common European return factor and its volatility. Common shocks do not show meaningful persistence since the 95% HDI of the parameter ρ includes zero. Shocks to the volatility process on the other hand seem to be highly persistent, a characteristic of financial markets known as 'volatility clustering' and first documented by Mandelbrot (1963). The standardised common shocks contribute somewhat to the fat tails of the excess return distributions as indicated by a moderately high degrees of freedom parameter ν_κ. The last two columns of the table suggest that our MCMC algorithm works well, i.e. the null hypothesis of non-convergence cannot be rejected and the (thinned) draws from the posterior distributions exhibit little serial correlation.

Table 2: Posterior estimates of common parameters

Parameter	Mean	S.D.	$P_{2.5}$	$P_{97.5}$	CD	IF
μ_g	−0.449	0.146	−0.743	−0.168	0.574	1.144
ϕ_g	0.988	0.003	0.982	0.992	0.984	1.530
σ_κ^2	0.022	0.003	0.016	0.029	0.501	1.788
ρ	0.010	0.012	−0.014	0.035	0.453	1.127
ν_κ	16.320	4.155	10.958	26.453	0.632	5.722

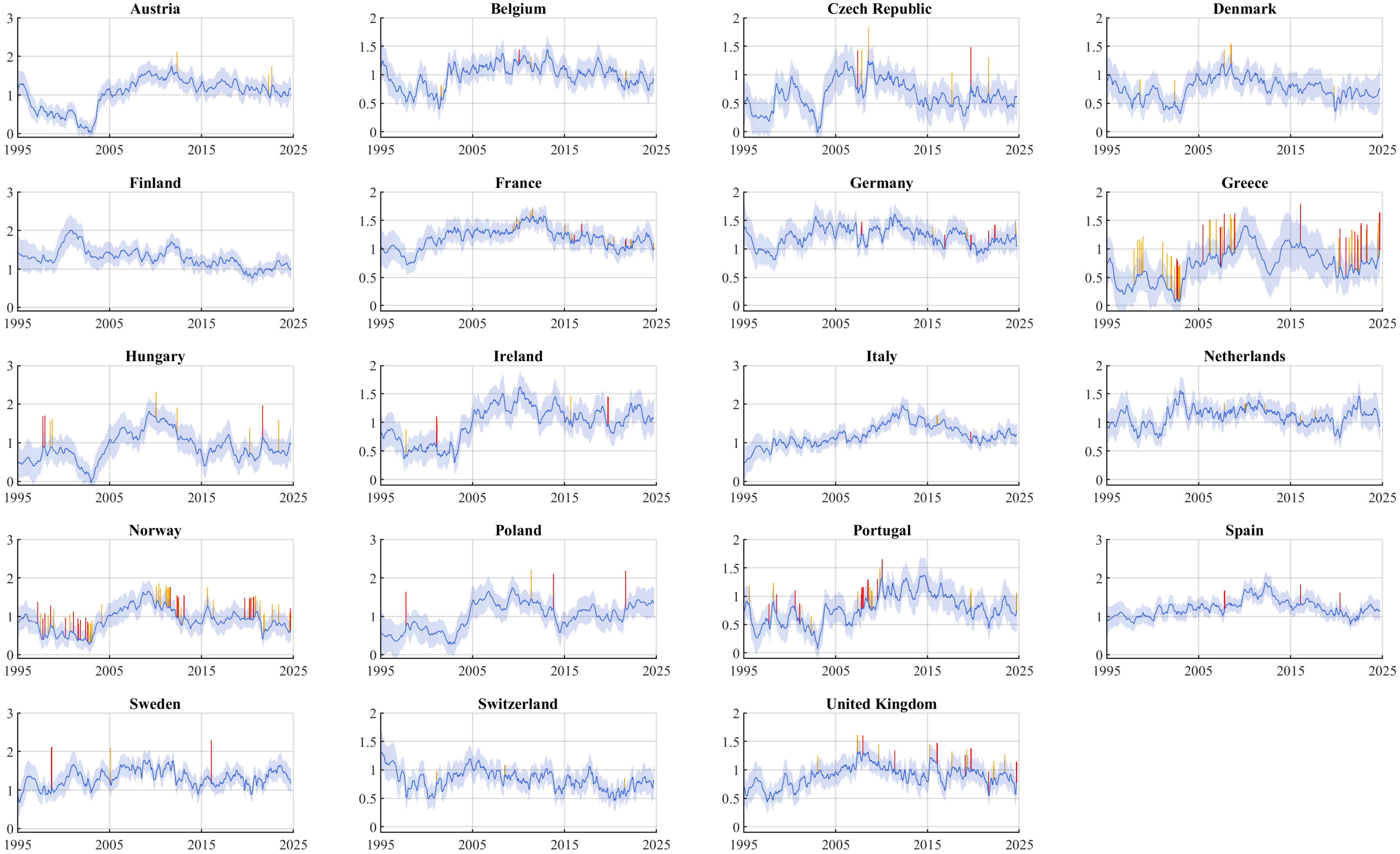
Notes: This table contains the posterior statistics (mean, standard deviation, and 95% highest density interval) of all common model parameters. CD and IF refer, respectively, to the p-value of the Geweke (1992) convergence diagnostic and the inefficiency factor, both computed using 4% tapered autocovariance matrices (LeSage, 1999).

Figure 2 presents the posterior estimates of the random walk component of the factor loadings $\widetilde{\beta}$, and the sum of $\widetilde{\beta}$ and the regime-switching component γ on days with a large probability to be in the high factor exposure regime, i.e. $\Pr(S_{it} = 1 > 0.8)$ and $\Pr(S_{it} = 1 > 0.9)$.[14] Overall, the random walk component captures slowly-evolving changes in countries' factor exposure as well as cyclical fluctuations. While in some countries, such as Hungary, Italy, and Poland, the fundamental exposure to the common factor somewhat increased, in other countries such as France or Germany, the random walk component does not show a clear trend. In addition to this basic exposure that is likely fundamental-driven or reflects changing integration over the cycle, most countries are showing occasional, and some more frequent, high-probability regime switches in their factor loadings, reflecting unusually large exposure to the common European factor.

Section 3.4 takes a closer look at dates with a high probability of increased common factor exposure and shows that many relate to well-known market events. Table C-1 in Appendix C contains the country-specific posterior statistics of the loading shift γ_1 and the transition probabilities q and p. First, the loading shifts are of significant magnitude and range from around 0.1 to 1.1. Second, conditional on being in the 'normal regime' the probability of switching to the contagion regime is relatively low in most countries. Once in the high common factor exposure regime, the probability to remain there is around 40% to 60% with the posterior standard deviations being relatively large.

[14] These thresholds are chosen arbitrarily and solely for illustrative purposes. Table 4 contains the number of days in the high factor exposure regime for different thresholds.

Figure 2: Factor loadings (random walk component and high exposure regime days)



Posterior mean $\widetilde{\beta}_{it}$ 95% HDI Posterior mean $\widetilde{\beta}_{it} + \gamma_{it}|(Pr(S_{it} = 1) > 0.8)$ Posterior mean $\widetilde{\beta}_{it} + \gamma_{it}|(Pr(S_{it} = 1) > 0.9)$

Figure 3: Stochastic volatility of country-specific shocks

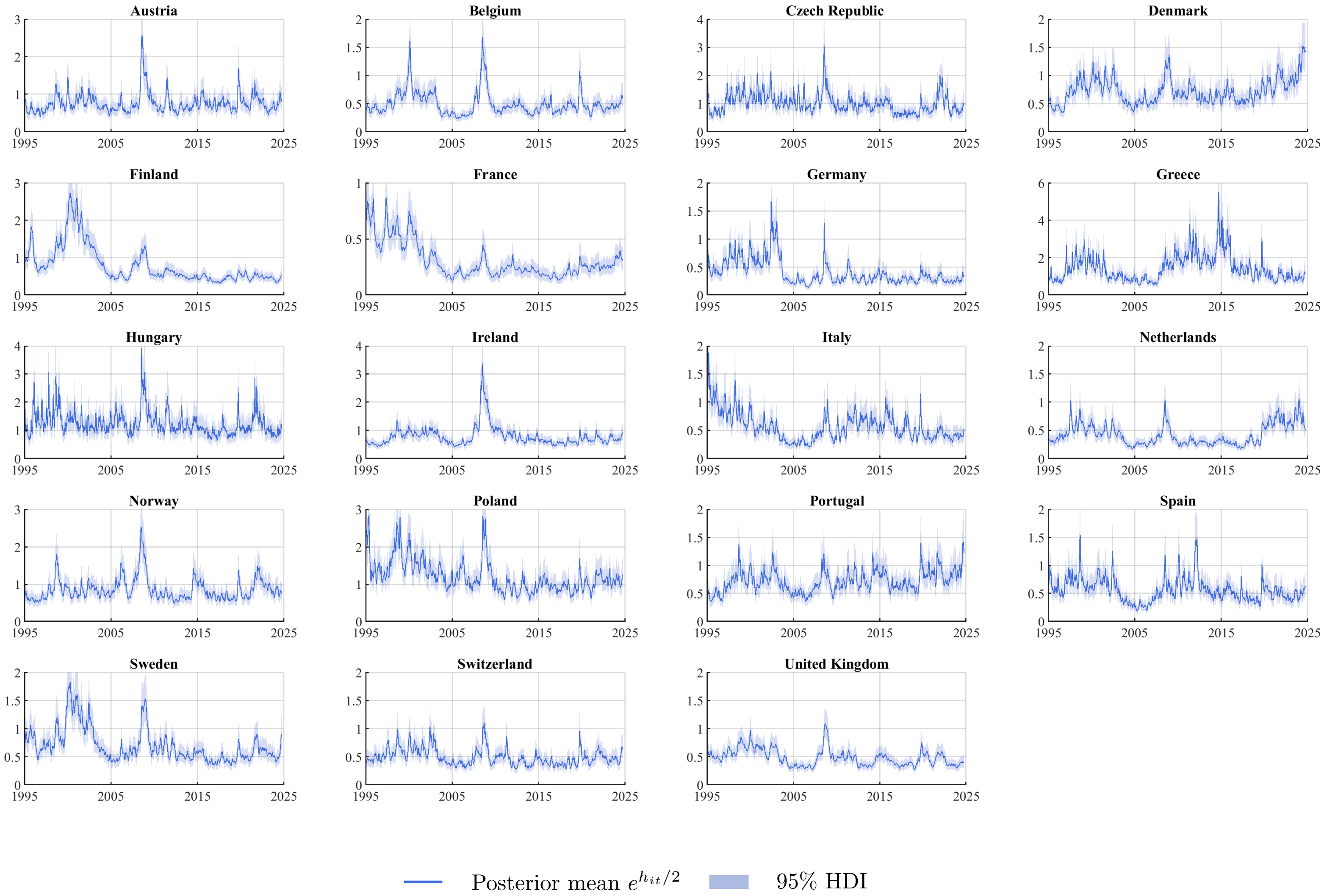


Figure 3 plots the stochastic volatility series of each country's idiosyncratic return shocks. While country-specific volatility shows certain similarities across countries, e.g. volatility shoots up during the financial crisis of 2007–08, the volatility series also have distinct differences. Table C-1 in Appendix C contains the remaining country-specific parameters, i.e. the stochastic volatility parameters, shock persistence parameters and the degrees of freedom of country-specific return shocks. Notably, the (standardised) country-specific shocks seem to drive the high kurtosis in the excess returns of many countries as indicated by relatively low degrees of freedom parameters ν_ϵ.

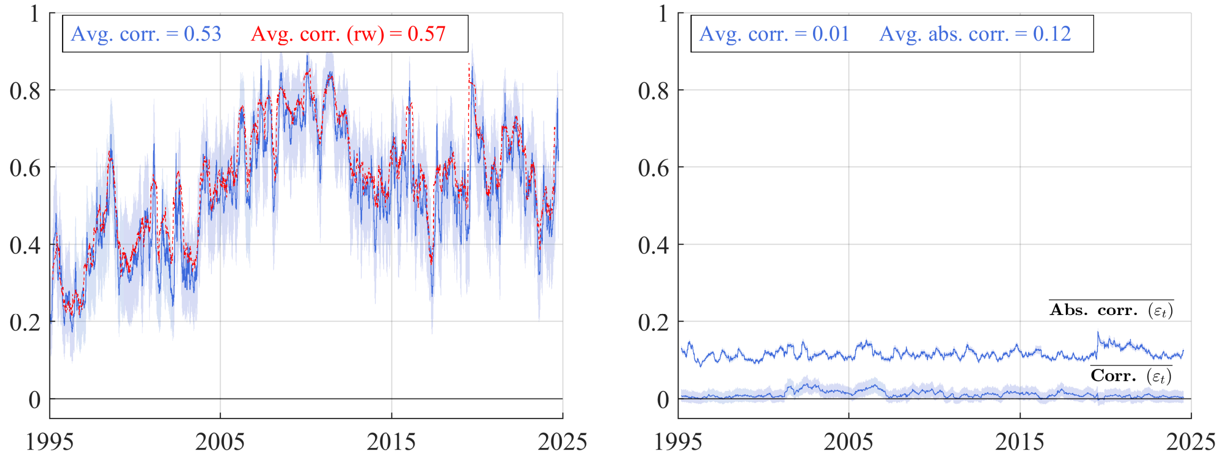
3.3 Cross-market correlation and financial integration

Before we discuss regime shifts in the factor loadings in detail, it is informative to assess how well the proposed factor model fits the correlation structure of European stock markets and how interdependence between markets has evolved over time. Figure 4(a) shows the average pairwise model-implied stock market correlation along with the average rolling window correlation, computed over a centred window of 100 days. Overall, both measures evolve very similarly over the sample period.[15] However, the model-implied measure features more pronounced spikes, i.e. sudden changes in the average cross-market correlation, whereas these dynamics are naturally difficult to capture for a rolling window measure. The average correlation increased from a low of around 0.2 in 1996 to almost 0.9 in 2010, before falling sharply and averaging around 0.5-0.6 in the last ten years. Figure 4(b) confirms that our one-factor specification with time-varying loadings captures most of the correlation structure of European stock markets. First, the average correlation of the residuals across markets is virtually zero.[16] Second, the average absolute residual correlation is also quite low and, in particular, does not exhibit sizable time variation or trends. The latter two results imply the existence of, on average, small and relatively stable negative and positive cross-market residual correlations. Due to these characteristics, we consider them of limited relevance for our analysis of financial market interdependence and contagion effects.

[15]For comparison, the average unconditional pairwise correlation across markets is 0.64.

[16]We measure the residual correlation on a rolling window basis since the model-implied cross-market correlation of ε is zero by assumption.

Figure 4: Time-varying cross-market correlations of excess returns and residuals



(a) Correlation of excess returns

(b) Residual correlation (rolling window)

Posterior mean 95% HDI Rolling window correlation of returns

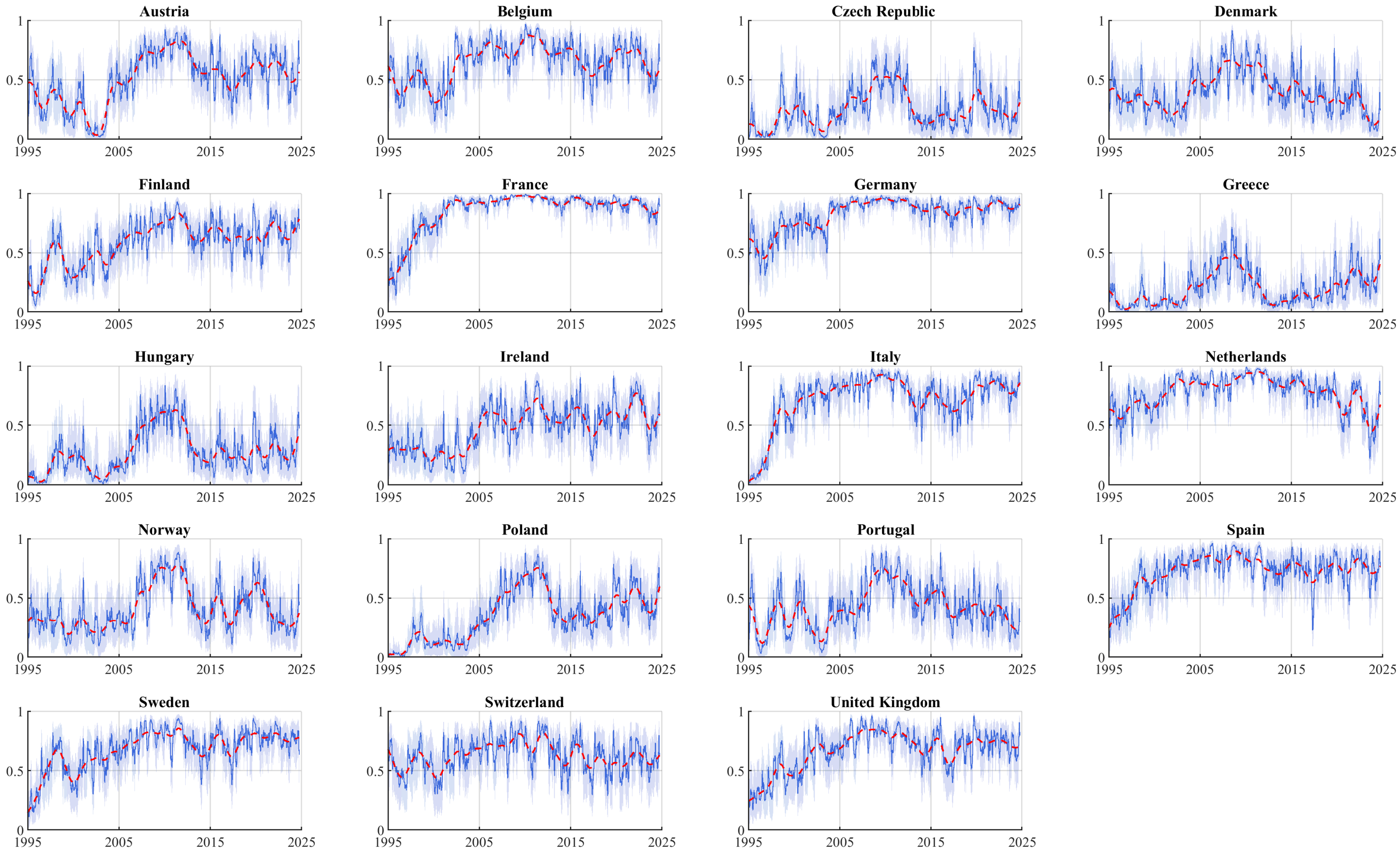
Notes: Figure 4(a) shows the model-implied average cross-market correlation of excess returns over time alongside a simple rolling window correlation measure. Figure 4(b) shows the posterior distribution of the average rolling window (absolute) correlation of the model's residuals across markets. The rolling window measures are computed using a centred 100-day window.

To get an idea of how interdependent, or alternatively, how integrated stock markets are, a natural measure is the share of variation in excess returns that is explained by the common component. In the case of a perfectly integrated market, one would expect all the variation in a country's excess returns to be explained by the common component whereas the dynamics in a separated market should be driven by the country-specific component (Bekaert and Harvey, 1995). Specifically, Pukthuanthong and Roll (2009) use the R^2 from a regression of returns on a certain number of principal components as a measure of integration.[17] We apply the same basic idea and compute the variance share explained by the random walk common component conditional on the unobserved states, i.e. the measure of financial market integration (FMI) adjusted for short-lived regime switches, as follows

$$FMI_{it} = \frac{Var[\widetilde{\beta}_{it} f_t | \widetilde{\beta}_{it}, g_t]}{Var[y_{it} | \widetilde{\beta}_{it}, g_t, h_{it}]} = \frac{\widetilde{\beta}_{it}^2 e^{g_t} \frac{\nu_\kappa}{(\nu_\kappa - 2)(1-\rho^2)}}{\widetilde{\beta}_{it}^2 e^{g_t} \frac{\nu_\kappa}{(\nu_\kappa - 2)(1-\rho^2)} + e^{h_{it}} \frac{\nu_{\epsilon,i}}{(\nu_{\epsilon,i} - 2)(1-\theta_i^2)}}. \tag{10}$$

[17]See Billio et al. (2017) for a comparison of different empirical approaches to assess market integration.

Figure 5: Measure of financial market integration (FMI)



Posterior mean FMI_{it} 95% HDI Trend FMI_{it} (Hodrick-Prescott filter with $\lambda = 10^8$)

Figure 5 shows the evolution of this integration measure per country. Consistent with Figure 4(a), most markets show an increasing degree of integration prior to and even during the Great Recession. This is in line with results reported in Lehkonen (2014). Using the integration measure of Pukthuanthong and Roll (2009) and daily equity data over the period 1987–2011, the author shows that average integration in developed countries exhibits an increasing trend until the end of the sample but drops during the financial crisis. Prior studies have discussed the importance of European political and economic integration, in particular the European Monetary Union, for the pre-GFC increase in stock market integration in the region (see, for example, Fratzscher, 2002; Baele, 2005; Hardouvelis et al., 2006; Bekaert et al., 2013). Moreover, the results match those reported in Niţoi and Pochea (2019) who use a Dynamic Conditional Correlation (DCC) model to measure stock market co-movement in the European Union. In a similar vein but focusing on tail dependence as a measure of cross-market linkages, Dominicy et al. (2017) report increasing tail dependence coefficients across equity markets until 2013 after those had significantly dropped in 2007. In addition, our results suggest that since around 2011/12, integration has decreased in the majority of European stock markets. Over the past ten years countries' integration levels have evolved differently, with some showing increasing integration (e.g. Greece, Italy, and Poland), others showing decreasing integration (e.g. Denmark, the Netherlands, and Portugal), and a third group with relatively stable integration levels (e.g. Finland, Germany, and Spain). While stock market integration still varies widely, with some countries almost perfectly integrated and others where excess returns are to a large extent determined by country-specific shocks, in most countries financial integration towards the end of the sample remains higher than at its beginning.

3.4 Sudden shifts in factor exposures and contagion

This section takes a closer look at the estimation results for the regime-switching component of the time-varying factor loadings. Table 3 contains the unconditional probabilities that, on a particular day, a market experiences elevated exposure to the common European factor. The results indicate that the risk of increased common factor exposure differs across markets with countries like Austria, Czech Republic, Poland, Spain, and Sweden being, unconditionally, at lower risk of contagious effects compared to other countries such as France, the Netherlands, Norway, Portugal, and Switzerland, which all have larger unconditional probabilities to be in the high factor exposure regime. However, the posterior distributions of all unconditional probabilities are relatively wide and, importantly, these probabilities do not take into account the estimated loading shifts γ_1. Thus, they alone are not informative about the return effects of potential regime shifts. Figure C-1 in Appendix C shows the probabilities to be in the high factor exposure regime on each day and for each of the 19 stock markets. The results complement the plots of the factor loadings in Figure 2. Overall, we observe distinct differences across markets regarding the risk of sudden increases in factor exposures.

Table 3: Unconditional probabilities of high common factor exposure regime (in %)

Country	Mean	$P_{2.5}$	$P_{97.5}$	Country	Mean	$P_{2.5}$	$P_{97.5}$
AT	13.61	5.52	28.76	IT	17.65	1.98	45.30
BE	28.41	9.58	49.39	NL	41.21	10.82	61.21
CZ	13.52	3.65	35.30	NO	36.15	22.54	50.24
DK	31.95	10.91	52.19	PL	11.34	1.49	51.60
FI	17.07	0.26	48.04	PT	34.93	20.19	50.69
FR	37.86	17.08	54.92	ES	7.43	2.04	20.26
DE	23.99	10.85	41.92	SE	2.84	0.25	36.43
GR	34.40	22.15	47.93	CH	32.97	6.52	62.25
HU	21.36	2.45	37.43	GB	18.83	8.86	32.87
IE	15.40	4.40	35.56				

Notes: This table contains the posterior distributions of the unconditional probabilities to be in the high common factor exposure regime: $\frac{(1-q_i)}{(2-q_i-p_i)} \times 100$.

Table 4 contains the number of days in the high factor exposure regime per country and the average expected effect on excess returns for different probability thresholds. The table confirms that contagion days, defined as those on which the exposure to the common European factor is elevated, are relatively rare events. The share of contagion days lies between 3.2% for $\Pr(S_{it} = 1) > 0.5$, and 0.1% for $\Pr(S_{it} = 1) > 0.9$. Moreover, on average, those days correspond with negative realisations of the common return factor as indicated by the largely negative expected return effects. This is in line with the intuition of financial market analysts and academics that usually associate events of contagion with negative, instead of positive, return shocks. This being said, our model specification is symmetric in the sense that it allows for 'positive contagion' effects, i.e. shifts in the factor loadings on days with positive common return shocks. In what follows, we will also shed light on some of these cases.

Table 4: Number of days with high common factor exposure and average return effects

	Probability of $S_{it} = 1$									
Country	$> 50\%$		$> 60\%$		$> 70\%$		$> 80\%$		$> 90\%$	
AT	54	(−0.52)	28	(−0.86)	16	(−0.99)	3	(0.21)	0	
BE	134	(−0.04)	45	(−0.09)	11	(0.06)	5	(0.44)	1	(1.57)
CZ	40	(−0.40)	17	(−0.31)	11	(−0.10)	7	(−0.95)	3	(−3.09)
DK	347	(−0.05)	121	(−0.12)	35	(−0.29)	9	(−0.63)	0	
FI	1	(−0.01)	0		0		0		0	
FR	563	(0.00)	162	(0.01)	59	(0.06)	18	(0.10)	3	(0.12)
DE	151	(−0.00)	57	(0.03)	26	(0.09)	9	(0.44)	5	(0.80)
GR	524	(−0.02)	207	(−0.06)	92	(−0.08)	46	(−0.10)	16	(0.02)
HU	202	(−0.09)	88	(−0.20)	33	(−0.32)	13	(−0.16)	4	(0.07)
IE	44	(−0.14)	21	(−0.20)	13	(−0.38)	12	(−0.47)	5	(−0.16)
IT	18	(−0.64)	5	(−1.86)	3	(−2.50)	2	(−2.94)	1	(−3.93)
NL	752	(−0.01)	162	(−0.06)	38	(−0.05)	7	(0.03)	0	
NO	903	(−0.06)	375	(−0.12)	176	(−0.28)	67	(−0.61)	23	(−1.00)
PL	18	(−0.67)	11	(−0.85)	10	(−1.12)	6	(−1.05)	4	(−1.78)
PT	603	(−0.01)	204	(−0.07)	67	(−0.22)	29	(−0.13)	10	(−0.28)
ES	23	(−0.20)	14	(−0.39)	11	(−0.28)	6	(−0.91)	6	(−0.91)
SE	8	(−0.38)	7	(−0.60)	6	(−0.66)	5	(−0.69)	4	(−0.59)
CH	212	(−0.04)	50	(−0.12)	10	(−0.12)	3	(−0.13)	0	
GB	187	(−0.09)	104	(−0.11)	58	(−0.15)	29	(−0.19)	17	(−0.41)
Total	4784	(−0.05)	1678	(−0.12)	675	(−0.21)	276	(−0.32)	102	(−0.54)

Notes: This table contains the number of days where $\Pr(S_{it} = 1)$ exceeds the threshold. The number in brackets refers to the average expected size of the return effect (in %), i.e. $\frac{1}{K} \sum Pr(S_{it} = 1)\gamma_{1,i} f_t$, where K denotes the number of high exposure days and the sum runs over all these dates.

When analysing the days with high probabilities of elevated common factor exposure in more detail, many of them relate to well-known market events. Table 5 shows selected dates with likely shifts in the country-specific loadings and we will discuss some of these in more detail. For illustrative purposes, here we show dates and countries for which the probability of $S_{it} = 1$ exceeds 80% and, in addition, exceeds 90% for at least one country. The first number refers to the expected return effect of the regime-switching component whereas the second number (in brackets) is the total excess return on that day. We identify sudden increases in the factor exposure of the stock markets in Hungary, Ireland, Norway, Poland and Portugal during the global crash due to the economic crisis in Asia in late October 1997. While these markets dropped significantly on 28/10/1997, they partly recovered one day later. Contagion effects of this crisis, especially affecting Eastern European countries, have been previously documented (see, e.g., Gelos and Sahay, 2001).

Around the time of the 'Russian cold' in 1998, which has been clearly identified as a common shock to European countries (see Figure 1), we identify excessive factor exposure in Greece, Norway, Portugal and Sweden with negative return effects between around 2% and 4% (whereas Sweden recovered shortly after). In addition, Hungary saw the largest negative excess return on 27/08/1998 (-14.9%), but the still high probability of widened common factor exposure on this day (0.78) is slightly below the (arbitrarily) chosen threshold for this table. In the same vein, Gelos and Sahay (2001) and Schotman and Zalewska (2006) find that the Hungarian stock market was much more strongly affected by both the Asian crisis and the 'Russian cold' compared to the remaining Eastern European markets. Moreover, we identify some excessive factor exposure around the burst of the dot-com bubble and during the international financial markets turmoil following the September 11 attacks. In the year 2002, which experienced a global stock market downturn with massive declines in July and September, we find a significantly widened factor exposure and negative return effects for Denmark and Norway. In addition, several contagious days in European stock markets are identified when the U.S. subprime mortgage market crisis began in August 2007 and when the Great Financial Crisis fully hit in January 2008. At this time, panic spread as market participants started to anticipate a recession in the U.S. and its potentially adverse consequences for Europe. Contagious spillovers from the U.S. to many European markets during this period were also found by Harb and Umutlu (2024), which test for breaks in correlations. By contrast, Bekaert et al. (2014) only find small evidence of equity market contagion in Europe during the GFC stemming from the U.S. and global financial markets. However, they find strong evidence of domestic cross-sector contagion, a phenomenon that our cross-country study does not consider.

Table 5: Selected days with high common factor exposure and expected return effects

Date	Countries			
01/04/1997	NO −1.6 (−5.4)			
28/10/1997	HU −3.2 (−19.1)	IE −1.8 (−7.6)	NO −2.3 (−5.2)	PL −3.8 (−11.6)
	PT −1.5 (−3.7)			
29/10/1997	HU 4.2 (12.4)	IE 2.2 (4.4)	NO 2.7 (4.6)	PL 4.4 (7.9)
	PT 1.9 (5.1)			
12/01/1998	GR −2.1 (−5.3)	HU −2.7 (−9.3)	NO −1.9 (−5.4)	
27/08/1998	GR −3.1 (−8.2)	NO −2.7 (−9.5)	PT −1.7 (−6.3)	
08/10/1998	SE −3.9 (−8.4)			
09/10/1998	SE 0.9 (3.0)			
12/10/1998	SE 5.3 (11.4)			
27/04/2000	NO −1.4 (−3.5)			
22/09/2000	PT 1.2 (4.1)			
14/03/2001	GR −1.4 (−5.4)	NO −1.3 (−3.7)		
22/03/2001	IE −2.8 (−6.7)	PT −2.0 (−5.0)	CH −1.1 (−7.1)	
23/03/2001	IE 1.5 (3.4)	PT 1.1 (3.3)		
26/03/2001	IE 1.5 (3.9)			
20/09/2001	GR −2.5 (−5.7)	NO −2.3 (−5.1)		
21/09/2001	BE −0.7 (−3.8)	NO −2.1 (−7.4)		
27/12/2001	NO 1.2 (3.6)			
22/07/2002	DK −1.8 (−6.1)	NO −2.7 (−5.4)		
23/07/2002	DK −1.1 (−4.9)	NO −1.7 (−5.6)		
25/07/2002	DK 1.4 (5.5)	GR 2.3 (3.0)	NO 2.0 (4.8)	
11/10/2002	GR 2.8 (4.9)	NO 2.1 (4.3)		
04/11/2002	GR 1.8 (3.7)	NO 1.3 (3.0)		
01/09/2005	GR 1.0 (2.9)			
16/08/2007	CZ −2.1 (−5.6)	GR −2.1 (−4.4)	PT −1.1 (−4.0)	
17/08/2007	GR 1.5 (4.7)			
21/01/2008	DE −1.3 (−8.4)	PT −2.0 (−7.0)	ES −2.7 (−9.1)	
23/01/2008	DE −0.6 (−5.2)	ES −1.4 (−5.1)		
24/01/2008	CZ 2.9 (11.4)	GR 3.3 (9.0)	NL 0.7 (7.0)	ES 2.4 (7.9)
05/02/2008	PT −1.2 (−4.4)	ES −1.7 (−6.5)		
17/03/2008	GB −0.8 (−5.3)			
25/03/2008	PT 1.3 (5.0)			
06/10/2008	DK −3.1 (−13.5)	PT −3.1 (−13.0)		
19/03/2009	GR 2.7 (8.3)	PT 1.4 (5.9)		
29/10/2009	PT 0.6 (3.0)			
10/05/2010	BE 1.6 (10.3)	FR 0.9 (10.3)	HU 5.0 (16.2)	NL 1.0 (9.0)
	PT 2.6 (11.8)			
22/09/2011	BE −0.9 (−6.5)	NO −2.2 (−8.0)	PL −3.6 (−11.2)	GB −1.5 (−6.5)
14/12/2011	NO −1.1 (−4.5)			
14/09/2012	AT 1.4 (6.2)	HU 1.9 (6.3)	NO 1.4 (4.6)	
23/10/2012	NO −1.1 (−3.9)			
20/06/2013	NO −2.0 (−6.0)			
03/03/2014	PL −2.1 (−6.1)			
20/06/2016	GB 1.3 (5.7)			
24/06/2016	FR −1.1 (−10.1)	GR −5.4 (−25.0)	IT −2.0 (−15.7)	ES −4.1 (−16.1)
	GB −2.8 (−11.5)			
27/06/2016	NL −0.6 (−5.0)	SE −4.7 (−10.5)	GB −1.5 (−6.1)	
28/06/2016	GB 0.9 (3.9)			
29/06/2016	GB 1.0 (5.1)			
24/04/2017	FR 0.5 (5.7)	DE 0.9 (4.8)		
02/08/2019	GB −0.7 (−2.7)			
05/08/2019	GB −0.5 (−2.3)			
09/03/2020	NO −3.9 (−10.7)	PT −2.4 (−9.0)		
12/03/2020	IT −3.9 (−20.5)			
16/03/2020	CZ −3.2 (−11.0)	IE −2.1 (−7.3)		
18/03/2020	CZ −3.9 (−10.5)	FR −0.7 (−7.1)	IE −2.9 (−9.5)	
23/03/2020	GB −1.0 (−6.0)			

Date	Countries											
24/03/2020	DE	1.9	(10.2)	PT	2.7	(10.7)	GB	2.9	(11.0)			
26/03/2020	DK	1.3	(5.4)	IE	1.8	(7.5)						
21/09/2020	GR	−2.7	(−5.6)	HU	−3.2	(−6.8)	NO	−2.3	(−6.3)			
09/11/2020	FR	0.6	(6.7)	GR	3.0	(8.0)	NO	2.5	(6.8)	ES	2.1	(7.9)
26/02/2021	NO	−1.2	(−4.6)									
19/07/2021	GR	−1.6	(−4.0)									
24/02/2022	CZ	−3.7	(−9.1)	GR	−3.6	(−7.9)	HU	−4.9	(−17.4)	PL	−5.5	(−16.5)
	GB	−2.1	(−6.0)									
25/02/2022	HU	3.7	(10.8)	PL	4.3	(11.1)	GB	1.7	(4.9)			
09/03/2022	BE	1.4	(7.8)	FR	0.9	(8.3)	DE	1.6	(9.2)			
05/07/2022	GR	−2.5	(−6.6)									
04/11/2022	AT	1.7	(7.4)	FR	0.4	(4.0)	GR	2.1	(4.1)			
10/11/2022	DE	0.9	(5.3)									
15/03/2023	AT	−2.4	(−9.6)	GR	−3.0	(−6.8)						
24/03/2023	GR	−1.7	(−5.2)	NO	−1.3	(−4.8)						
14/11/2023	GR	1.6	(4.8)									
04/04/2025	NO	−3.5	(−9.4)	GB	−2.3	(−6.8)						
07/04/2025	FR	−0.6	(−5.5)	GR	−3.2	(−8.7)	PT	−1.6	(−8.6)	GB	−1.8	(−6.0)
08/04/2025	GR	1.4	(6.8)	GB	0.8	(2.6)						
09/04/2025	NO	−0.9	(−3.6)	GB	−0.7	(−3.0)						

Notes: This table contains the dates where the model identifies elevated exposure to the common factor ($S_{it} = 1$) with probability > 0.8 and additionally, for at least one country, with probability > 0.9. The first number refers to the expected return effect ($\Pr(S_{it} = 1)\gamma_{1,i} f_t$) whereas the second number (in brackets) is the total excess return on that day (both in %).

On 10/05/2010 we observe a case of positive excess factor exposure, when several European markets rose shortly in reaction to the agreement of support measures between European policymakers and the IMF in the context of the sovereign debt crisis. When the Federal Reserve released a worsened outlook for the global economy on 21/09/2011 and 'Operation Twist' did not succeed in containing financial markets' concerns, several European markets reacted much more strongly than what would have been implied by market linkages during 'normal times'. Also, the intensification of the Ukraine crisis in early March 2014 unsettled investors in different markets but only its neighbouring country Poland seemed to have been contagiously affected. In addition, the negative stock market shock due to the 'Brexit' vote on 23/06/2016 (the result was announced on the morning of 24/06/2016) appears to have spread to several other markets to an extent that cannot be explained by 'normal' market linkages. We find elevated factor exposure in France, Greece, Italy, and Spain. This is broadly in line with Burdekin et al. (2018), who find that the last three countries, as well as Ireland and Portugal, were experiencing the worst adverse stock market effects following the 'Brexit' referendum. In the case of Ireland, Li (2019) reports a peak of the contagious effect three days after the vote. In our case, we also find an increased probability of elevated exposure (around 65%) in Ireland on 27/06/2016, however, below the threshold for inclusion in Table 5. Similarly, the 'Brexit' announcement had a particularly strong contagious impact on Sweden on the Monday following the vote on Friday, supporting results reported in earlier studies (Aristeidis and Elias, 2018). The drop was in this case driven by the banking sector and by losses of companies with a large international exposure such as H&M. The change in the loadings of the U.K. itself should not be interpreted as contagion but merely as evidence that it was the origin of this particular common European shock. Moreover, while equity markets in countries like the Netherlands and Germany were also hit by the 'Brexit' news shock, the model does only classify the shock transmission for the former as contagious.

The Covid-19 pandemic was a major global shock that – in addition to major human tragedy – caused large turmoil in financial markets (see, for example, Baker et al., 2020; Iwanicz-Drozdowska et al., 2021; Arteaga-Garavito et al., 2024). The large-scale spread of the Covid-19 pandemic in Europe started in March 2020, and we identify excessive exposure in various countries. For some countries, these results are aligned with those in Harb and Umutlu (2024), while for others they differ. When Russia invaded Ukraine on 24/02/2022, countries in close proximity saw their stock markets plummeting (Yousaf et al., 2022; Federle et al., 2024). Our analysis finds that the exposure to the common factor on that day was elevated for Czech Republic, Greece, Hungary, Poland, as well as the United Kingdom. Federle et al. (2024) discuss potential reasons for this 'proximity penalty', notably trade linkages as well as disaster risk, i.e. the risk of getting involved in the conflict. The last notable occurrence of widened factor exposure to common shocks relates to the tariff announcements by the U.S. government in early-April 2025, affecting several European countries particularly strongly.

We conclude this section with a few more general remarks. First, several well-known stock market crashes from the recent past do not go along with suddenly increasing common factor exposures. Those events have clearly constituted common return shocks but seem to have transmitted through 'normal' market linkages. These include, for example, the U.S. stock market's 'flash crash' on 06/05/2010, in which case the overall limited evidence of contagion is in line with previous findings in the literature (Jansen, 2021).[18] Other such cases are the 2015–16 global stock market sell-off as well as 'Black Monday' on

[18]However, more generally, identifying contagion originating from extremely short-lived events, where a market drops sharply and subsequently recovers within a single day, would require data of higher frequency than the daily one used in our analysis (see, for example, Bongaerts et al., 2022).

08/08/2011 caused by a downgrading of the U.S. sovereign credit rating. As previously mentioned, Table 5 illustrates selected dates and these depend on the chosen probability threshold. Additional event dates would show up when lowering this threshold. Finally, we cannot rule out that the model occasionally identifies idiosyncratic shocks as regime changes in the factor exposures. A possible solution could be to extend the model to also allow for regime switches in the volatility of idiosyncratic shocks to avoid that such events are captured by the regime-switching component of the loadings. This illustrates a point relevant for most reduced-form approaches, which is to not take the model output simply at face value but to combine it with information outside the model to build a narrative.

3.5 Out-of-sample forecasting of downside risk

Having discussed the main empirical results, this section provides additional statistical support for our proposed specification through a relatively simple out-of-sample forecasting exercise. Since forecasting is not the main objective of our analysis, here we are only interested in answering two selected questions. First, does adding a Markov-switching component to the factor loadings improve the out-of-sample performance and, second, can our model compete with a frequently used time-varying volatility (GARCH) model?

We forecast two commonly used measures of downside risk in financial markets, i.e. Value-at-Risk (VaR) and expected shortfall (ES). VaR refers to the p%-quantile of the predictive excess return distribution, while ES is the expected excess return below the VaR level.[19] Our forecast comparison includes four models, which in order of increasing complexity are

1. The 'naive' historical benchmark, where VaR and ES forecasts are computed as their unconditional counterparts over the in-sample period.

2. A GARCH(1,1) model where the standardised errors follow a t-distribution (Bollerslev, 1986, 1987).

[19] The formal definitions are

$$Pr(y_{i,t+h} \leq VaR^p_{i,t+h|t}) = p, \quad \text{and}$$
$$ES^p_{i,t+h|t} = \mathbb{E}(y_{i,t+h} | y_{i,t+h} \leq VaR^p_{i,t+h|t}).$$

3. A simplified version of the previously introduced factor model which does not allow for Markov-switching regimes in the factor loadings, i.e. $\gamma_{it} = 0 \ \forall \ i = 1, ..., N$ and $t = 1, ..., T$. This model thus assumes that the time-varying loadings follow a random walk process and is labeled 'Factor (rw)'.

4. The factor model with composite loadings outlined in Section 2.1. This model is labeled 'Factor (full)'.

For each of these models, we generate a series of one-day-ahead ($h = 1$) VaR and ES forecasts for $p \in \{1\%, 5\%\}$. We initially estimate the models with data until 31/12/2009 before recursively, and using an extending window scheme, generating out-of-sample forecasts for the period 01/01/2010–30/04/2025 ($T_{oos} = 3,962$).

While the one-step-ahead VaR/ES forecasts of the GARCH model can be obtained analytically, for the factor specifications we embed this in the MCMC algorithm. Specifically, for each Gibbs draw of the model parameters, we generate a corresponding draw from the one-step-ahead predictive distribution of $y_{i,t+1}$. The latter requires generating draws for κ_{t+1}, $\epsilon_{i,t+1}$, $\eta_{i,t+1}$, $\psi_{i,t+1}$, $\omega_{i,t+1}$ and $S_{i,t+1}|S_{it}$. These can be used to calculate the set of the one-step-ahead unobserved states based on Equations (2)-(8), i.e. g_{t+1}, f_{t+1}, $h_{i,t+1}$, $\varepsilon_{i,t+1}$, $\widetilde{\beta}_{i,t+1}$, $\gamma_{i,t+1}$, and $\beta_{i,t+1}$. Lastly, $y_{i,t+1}$ is obtained based on Equation (1). The forecasts for VaR/ES are then computed based on all draws of $y_{i,t+1}$.[20] To evaluate the VaR forecasts, we report the average tick loss or quantile score across countries (see, e.g., Koenker and Bassett, 1978; Brownlees and Souza, 2021), while in case of ES forecasts we report the VaR-ES score (see, e.g., Fissler et al., 2015; Carriero et al., 2024). In addition, and similarly to Brownlees and Souza (2021), we also report the results of pairwise model forecast comparisons using Diebold and Mariano (1995) tests.[21]

[20] For computational reasons, in this section we reduce the number of MCMC draws to 220,000, where we drop the first 20,000 draws as 'burn-in' and do not apply 'thinning'. The results here are thus based on 200,000 effective MCMC draws.

[21] The two factor specifications are nested, potentially rendering the test invalid (see, e.g., Clark and McCracken, 2001). However, alternative approaches are more complex and less frequently used even in the nested case.

Table 6: Results of out-of-sample forecasting exercise

			Model			
			Hist.	GARCH-t	Factor (rw)	Factor (full)
TL	1%	Avg. loss	0.062	0.053	0.053	**0.052**
		Hist.	–	19 (19)	19 (19)	19 (19)
		GARCH-t	0 (0)	–	1 (1)	1 (1)
		Factor (rw)	0 (0)	1 (1)	–	5 (8)
		Factor (full)	0 (0)	0 (1)	0 (0)	–
	5%	Avg. loss	0.188	0.172	**0.170**	**0.170**
		Hist.	–	18 (19)	19 (19)	19 (19)
		GARCH-t	0 (0)	–	3 (6)	5 (8)
		Factor (rw)	0 (0)	0 (0)	–	0 (3)
		Factor (full)	0 (0)	0 (0)	0 (1)	–
VaR-ES	1%	Avg. loss	0.752	**0.730**	0.738	0.735
		Hist.	–	17 (19)	5 (8)	8 (12)
		GARCH-t	0 (0)	–	0 (1)	1 (2)
		Factor (rw)	0 (0)	1 (8)	–	8 (13)
		Factor (full)	0 (0)	1 (3)	0 (0)	–
	5%	Avg. loss	0.856	0.814	0.813	**0.812**
		Hist.	–	19 (19)	19 (19)	19 (19)
		GARCH-t	0 (0)	–	2 (4)	3 (5)
		Factor (rw)	0 (0)	0 (0)	–	4 (7)
		Factor (full)	0 (0)	0 (0)	0 (0)	–

Notes: This table shows the average loss metrics (TL and VaR-ES) across countries. It also contains the results of Diebold and Mariano (1995) tests (using White (1980) HC standard errors). Specifically, we report the number among the 19 countries for which the model in the column produces more precise Value-at-Risk and expected shortfall forecasts than the model in the respective row at the 5% (10%) significance level (one-sided test).

Table 6 summarises the results of this stylised forecasting exercise. First, our proposed factor specification with composite loadings – with the exception of 1%-ES – is always the model, or among the models, producing the lowest average loss measure. Second, in almost all cases it significantly outperforms the other three approaches for at least as many countries than vice versa, and in most cases for many more. Third, while the benefits of our proposed model compared to the GARCH-t model seem to be strongest for both risk measures at the 5% level, compared to the nested factor specification they are more pronounced at the 1% level. The latter indicates that the regime-switching component of the factor loadings especially helps to improve forecasts of the extreme left tail of the predictive return distribution.

In summary, the results in this section provide statistical support for our empirical specification, highlighting the value added of a regime-switching component in the factor loadings compared to a nested specification with only smoother time variation. The model also generates competitive out-of-sample forecasts of downside risk compared to a widely used time-varying volatility model.

3.6 Robustness checks

Prior sensitivity

As discussed in Section 2.2, our prior configurations are already relatively loose and the presented results are overall not sensitive to changes in these prior values. However, we set a somewhat tighter prior on the conditional probability to remain in the 'normal regime'. Table C-2 in Appendix C contains the estimated transition probabilities and the factor loading shifts in the high factor exposure regime for alternative prior configurations of q and p (see Appendix C for further details and discussion). When relaxing the prior distribution of the conditional probability $\Pr(S_t = 0|S_{t-1} = 0) = q$, the posterior means of this parameter drop moderately for most countries, resulting in a larger number of days in the high exposure regime. When relaxing the prior distribution of the conditional probability to remain in the 'contagion regime', $\Pr(S_t = 1|S_{t-1} = 1) = p$, most posterior means of this parameter drop while the total number of days with elevated factor exposure remains similar to the baseline for most countries (with the exception of Switzerland, further discussed in Appendix C). Overall, these sensitivity checks are partially in line with Bianchi et al. (2017) who, using a somewhat different modeling approach, report that the prior distributions of both probabilities matter but find that the impact of the latter on posterior outcomes is much stronger.

Infrequent jumps in the mean equation

This robustness check addresses potential concerns that the regime switches in countries' factor exposure to the common European factor, which we have been interpreting as indicative of contagious transmission of common return shocks, are simply capturing jumps in the mean equation. While one could argue that fat-tailed shocks are sufficient to capture occasional extreme returns, here we explicitly include a jump component in the mean equation following Chib et al. (2006), i.e. we augment Equation (1) as follows

$$y_{it} = \beta_{it} f_t + k_{it}\zeta_{it} + \varepsilon_{it}, \qquad i = 1, ..., N, \quad t = 1, ..., T, \tag{11}$$

where $\zeta_{it} \in [0, 1]$ is a binary variable that takes the value one with probability w_i and k_{it} are the jump sizes modeled as $k_{it} \sim \mathcal{N}(\mu_{k,i}, \sigma^2_{k,i})$. In choosing the priors for these additional parameters, we follow Chan and Grant (2016). Specifically, the jump intensity w_i is assumed to follow a uniform distribution, i.e. $w_i \sim \mathcal{U}(0, 0.1)$. The average jump size and the log-jump variance $\delta_i = (\mu_{k,i}, \log(\sigma^2_{\kappa,i}))$ are assumed to be distributed as $\delta_i \sim \mathcal{N}(\delta_0, V_\delta)$. The prior hyperparameters are set to $\delta_0 = (0, \log(10))'$ and $V_\delta = \text{diag}(10, 1)$. When estimating this extended version of our baseline model, the results remain essentially unchanged. We find the jump component in Equation (11) to be only of minor importance. In particular, the previously documented regime changes in the factor exposures to the common European factor (see Table 4) are largely unaffected by allowing for jumps in the excess return equation (see Table C-3 in Appendix C).

4 Concluding remarks

This paper has analysed financial market interdependence and contagion for 19 European equity markets over the period 02/01/1995—30/04/2025, using an unobserved common factor model. We model the factor loadings as the sum of a persistent component, measuring both slowly evolving structural dynamics and cyclical variation in markets' interdependence, and a regime-switching component, capturing sudden increases in countries' exposure to the common European factor. The latter is often indicative of contagious shock transmission. We estimate the model using MCMC methods combined with fast sparse matrix algorithms.

Our results can be summarised as follows. First, the proposed one-factor specification captures most of the cross-market correlation in our dataset of daily excess returns across European stock markets. Second, before 2011/12, the average pairwise correlation coefficient of European stock markets has been trending up. However, after the GFC, we find some evidence of lower interdependence. Third, we document occasional and sudden increases in the factor exposure of various countries to the common factor during different periods. Many of these can be associated with well-known market events, often constituting evidence of contagion. Lastly, we provide statistical support for our factor specification through an out-of-sample forecasting exercise of downside risk in equity markets. We show that i) composite factor loadings can improve forecasts compared to having only a slow-moving source of time-varying factor exposure and ii) our model competes well with a standard time-varying volatility (GARCH) model.

These insights could help both policy makers and market participants. Countries that are more exposed to common shocks than what would be expected by 'normal' market linkages may be concerned about the resilience of their financial markets during future periods of turmoil. While certain policy measures may be effective if the reason for a country's vulnerability is domestic, it is more difficult to shield against the adverse impact of unpredictable economic and political instability abroad. Market participants could use the model to monitor and forecast excessive factor exposure, potentially providing valuable input for portfolio allocation decisions.

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Appendix A Details on the MCMC algorithm

In this appendix, details are given on the blocking scheme of the MCMC algorithm and the conditional posterior distributions of the factor stochastic volatility model with time-varying and composite factor loadings introduced in Section 2. Before describing the various blocks of the Gibbs sampling algorithm in detail, a few remarks regarding different aspects of the estimation approach are made:

1. While the time-varying unobserved states of the linear Gaussian state space models in Blocks 1(a), 2 and 3 could in principle be filtered using the standard Kalman filter and subsequently be sampled using the algorithm outlined in Carter and Kohn (1994), this procedure turns out to be very slow when estimating the model using daily data with $T \sim 8,000$ for $N = 19$ countries. Instead, we use more efficient algorithms based on sparse matrix techniques that have been proposed by Chan and Jeliazkov (2009) and McCausland et al. (2011). The reader is referred to pp. 5-8 in Chan and Hsiao (2014) for a detailed outline of the so-called precision sampler.

2. In order to transform the model with Student-t distributed (common and country-specific) shocks into a conditionally Gaussian framework, we make use of the fact that the Student-t distribution can be expressed as a scale mixture of normal distributions. Specifically, Geweke (1993) and Chan and Hsiao (2014) show how to use this insight to set up efficient Gibbs sampling algorithms for simple linear models and stochastic volatility models, respectively. To illustrate the basic idea, consider the following model

$$y_t = \varepsilon_t, \qquad \varepsilon_t \sim t(\nu), \tag{A-1}$$

which can equivalently be written as

$$y_t = \lambda_t^{1/2}\epsilon_t, \qquad \lambda_t|\nu \sim \mathcal{IG}(\nu/2, \nu/2), \quad \epsilon_t \sim \mathcal{N}(0,1). \tag{A-2}$$

Therefore, conditional on the scale mixture weights λ, the model is Gaussian. We will use this insight in the following when developing a Gibbs sampler for the factor model with time-varying and composite loadings.

3. The country-specific return components, or equivalently, the country-specific error terms of our factor model, are assumed to exhibit AR(1) dynamics. To deal with this fact in our Gibbs sampling algorithm (where the state space representations assume uncorrelated errors), we apply a simple (Cochrane-Orcutt) transformation of the model which re-establishes the assumption of serially uncorrelated error terms (see, e.g., Zellner and Tiao, 1964).

Block 1: Sample the composite factor loadings β

Block 1(a): Sample the random walk component $\widetilde{\beta}$

For the purpose of sampling the latent random walk factor loading series $\widetilde{\beta}$, we first specify a general state space model of the following form as given in Durbin and Koopman (2012)

$$w_t = Z_t \kappa_t + e_t, \qquad e_t \sim \mathcal{N}(0, H_t), \tag{A-3}$$

$$\kappa_{t+1} = d_t + T_t \kappa_t + R_t \eta_t, \qquad \eta_t \sim \mathcal{N}(0, Q_t), \tag{A-4}$$

where w_t is a vector of observed data and κ_t the unobserved state. The matrices Z_t, T_t, H_t, Q_t, R_t, and d_t are assumed to be known (conditioned upon). The error terms e_t and η_t are assumed to be serially uncorrelated and independent of each other at all points in time. The specific linear state space model used in this block to sample the time-varying states $\widetilde{\beta}$ takes the following form

$$\underbrace{(\widetilde{y}_t - S_t \gamma_1 f_t)}_{w_t} = \underbrace{\left[I_N f_t\right]}_{Z_t} \underbrace{\left[\widetilde{\beta}_t\right]}_{\kappa_t} + \underbrace{\epsilon_t}_{e_t}, \tag{A-5}$$

$$\underbrace{\left[\widetilde{\beta}_{t+1}\right]}_{\kappa_{t+1}} = \underbrace{\left[I_N\right]}_{T_t} \underbrace{\left[\widetilde{\beta}_t\right]}_{\kappa_t} + \underbrace{\left[I_N\right]}_{R_t} \underbrace{\left[\omega_t\right]}_{\eta_t}, \tag{A-6}$$

with $\widetilde{y}_t = y_t - \theta \varepsilon_{t-1}$ being the (Cochrane-Orcutt) transformed dependent variable (the same notation is maintained in the following blocks), $H_t = I_N(e^{h_t} \odot \lambda_{\epsilon,t})$, $Q_t = \text{diag}(\sigma_\omega^2)$ and where $\odot$ is the element-wise (Hadamard) product of two vectors. Since $\widetilde{\beta}$ is country-specific, sampling is implemented country-by-country.

Block 1(b): Sample the regime-switching component γ

In this block we sample the regime-switching components of the factor loadings, i.e. its constituent components which are the regime indicators S, the transition probabilities q and p, and the loading shifts γ_1. The sampling approach closely follows Albert and Chib (1993) and Kim and Nelson (1999). Since all these components are country-specific, they are sampled country-by-country.

Sample the regime indicators S

To sample the regime indicators S, we apply the multi-move sampler outlined in Kim and Nelson (1999) which samples S_t for $t = 1, ..., T$ as a block from the corresponding joint conditional posterior distribution. Specifically, for each $i = 1, ..., N$, we sample S_i from

$$P(S_i|\widetilde{y}_i, f, \widetilde{\beta}_i, h_i, \lambda_{\varepsilon,i}, \gamma_{1,i}, q_i, p_i). \tag{A-7}$$

The filtered probabilities $\Pr(S_{it} = s_{it}, S_{i,t-1} = s_{i,t-1}, ..., S_{i,t-r+1} = s_{i,t-r+1}|\widetilde{y}_{it}, \widetilde{y}_{i,t-1}, ..., \widetilde{y}_{i,-r+1})$, which are required for the multi-move sampler, are in a first step obtained through the basic filter of Hamilton (1989).

Sample the transition probabilities q and p

Conditional on the regime indicators S_i, the transition probabilities q_i and p_i follow posterior beta distributions

$$q_i|S_i \sim \text{beta}(u_{00} + n^i_{00}, u_{01} + n^i_{01}), \tag{A-8}$$

$$p_i|S_i \sim \text{beta}(u_{11} + n^i_{11}, u_{10} + n^i_{10}), \tag{A-9}$$

where u_{00}, u_{01}, u_{11} and u_{10} are the prior parameters specified in Table 1 and $n^i_{00}, n^i_{01}, n^i_{11}$ and n^i_{10} are (given the regime indicators S_i) the number of transitions n^i_{kj} from regime k to j for $k = [0, 1]$ and $j = [0, 1]$.

Sample the loading shifts γ_1

The conditional posterior distributions of γ_1 are truncated normal. Following Albert and Chib (1993), the conditional distribution of each $\gamma_{1,i}$ is

$$\gamma_{1,i}|\widetilde{y}_i, f, \widetilde{\beta}_i, S_i, h_i, \lambda_{\varepsilon,i} \sim \mathcal{N}(\hat{\gamma}_{1,i}, D_{\gamma_{1,i}})I(\gamma_{1,i} > 0), \tag{A-10}$$

with

$$D_{\gamma_{1,i}} = (V_{\gamma_{1,i}}^{-1} + X'_{\gamma_{1,i}}\Sigma_{\gamma_{1,i}}^{-1}X_{\gamma_{1,i}})^{-1}, \tag{A-11}$$

$$\hat{\gamma}_{1,i} = D_{\gamma_{1,i}}(V_{\gamma_{1,i}}^{-1}\gamma_{10,i} + X'_{\gamma_{1,i}}\Sigma_{\gamma_{1,i}}^{-1}z_{\gamma_{1,i}}), \tag{A-12}$$

where $X_{\gamma_{1,i}} = S_i \odot f$, $z_{\gamma_{1,i}} = \widetilde{y}_i - \widetilde{\beta}_i \odot f$ and $\Sigma_{\gamma_{1,i}} = \text{diag}(e_i^h \odot \lambda_{\varepsilon,i})$.

Block 2: Sample the common factor f

In order to sample the common factor f, we explore the following state space model

$$\underbrace{\widetilde{y}_t}_{w_t} = \underbrace{\begin{bmatrix}\beta_t\end{bmatrix}}_{Z_t}\underbrace{f_t}_{\kappa_t} + \underbrace{\epsilon_t}_{e_t}, \tag{A-13}$$

$$\underbrace{f_{t+1}}_{\kappa_{t+1}} = \underbrace{\begin{bmatrix}\rho\end{bmatrix}}_{T_t}\underbrace{f_t}_{\kappa_t} + \underbrace{\begin{bmatrix}1\end{bmatrix}}_{R_t}\underbrace{\kappa_t}_{\eta_t}, \tag{A-14}$$

where $H_t = I_N(e^{h_t} \odot \lambda_{\epsilon,t})$ and $Q_t = e^{g_t}\lambda_{\kappa,t}$.

Block 3: Sample the stochastic volatility series g and h

In order to sample the stochastic volatility series that enter the model in a nonlinear way, we rely on the approach developed in Kim et al. (1998). To illustrate the idea, consider the following simple stochastic volatility model:

$$y_t = e^{h_t/2}\varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0,1). \tag{A-15}$$

Following Kim et al. (1998) this expression can be linearised by taking the natural-log of the squares

$$\ln\left(y_t^2 + c\right) = h_t + \widetilde{\varepsilon}_t, \tag{A-16}$$

where $c = 0.1^{16}$ is an offset constant and $\widetilde{\varepsilon}_t = \ln(\varepsilon_t^2)$. The latter follows a log-chi-square distribution that can be approximated by a mixture of M normal distributions as follows

$$f(\widetilde{\varepsilon}_t) = \sum_{j=1}^{M} q_j f_{\mathcal{N}}(\widetilde{\varepsilon}_t | m_j - 1.2704, v_j^2), \tag{A-17}$$

where q_j is the component probability of a specific normal distribution with mean $m_j - 1.2704$ and variance v_j^2. This mixture can equivalently by expressed as

$$\widetilde{\varepsilon}_t | (\iota_t = j) \sim \mathcal{N}(m_j - 1.2704, v_j^2), \quad \text{with} \quad \Pr(\iota_t = j) = q_j. \tag{A-18}$$

Here, ι_t is a mixture indicator that can be sampled from

$$p(\iota_t = j | h_t, \widetilde{\varepsilon}_t) \propto q_j f_{\mathcal{N}}(\widetilde{\varepsilon}_t | h_t + m_j - 1.2704, v_j^2), \tag{A-19}$$

with the values for q_j, m_j, and v_j^2 for $M = 10$ taken from Table 1 in Omori et al. (2007).

Block 3(a): Sample the stochastic volatility of common shocks g

Sample the mixture indicator ξ

Based on the previously outlined procedure, the mixture indicator ξ required for sampling the stochastic volatility g of common shocks follows a ten-point distribution. In particular, each ξ_t has probability

$$p(\xi_t = j | f_t, g_t, \lambda_{\kappa,t}, \rho) = \frac{1}{k_t} q_j p_{\mathcal{N}}\left(\widetilde{f}_t; g_t + m_j, v_j^2\right), \tag{A-20}$$

where $\widetilde{f}_t = \ln\left([(f_t - \rho f_{t-1})/\lambda_{\kappa,t}^{0.5}]^2 + c\right)$ and $k_t = \sum_{j=1}^{10} q_j p_{\mathcal{N}}\left(\widetilde{f}_t; g_t + m_j, v_j^2\right)$ is a normalising constant. Practical implementation of the indicator sampling is done by using the inverse-transform method as in Chan and Hsiao (2014).[22]

Sample the volatility series g

The unobserved volatility process g of common shocks can now be sampled from the following state space model

$$\underbrace{\widetilde{f}_t - (m_{\xi_t} - 1.2704)}_{w_t} = \underbrace{\begin{bmatrix}1\end{bmatrix}}_{Z_t} \underbrace{\begin{bmatrix}g_t\end{bmatrix}}_{\kappa_t} + \underbrace{\widetilde{\kappa}'_t}_{e_t}, \tag{A-21}$$

$$\underbrace{g_{t+1}}_{\kappa_{t+1}} = \underbrace{\begin{bmatrix}1\end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix}g_t\end{bmatrix}}_{\kappa_t} + \underbrace{\begin{bmatrix}1\end{bmatrix}}_{R_t} \underbrace{\begin{bmatrix}\eta_t\end{bmatrix}}_{\eta_t}, \tag{A-22}$$

with $\widetilde{f}$ as defined above, $\widetilde{\kappa}'_t = \ln(\kappa'^2_t)$, $\kappa'_t = \kappa_t/\lambda^{0.5}_{\kappa,t}$, $H_t = v^2_{\xi_t}$ and $Q_t = \sigma^2_\eta$.

Block 3(b): Sample the volatility of country-specific shocks h

Sample the mixture indicator ι

As before, the mixture indicator ι required for sampling the stochastic volatilities h of country-specific shocks follows a ten-point distribution. In particular, each ι_{it} has probability

$$p(\iota_{it} = j|\widetilde{y}_{it}, h_{it}, f_t, \beta_{it}, \lambda_{\epsilon,it}) = \frac{1}{k_t} q_j p_{\mathcal{N}}\left(\widetilde{\widetilde{y}}_{it}; h_{it} + m_j, v^2_j\right), \tag{A-23}$$

where $\widetilde{\widetilde{y}}_{it} = \ln\left([(\widetilde{y}_{it} - \beta_{it} f_t)/\lambda^{0.5}_{\varepsilon,it}]^2 + c\right)$ and $k_t = \sum_{j=1}^{10} q_j p_{\mathcal{N}}\left(\widetilde{\widetilde{y}}_{it}; h_{it} + m_j, v^2_j\right)$ is a normalising constant. Sampling is again done by using the inverse-transform method.

[22]See Algorithm 3.2. in Kroese et al. (2013) for a textbook treatment of the inverse-transform method.

Sample the volatility series h

To sample the country-specific stochastic volatility series, the specific state space model used is

$$\underbrace{\widetilde{\widetilde{y}}_t - m_{\iota_t}}_{w_t} = \underbrace{\begin{bmatrix}1\end{bmatrix}}_{Z_t} \underbrace{h_t}_{\kappa_t} + \underbrace{\widetilde{\epsilon}'_t}_{e_t}, \tag{A-24}$$

$$\underbrace{h_{t+1}}_{\kappa_{t+1}} = \underbrace{\begin{bmatrix}\mu_h \odot (1-\phi_h)\end{bmatrix}}_{d_t} + \underbrace{\begin{bmatrix}I_N \phi_h\end{bmatrix}}_{T_t} \underbrace{h_t}_{\kappa_t} + \underbrace{\begin{bmatrix}1\end{bmatrix}}_{R_t} \underbrace{\kappa_t}_{\eta_t}, \tag{A-25}$$

where $\widetilde{\widetilde{y}}$ is as defined above, $\widetilde{\epsilon}'_t = \ln(\epsilon_t'^2)$, $\epsilon'_t = \epsilon_t \oslash \lambda_{\epsilon,t}^{0.5}$, $H_t = v_{\iota_t}^2$ and $Q_t = \sigma_\psi^2$. $\oslash$ refers to the element-wise (Hadamard) division of two vectors. Since h is country-specific, sampling is implemented country-by-country.

Block 4: Sample the degrees of freedom parameters

Block 4(a): Sample the degrees of freedom of common shocks ν_κ

Sample the latent scale mixture weights λ_κ

Following, e.g. Chan and Hsiao (2014), the conditional posterior distribution of the scale mixture weights λ_κ is inverse-gamma. Specifically, each $\lambda_{\kappa,t}$ is distributed as

$$(\lambda_{\kappa,t}|f_t, g_t, \rho, \nu_\kappa) \sim \mathcal{IG}\left(\frac{\nu_\kappa + 1}{2}, \frac{\nu_\kappa + e^{-g_t}(f_t - \rho f_{t-1})^2}{2}\right). \tag{A-26}$$

Sample the degrees of freedom ν_κ

The description of the sampling approach closely follows Chan and Hsiao (2014). The log-density $\log p(\nu_\kappa|\lambda_\kappa)$ can be derived using the fact that $\lambda_{\kappa,t} \sim \mathcal{IG}(\nu_\kappa/2, \nu_\kappa/2)$ and the prior distribution $\nu_\kappa \sim \mathcal{U}(0, \bar{\nu})$ as

$$\log p(\nu_\kappa|\lambda_\kappa) = \frac{T\nu_\kappa}{2}\log(\nu_\kappa/2) - T\log\Gamma(\nu_\kappa/2) - (\nu_\kappa/2+1)\sum_{t=1}^{T}\log\lambda_{\kappa,t} - \frac{\nu_\kappa}{2}\sum_{t=1}^{T}\lambda_t^{-1} + k, \tag{A-27}$$

for $0 < \nu_\kappa < \bar{\nu}$ and k is a normalisation constant. The first and second derivative of the log-density with respect to ν_κ are then given by

$$\frac{d \log p(\nu_\kappa|\lambda_\kappa)}{d\nu_\kappa} = \frac{T}{2}\log(\nu_\kappa/2) + \frac{T}{2} - \frac{T}{2}\Psi(\nu_\kappa/2) - \frac{1}{2}\sum_{t=1}^{T}\log\lambda_{\kappa,t} - \frac{1}{2}\sum_{t=1}^{T}\lambda_{\kappa,t}^{-1}, \quad \text{(A-28)}$$

$$\frac{d^2 \log p(\nu_\kappa|\lambda_\kappa)}{d\nu_\kappa^2} = \frac{T}{2\nu_\kappa} - \frac{T}{4}\Psi'(\nu_\kappa/2), \quad \text{(A-29)}$$

where $\Psi(x) = \frac{d}{dx}\log\Gamma(x)$ and $\Psi'(x) = \frac{d}{dx}\Psi(x)$ are the digamma and trigamma function, respectively. Since the first and second derivatives can be evaluated easily, log $p(\nu_\kappa|\lambda_\kappa)$ can be maximised by well-known algorithms (e.g. the Newton-Raphson method). In addition, the mode and the negative Hessian evaluated at the mode, denoted $\hat{\nu_\kappa}$ and K_{ν_κ}, are obtained. Finally, an independence-chain Metropolis-Hastings step can be implemented with proposal distribution $\mathcal{N}(\hat{\nu_\kappa}, K_{\nu_\kappa}^{-1})$.

Block 4(b): Sample the degrees of freedom of country-specific shocks ν_ϵ

Sample the latent scale mixture weights λ_ϵ

Following, e.g. Chan and Hsiao (2014), the conditional posterior distributions of the scale mixture weights λ_ϵ are inverse-gamma. Specifically, each $\lambda_{\epsilon,i,t}$ is distributed as

$$(\lambda_{\epsilon,i,t}|\widetilde{y}_{it}, h_{it}, \beta_{it}, f_t) \sim \mathcal{IG}\left(\frac{\nu_{\epsilon,i}+1}{2}, \frac{\nu_{\epsilon,i} + e^{-h_{it}}(\widetilde{y}_{it} - \beta_{it} f_t)^2}{2}\right) \quad \text{(A-30)}$$

Sample the degrees of freedom ν_ϵ

Sampling of the degrees of freedom of country-specific shocks ν_ϵ is done in the same way as for the degrees of freedom of common shocks, ν_κ. The derivations outlined above can be used and replacing ν_κ and λ_κ by $\nu_{\epsilon,i}$ and $\lambda_{\epsilon,i}$ while looping over $i = 1, ..., N$.

Block 5: Sample the constant stochastic volatility parameters

Block 5(a): Sample the volatility AR(1) coefficients ϕ_g and ϕ_h

Following Kim et al. (1998) and using the notation of Chan and Hsiao (2014), the conditional posterior distribution of the persistence parameter ϕ_τ, where $\tau = (g, h_i)$, $i = 1, ..., N$, is

$$p(\phi_\tau|\tau, \mu_\tau, \sigma_\tau^2) \propto p(\phi_\tau)g(\phi_\tau)\text{exp}\left(-\frac{1}{2\sigma_\tau^2}\sum_{t=2}^{T}(\tau_t - \mu_\tau - \phi_\tau(\tau_{t-1} - \mu_\tau))^2\right), \quad \text{(A-31)}$$

with

$$g(\phi_\tau) = (1 - \phi_\tau^2)^{1/2}\text{exp}\left(-\frac{1}{2\sigma_\tau^2}(1 - \phi_\tau^2)(\tau_1 - \mu_\tau)^2\right), \quad \text{(A-32)}$$

and $p(\phi_\tau)$ is the truncated normal prior defined in Table 1. Due to the stationarity condition $|\phi_\tau| < 1$, this distribution is non-standard and sampling is achieved using the Metropolis-Hastings algorithm. In particular, the proposal density is $\mathcal{N}(\hat{\phi}_\tau, D_{\phi_\tau})\mathbb{I}(|\phi_\tau| < 1)$ with

$$D_{\phi_\tau} = (V_{\phi_\tau}^{-1} + X_{\phi_\tau}' X_{\phi_\tau}/\sigma_\tau^2)^{-1}, \quad \text{(A-33)}$$

$$\hat{\phi}_\tau = D_{\phi_\tau}(V_{\phi_\tau}^{-1}\phi_{\tau 0} + X_{\phi_\tau}' z_{\phi_\tau}/\sigma_\tau^2), \quad \text{(A-34)}$$

where $X_{\phi_\tau} = (\tau_1 - \mu_\tau, ..., \tau_{T-1} - \mu_\tau)'$ and $z_{\phi_\tau} = (\tau_2 - \mu_\tau, ..., \tau_T - \mu_\tau)'$ (Chan and Hsiao, 2014). Conditional on the current state ϕ_τ, a proposal ϕ_τ^* is accepted with probability $\min(1, g(\phi_\tau^*)/g(\phi_\tau))$. In case of rejection, the Markov chain remains at the current state ϕ_τ.

Block 5(b): Sample the volatility constants μ_g and μ_h

The conditional posterior distributions of the volatility constants are standard and samples can be readily obtained. Following Kim et al. (1998) and the notation of Chan and Hsiao (2014), the conditional distribution of μ_τ, where $\tau = (g, h_i)$, $i = 1, ..., N$, is

$$\mu_\tau|\tau, \phi_\tau, \sigma_\tau^2 \sim \mathcal{N}(\hat{\mu}_\tau, D_{\mu_\tau}), \quad \text{(A-35)}$$

with

$$D_{\mu_\tau} = (V_{\mu_\tau}^{-1} + X'_{\mu_\tau}\Sigma_\tau^{-1}X_{\mu_\tau})^{-1}, \tag{A-36}$$

$$\hat{\mu}_\tau = D_{\mu_\tau}(V_{\mu_\tau}^{-1}\mu_{\tau 0} + X'_{\mu_\tau}\Sigma_\tau^{-1}z_{\mu_\tau}), \tag{A-37}$$

where $X_{\mu_\tau} = (1, 1-\phi_\tau, ..., 1-\phi_\tau)'$, $z_{\mu_\tau} = (\tau_1, \tau_2 - \phi_\tau\tau_1, ..., \tau_T - \phi_\tau\tau_{T-1})'$ and $\Sigma_\tau = \text{diag}(\sigma_\tau^2/(1-\phi_\tau^2), \sigma_\tau^2, ..., \sigma_\tau^2)$.

Block 5(c): Sample the shock variances σ_η^2 and σ_ψ^2

The shock variances of the (log-)volatilities g_t and h_t have inverse-gamma conditional posterior distributions (Kim et al., 1998). Specifically, the conditional posterior distribution of σ_τ^2, where $\tau = (g, h_i)$, $i = 1, ..., N$, is

$$\sigma_\tau^2|\tau, \mu_\tau, \phi_\tau \sim \mathcal{IG}(c_{\tau 0} + T/2, C_\tau), \tag{A-38}$$

where notation follows Chan and Hsiao (2014) and

$$C_\tau = C_{\tau 0} + \left[(1-\phi_\tau^2)(\tau_1 - \mu_\tau)^2 + \sum_{t=2}^{T}(\tau_t - \mu_\tau - \phi_\tau(\tau_{t-1} - \mu_\tau))^2\right]/2. \tag{A-39}$$

Block 6: Sample the shock variances of the random walk loading component σ_ω^2

The shock variances of the random walk factor loading component $\widetilde{\beta}$ has an inverse-gamma conditional posterior distribution (Kim et al., 1998). Specifically, the conditional posterior distribution of each $\sigma_{\omega,i}^2$, $i = 1, ..., N$, is

$$\sigma_{\omega,i}^2|\widetilde{\beta}_i \sim \mathcal{IG}(c_{\widetilde{\beta}_i 0} + T/2, C_{\widetilde{\beta}_i}), \tag{A-40}$$

where notation follows Chan and Hsiao (2014) and

$$C_{\widetilde{\beta}_i} = C_{\widetilde{\beta}_i 0} + \left[\sum_{t=2}^{T}(\widetilde{\beta}_{it} - \widetilde{\beta}_{i,t-1})^2\right]/2. \tag{A-41}$$

Block 7: Sample the persistence parameters of the return factors

Block 7(a): Sample the AR(1) parameter of the common factor ρ

Using the notation of Chan and Hsiao (2014), the conditional posterior distribution of the persistence parameter of the common factor, ρ, is

$$p(\rho|f, g, \lambda_\kappa) \propto p(\rho)g(\rho)\text{exp}\left(\sum_{t=2}^{T}[(f_t - \rho f_{t-1})e^{-g_t/2}\lambda_{\kappa,t}^{-0.5}]^2\right), \tag{A-42}$$

$$\text{with} \qquad g(\rho) = (1-\rho^2)^{1/2}\text{exp}\left((1-\rho^2)(f_1 e^{g_1/2}\lambda_{\kappa,1}^{0.5})^2\right), \tag{A-43}$$

and $p(\rho)$ is the truncated normal prior defined in Table 1. Due to the stationarity condition $|\rho| < 1$, this distribution is non-standard and sampling is achieved using the Metropolis-Hastings algorithm. In particular, the proposal density is $\mathcal{N}(\hat{\rho}, D_\rho)\mathbb{I}(|\rho| < 1)$ with

$$D_\rho = (V_\rho^{-1} + X_\rho' X_\rho)^{-1}, \tag{A-44}$$

$$\hat{\rho} = D_\rho(V_\rho^{-1}\rho_0 + X_\rho' z_\rho), \tag{A-45}$$

where $X_\rho = (f_1 e^{-g_1/2}\lambda_{\kappa,1}^{-0.5}, ..., f_{T-1}e^{-g_{T-1}/2}\lambda_{\kappa,T-1}^{-0.5})'$ and $z_\rho = (f_2 e^{-g_2/2}\lambda_{\kappa,2}^{-0.5}, ..., f_T e^{-g_T/2}\lambda_{\kappa,T}^{-0.5})'$. Conditional on the current state ρ, a proposal ρ^* is accepted with probability $\min(1, g(\rho^*)/g(\rho))$. In case of rejection, the Markov chain remains at the current state ρ.

Block 7(b): Sample the AR(1) parameters of country-specific return factors θ

Using the notation of Chan and Hsiao (2014), the conditional posterior distributions of the persistence parameters of the country-specific return components, θ_i for $i = 1, ...N$, is

$$p(\theta_i|y_i, \beta_i, f, \lambda_{\epsilon,i}) \propto p(\theta_i)g(\theta_i)\text{exp}\left(\sum_{t=2}^{T}[(\varepsilon_{it} - \theta_i\varepsilon_{i,t-1})e^{-h_{it}/2}\lambda_{\epsilon,i,t}^{-0.5}]^2\right), \tag{A-46}$$

$$\text{with} \qquad g(\theta_i) = (1-\theta_i^2)^{1/2}\text{exp}\left((1-\theta_i^2)(\epsilon_{i1}e^{h_{i1}/2}\lambda_{\epsilon,i,1}^{0.5})^2\right), \tag{A-47}$$

and where $\varepsilon = y - \beta f$ and $p(\theta_i)$ is the truncated normal prior defined in Table 1. Due to the stationarity condition $|\theta_i| < 1$, this distribution is non-standard and sampling is achieved using the Metropolis-Hastings algorithm. In particular, the proposal density is $\mathcal{N}(\hat{\theta}_i, D_{\theta_i})\mathbb{I}(|\theta_i| < 1)$ with

$$D_{\theta_i} = (V_{\theta_i}^{-1} + X_{\theta_i}' X_{\theta_i})^{-1}, \tag{A-48}$$

$$\hat{\theta}_i = D_{\theta_i}(V_{\theta_i}^{-1}\theta_{0,i} + X_\theta' z_{\theta_i}), \tag{A-49}$$

where $X_{\theta_i} = (\varepsilon_1 e^{-h_{i1}/2}\lambda_{\epsilon,i,1}^{-0.5}, ..., \varepsilon_{i,T-1}e^{-h_{i,T-1}/2}\lambda_{\epsilon,i,T-1}^{-0.5})'$ and $z_{\theta_i} = (\varepsilon_{i2}e^{-h_{i2}/2}\lambda_{\epsilon,i,2}^{-0.5}, ..., \varepsilon_T e^{-h_{i,T/2}}\lambda_{\epsilon,i,T}^{-0.5})'$. Conditional on the current state θ_i, a proposal θ_i^* is accepted with probability $\min(1, g(\theta_i^*)/g(\theta_i))$. In case of rejection, the Markov chain remains at the current state θ_i.

Appendix B Dataset

Figure B-1: Time series plots of MSCI equity price indices (in USD)

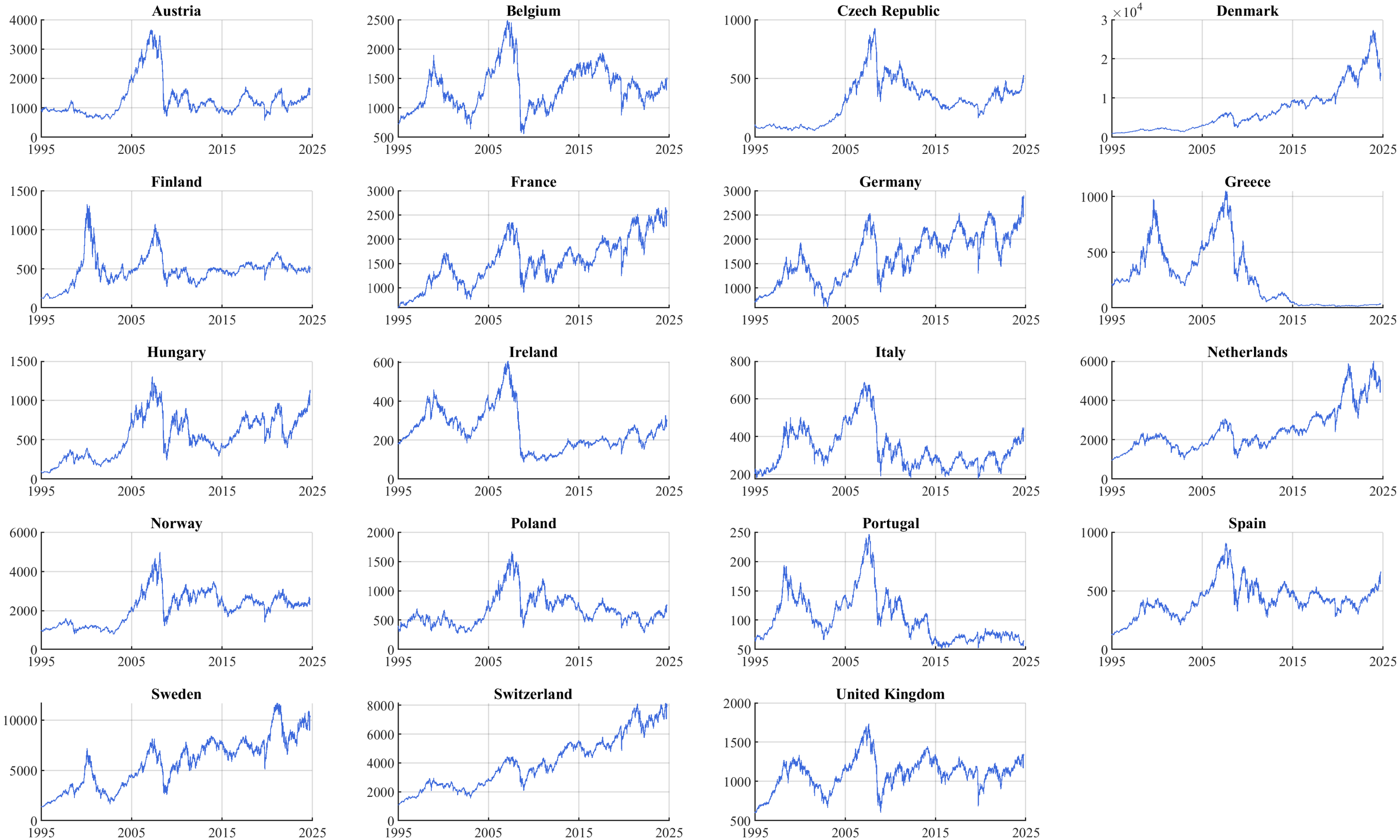


Figure B-2: Time series plots of excess returns (in %)

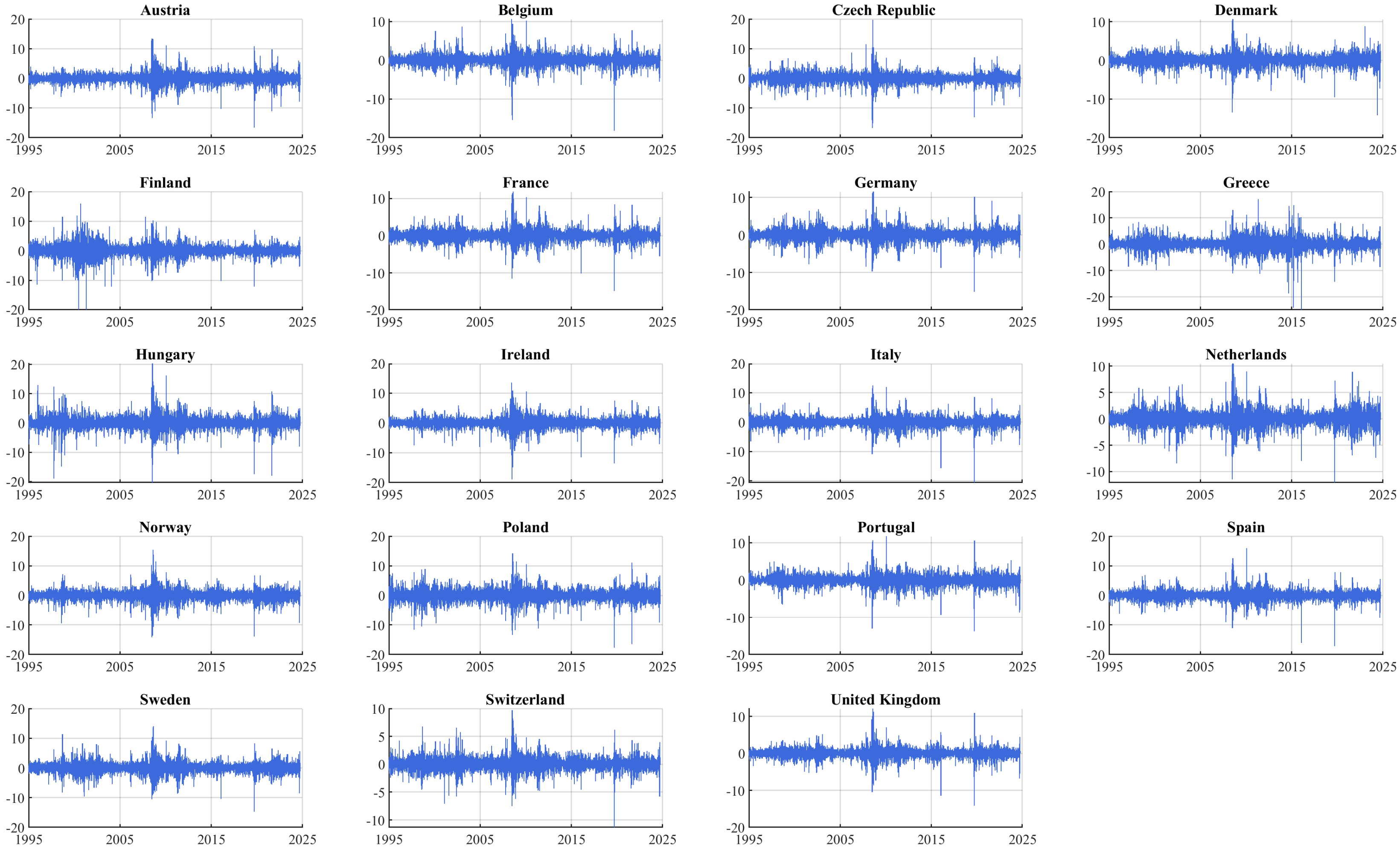


Table B-1: Summary statistics of excess returns

Country	Mean	S.D.	Min.	Max.	Skew.	Kurt.	Jarque-Bera
Austria	0.00	1.65	−16.65	13.35	−0.44	11.98	0.00
Belgium	0.00	1.38	−18.22	10.66	−0.65	13.99	0.00
Czech Republic	0.01	1.60	−16.75	19.72	−0.36	13.92	0.00
Denmark	0.03	1.37	−14.21	10.71	−0.41	10.21	0.00
Finland	0.01	1.92	−20.08	15.90	−0.38	10.75	0.00
France	0.01	1.44	−14.90	11.84	−0.23	10.52	0.00
Germany	0.01	1.49	−15.10	11.59	−0.23	9.28	0.00
Greece	−0.03	2.20	−25.06	17.17	−0.49	12.37	0.00
Hungary	0.02	2.09	−20.35	20.31	−0.42	13.01	0.00
Ireland	0.00	1.62	−18.93	13.60	−0.68	12.99	0.00
Italy	0.00	1.59	−20.55	12.47	−0.53	12.40	0.00
Netherlands	0.01	1.43	−12.09	10.53	−0.22	9.09	0.00
Norway	0.01	1.70	−14.23	15.39	−0.52	10.75	0.00
Poland	0.00	1.94	−17.65	14.23	−0.30	8.11	0.00
Portugal	−0.01	1.37	−13.83	11.82	−0.33	10.01	0.00
Spain	0.01	1.56	−17.22	16.00	−0.30	12.06	0.00
Sweden	0.02	1.72	−14.81	14.05	−0.10	8.38	0.00
Switzerland	0.02	1.13	−11.33	9.73	−0.20	9.18	0.00
United Kingdom	0.00	1.27	−14.21	12.16	−0.42	14.08	0.00

Notes: This table contains summary statistics of daily excess equity returns for 19 European stock markets over the period 02/01/1995–30/04/2025. The last column contains p-values of the Jarque-Bera test where the null hypothesis is normality.

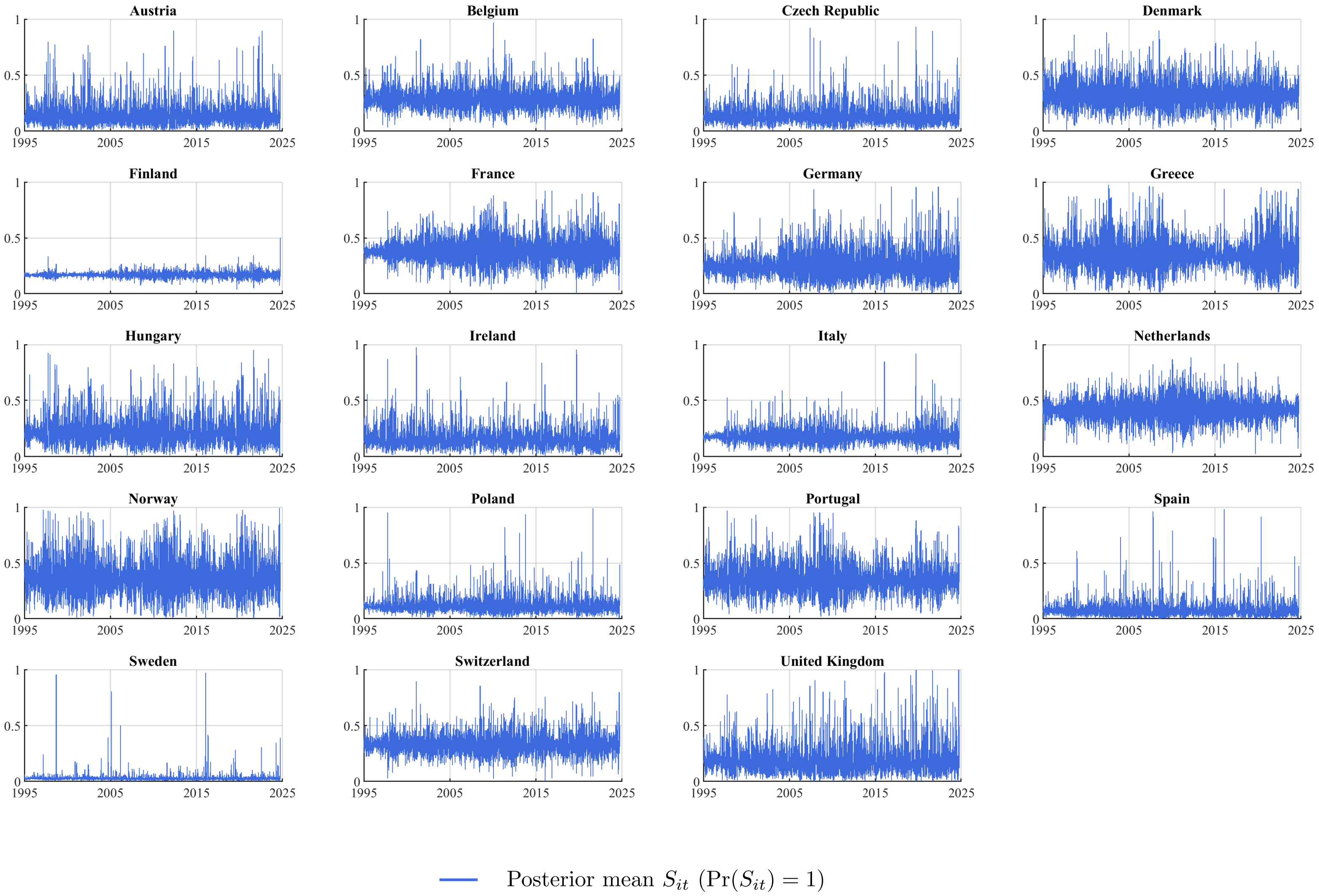
Appendix C Additional results

Table C-1: Posterior estimates of country-specific parameters

Country	μ_h	ϕ_h	σ^2_ψ	θ	ν_ϵ	γ_1	q	p	σ^2_ω
Austria	-0.663	0.983	0.014	-0.012	9.295	0.603	0.902	0.402	0.00061
	(0.088)	(0.004)	(0.003)	(0.013)	(1.177)	(0.099)	(0.056)	(0.084)	(0.00011)
Belgium	-1.557	0.992	0.009	0.022	5.352	0.236	0.797	0.507	0.00050
	(0.153)	(0.002)	(0.002)	(0.014)	(0.358)	(0.042)	(0.095)	(0.092)	(0.00008)
Czech Republic	-0.121	0.979	0.022	0.052	9.387	0.713	0.913	0.483	0.00078
	(0.087)	(0.005)	(0.005)	(0.013)	(1.222)	(0.153)	(0.069)	(0.098)	(0.00016)
Denmark	-0.757	0.990	0.009	-0.033	7.119	0.416	0.746	0.486	0.00053
	(0.115)	(0.003)	(0.002)	(0.013)	(0.625)	(0.066)	(0.116)	(0.092)	(0.00010)
Finland	-0.742	0.998	0.006	-0.012	4.656	0.273	0.879	0.489	0.00049
	(0.424)	(0.001)	(0.001)	(0.013)	(0.257)	(0.364)	(0.121)	(0.101)	(0.00008)
France	-2.466	0.997	0.006	-0.028	8.429	0.148	0.650	0.442	0.00031
	(0.360)	(0.001)	(0.001)	(0.015)	(1.215)	(0.044)	(0.118)	(0.088)	(0.00004)
Germany	-2.051	0.992	0.016	-0.044	10.102	0.254	0.794	0.370	0.00045
	(0.192)	(0.002)	(0.003)	(0.014)	(1.799)	(0.038)	(0.089)	(0.080)	(0.00007)
Greece	0.481	0.988	0.022	0.046	12.526	0.711	0.723	0.475	0.00072
	(0.150)	(0.003)	(0.004)	(0.013)	(2.341)	(0.062)	(0.071)	(0.079)	(0.00016)
Hungary	0.304	0.970	0.027	0.057	10.791	0.887	0.875	0.560	0.00081
	(0.076)	(0.007)	(0.007)	(0.013)	(2.290)	(0.276)	(0.063)	(0.080)	(0.00018)
Ireland	-0.635	0.992	0.008	0.000	7.685	0.517	0.912	0.541	0.00058
	(0.147)	(0.002)	(0.002)	(0.013)	(0.736)	(0.114)	(0.059)	(0.083)	(0.00011)
Italy	-1.327	0.990	0.016	-0.030	8.991	0.287	0.859	0.424	0.00048
	(0.159)	(0.002)	(0.003)	(0.013)	(1.180)	(0.108)	(0.122)	(0.099)	(0.00008)
Netherlands	-1.913	0.994	0.010	0.000	7.539	0.173	0.613	0.478	0.00046
	(0.201)	(0.002)	(0.002)	(0.014)	(0.832)	(0.044)	(0.154)	(0.096)	(0.00007)
Norway	-0.453	0.989	0.009	-0.033	10.293	0.576	0.740	0.544	0.00067
	(0.114)	(0.003)	(0.002)	(0.013)	(1.442)	(0.045)	(0.068)	(0.069)	(0.00013)
Poland	0.272	0.989	0.011	0.021	12.734	0.958	0.911	0.442	0.00072
	(0.118)	(0.003)	(0.002)	(0.013)	(2.230)	(0.243)	(0.132)	(0.093)	(0.00015)
Portugal	-0.745	0.984	0.012	0.073	9.330	0.390	0.750	0.541	0.00067
	(0.090)	(0.004)	(0.003)	(0.013)	(1.169)	(0.039)	(0.078)	(0.085)	(0.00012)
Spain	-1.305	0.986	0.017	0.034	9.584	0.518	0.956	0.463	0.00048
	(0.119)	(0.003)	(0.004)	(0.014)	(1.396)	(0.111)	(0.031)	(0.095)	(0.00008)
Sweden	-0.881	0.993	0.008	-0.054	9.526	1.137	0.979	0.463	0.00082
	(0.174)	(0.002)	(0.002)	(0.013)	(1.109)	(0.269)	(0.073)	(0.089)	(0.00015)
Switzerland	-1.515	0.985	0.011	-0.012	11.554	0.215	0.763	0.549	0.00053
	(0.092)	(0.003)	(0.003)	(0.013)	(1.964)	(0.054)	(0.135)	(0.104)	(0.00009)
United Kingdom	-1.554	0.993	0.006	-0.056	14.800	0.374	0.899	0.572	0.00053
	(0.137)	(0.002)	(0.001)	(0.013)	(3.254)	(0.043)	(0.043)	(0.067)	(0.00009)
CD	0.49	0.47	0.49	0.63	0.56	0.46	0.44	0.54	0.40
	1 (1)	0 (1)	0 (2)	0 (1)	0 (1)	0 (1)	1 (1)	0 (2)	0 (1)
IF	1.15	2.32	3.70	0.90	2.99	8.23	13.61	1.75	2.66

Notes: This table contains the posterior means (standard deviations) of all country-specific model parameters. CD refers to the average p-value of the Geweke (1992) convergence diagnostic across countries and where we also report the number of countries for which the test rejects the null hypothesis of convergence at the 1% (5%) level. IF is the average inefficiency factor. Both diagnostics are computed using 4% tapered autocovariance matrices (LeSage, 1999).

Figure C-1: Probabilities of high exposure regime in factor loadings



Prior sensitivity: regime transition probabilities

Table C-2 contains additional results to assess the sensitivity of the baseline results with respect to changes in the prior configurations of the regime transition probabilities q and p. Scenario (1) uses a looser specification for the conditional probability to stay in the 'normal regime'. The prior configuration in (1) implies an expected value of 0.8 with a prior standard deviation of 0.16 (see Kim and Nelson, 1999). Even though this scenario imposes less prior information than the baseline configuration, it still reflects our belief that conditional on being in the 'normal regime', the probability of staying in this regime is higher than switching to the 'contagion regime'. As outlined in Section 3.6, loosening the prior for q results in a drop of the posterior mean of q for all countries, which are in most cases moderate or minor, and in a few cases sizable (e.g. Sweden). This configuration also results in a larger number of days in the high common factor exposure regime given a certain probability threshold (not reported). However, the changed prior does not meaningfully affect the remaining results presented in the paper. Thus, the baseline estimation produces a conservative estimate for the number of days with an increased common factor exposure.

Scenario (2) of Table C-2 is an estimation using a less informative prior for the conditional probability to stay in the 'contagion regime', p. This alternative configuration implies a uniform prior for p and leads to a drop in most of the posterior means of p. A notable exception is Switzerland, where the posterior mean of p increases to above 0.9. While for most countries the number of identified days with elevated common factor exposure remains similar to the baseline in Table 4, in the particular case of Switzerland, the looser prior for p strongly affects the 'identification' of both regimes, resulting in this market spending most days in the high exposure regime. Therefore, we conclude that a certain amount of prior information is helpful to distinguish the two regimes. Finally, the remaining results for most countries are largely unaffected by this change to the prior configuration.

Table C-2: Alternative prior configurations for transition probabilities

	Baseline results			(1) Alternative prior for q			(2) Alternative prior for p		
				$q \sim$ beta$(4.2, 1.05)$			$p \sim$ beta$(1, 1)$		
Country	γ_1	q	p	γ_1	q	p	γ_1	q	p
Austria	0.603	0.902	0.402	0.579	0.868	0.395	0.612	0.873	0.202
	(0.099)	(0.056)	(0.084)	(0.109)	(0.095)	(0.083)	(0.092)	(0.059)	(0.123)
Belgium	0.236	0.797	0.507	0.234	0.728	0.515	0.234	0.787	0.511
	(0.042)	(0.095)	(0.092)	(0.039)	(0.12)	(0.091)	(0.053)	(0.1)	(0.205)
Czech Republic	0.713	0.913	0.483	0.676	0.869	0.472	0.728	0.899	0.363
	(0.153)	(0.069)	(0.098)	(0.156)	(0.102)	(0.096)	(0.152)	(0.068)	(0.218)
Denmark	0.416	0.746	0.486	0.410	0.650	0.487	0.424	0.750	0.460
	(0.066)	(0.116)	(0.092)	(0.052)	(0.129)	(0.09)	(0.069)	(0.115)	(0.189)
Finland	0.273	0.879	0.489	0.172	0.746	0.491	0.294	0.875	0.413
	(0.364)	(0.121)	(0.101)	(0.192)	(0.179)	(0.102)	(0.374)	(0.118)	(0.282)
France	0.148	0.650	0.442	0.147	0.548	0.456	0.158	0.688	0.238
	(0.044)	(0.118)	(0.088)	(0.022)	(0.133)	(0.089)	(0.06)	(0.124)	(0.162)
Germany	0.254	0.794	0.370	0.241	0.705	0.378	0.280	0.790	0.141
	(0.038)	(0.089)	(0.08)	(0.036)	(0.132)	(0.082)	(0.041)	(0.075)	(0.102)
Greece	0.711	0.723	0.475	0.729	0.693	0.474	0.724	0.721	0.432
	(0.062)	(0.071)	(0.079)	(0.063)	(0.078)	(0.078)	(0.067)	(0.07)	(0.127)
Hungary	0.887	0.875	0.560	0.843	0.849	0.552	0.880	0.890	0.619
	(0.276)	(0.063)	(0.08)	(0.183)	(0.067)	(0.078)	(0.271)	(0.059)	(0.116)
Ireland	0.517	0.912	0.541	0.487	0.871	0.537	0.496	0.903	0.585
	(0.114)	(0.059)	(0.083)	(0.099)	(0.09)	(0.087)	(0.122)	(0.068)	(0.14)
Italy	0.287	0.859	0.424	0.250	0.723	0.415	0.313	0.838	0.148
	(0.108)	(0.122)	(0.099)	(0.09)	(0.191)	(0.096)	(0.085)	(0.102)	(0.132)
Netherlands	0.173	0.613	0.478	0.181	0.471	0.489	0.181	0.633	0.344
	(0.044)	(0.154)	(0.096)	(0.031)	(0.15)	(0.095)	(0.045)	(0.148)	(0.221)
Norway	0.576	0.740	0.544	0.590	0.712	0.551	0.578	0.730	0.581
	(0.045)	(0.068)	(0.069)	(0.044)	(0.074)	(0.068)	(0.044)	(0.069)	(0.087)
Poland	0.958	0.911	0.442	0.720	0.638	0.468	0.948	0.908	0.275
	(0.243)	(0.132)	(0.093)	(0.227)	(0.257)	(0.096)	(0.204)	(0.09)	(0.157)
Portugal	0.390	0.750	0.541	0.397	0.705	0.542	0.392	0.759	0.604
	(0.039)	(0.078)	(0.085)	(0.04)	(0.088)	(0.084)	(0.041)	(0.078)	(0.138)
Spain	0.518	0.956	0.463	0.467	0.930	0.464	0.507	0.944	0.351
	(0.111)	(0.031)	(0.095)	(0.117)	(0.061)	(0.095)	(0.11)	(0.038)	(0.182)
Sweden	1.137	0.979	0.463	0.547	0.652	0.473	0.957	0.920	0.409
	(0.269)	(0.073)	(0.089)	(0.407)	(0.253)	(0.093)	(0.432)	(0.143)	(0.24)
Switzerland	0.215	0.763	0.549	0.218	0.625	0.586	0.327	0.623	0.922
	(0.054)	(0.135)	(0.104)	(0.043)	(0.163)	(0.109)	(0.07)	(0.117)	(0.08)
United Kingdom	0.374	0.899	0.572	0.380	0.890	0.569	0.373	0.905	0.622
	(0.043)	(0.043)	(0.067)	(0.046)	(0.048)	(0.068)	(0.044)	(0.044)	(0.086)
CD	0.46	0.44	0.54	0.58	0.49	0.47	0.37	0.53	0.43
	0 (1)	1 (1)	0 (2)	1 (1)	0 (2)	0 (2)	0 (3)	0 (1)	1 (3)
IF	8.23	13.61	1.75	19.62	22.26	3.09	14.08	15.49	10.42

Notes: This table contains the posterior means (standard deviations) of γ_1, q and p. CD refers to the average p-value of the Geweke (1992) convergence diagnostic across countries and where we also report the number of countries for which the test rejects the null hypothesis of convergence at the 1% (5%) level. IF is the average inefficiency factor. Both diagnostics are computed using 4% tapered autocovariance matrices (LeSage, 1999).

Regime switches in factor loadings when allowing for infrequent jumps in the mean equation

Table C-3: Number of days with high common factor exposure and average return effects based on the specification in Equation (11)

	Probability of $S_{it} = 1$									
Country	$> 50\%$		$> 60\%$		$> 70\%$		$> 80\%$		$> 90\%$	
AT	54	(−0.50)	28	(−0.87)	16	(−0.99)	3	(0.20)	0	
BE	129	(−0.04)	41	(−0.09)	10	(0.01)	5	(0.44)	1	(1.56)
CZ	39	(−0.43)	19	(−0.39)	10	(−0.14)	6	(−0.86)	3	(−3.04)
DK	356	(−0.06)	124	(−0.11)	35	(−0.29)	9	(−0.63)	1	(−3.10)
FI	0		0		0		0		0	
FR	617	(−0.00)	185	(0.01)	67	(0.05)	20	(0.04)	4	(0.23)
DE	157	(−0.00)	59	(0.03)	26	(0.09)	9	(0.44)	5	(0.80)
GR	520	(−0.02)	211	(−0.07)	92	(−0.05)	46	(−0.10)	17	(−0.15)
HU	206	(−0.10)	94	(−0.19)	33	(−0.31)	15	(0.19)	4	(0.07)
IE	46	(−0.14)	21	(−0.19)	12	(−0.47)	12	(−0.47)	5	(−0.15)
IT	17	(−0.69)	6	(−1.67)	3	(−2.62)	2	(−3.08)	1	(−4.08)
NL	677	(−0.01)	147	(−0.06)	32	(−0.03)	6	(−0.12)	0	
NO	909	(−0.06)	385	(−0.12)	185	(−0.26)	71	(−0.60)	22	(−1.16)
PL	17	(−0.63)	11	(−0.86)	9	(−1.06)	6	(−1.07)	4	(−1.81)
PT	626	(−0.01)	215	(−0.08)	71	(−0.25)	31	(−0.13)	10	(−0.28)
ES	22	(−0.26)	15	(−0.42)	10	(−0.22)	6	(−0.95)	6	(−0.95)
SE	8	(−0.35)	7	(−0.56)	5	(−0.64)	4	(−0.56)	3	(−1.01)
CH	170	(−0.06)	39	(−0.10)	8	(−0.13)	2	(0.16)	0	
GB	185	(−0.09)	104	(−0.12)	60	(−0.16)	28	(−0.18)	17	(−0.42)
Total	4755	(−0.05)	1711	(−0.12)	684	(−0.21)	281	(−0.30)	103	(−0.62)

Notes: This table contains the number of days where $\Pr(S_{it} = 1)$ exceeds the threshold. The number in brackets refers to the average expected size of the return effect (in %), i.e. $\frac{1}{K} \sum Pr(S_{it} = 1)\gamma_{1,i} f_t$, where K denotes the number of high exposure days and the sum runs over all these dates.

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