Financial Integration in a Changing World

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Abstract

Given the rapidly evolving nature of financial globalization, this paper models and predicts financial integration in a changing world. Importantly, this paper allows national exposure to the global financial cycle to vary over time, as indicated by the time-varying factor loadings. By decomposing financial integration into global risk, local risk and estimation risk, we argue that greater integration is mainly driven by the greater importance of global factors, not diminishing local effects. Financial integration is highly predictable, which is important for international diversification and risk management. We identify the CBOE volatility index (VIX) as a strong predictor of financial integration. This reflects the vulnerability of financial markets to extreme events in the United States.

JEL classification: C11, C32, F36, F37, G11, G15.

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1 Introduction

Financial integration has been an important area of study for both academic researchers and policy makers. The surge of cross-border financial flows has led to greater investment and growth opportunities, more efficient capital allocation and improved international risk-sharing possibilities (Carrieri et al., 2007; Pukthuanthong and Roll, 2009; Eiling and Gerard, 2014). However, financial integration also increases spillovers and contagion risk, in the sense that the international financial system is more vulnerable to global shocks or shocks that originate in one country (Kose et al., 2009; Berger and Pozzi, 2013; Castiglionesi et al., 2017). It is therefore essential to accurately measure financial integration and to identify the fundamentals that drive integration.

A natural way to measure financial integration is through a dynamic factor model, in which the expected stock return is driven by the estimated world market return (global factors) extracted from stock markets.[1] This method is in line with asset pricing theory, particularly with the International CAPM (ICAPM), and the global financial cycle, proposed by Rey (2015).[2] Integration is therefore calculated as the fraction of a country's stock return explained by global factors.[3] If the fraction explained by global factors is small, with local effects more crucial than global effects, the country tends to be segmented from financial globalization. Whereas if the expected returns of the country can largely be explained by the global factors, a high degree of financial integration is evident. However, a common assumption in the previous literature of using ICAPM to measure integration is that both the process driving volatility and

[1]We adopt a *de facto* measure of financial integration which explores observable phenomena resulting from changeable stock markets, instead of the *de jure* measure that heavily relies on the analysis of capital account openness and legal restrictions, see Chinn and Ito (2008) and Abiad et al. (2010) for details. This is partly because the process of financial integration can be gradual and even though regulatory changes can be officially dated, the effect of these policies frequently come with a delay. The *De facto* measure, therefore, shall encompass *de jure* changes.

[2]For ICAPM, see among others, Harvey (1991) and Bekaert and Harvey (1995) for more details. For global financial cycle, see Fratzscher (2012), Cerutti et al. (2015) and Byrne and Fiess (2016).

[3]See Bekaert and Harvey (1995), Carrieri et al. (2007), Bekaert et al. (2009), Berger and Pozzi (2013) and Eiling and Gerard (2014) for details.

the linkage between global factors and individual stock return do not vary over time. Nonetheless, this assumption of structural stability seems to be implausible, especially when the exposures to global factors and local factors are time-varying due to regulatory and economic changes.[4] For example, Bekaert et al. (2009) establish risk-based factor models to study international stock return comovement and underline the importance of time-varying factor loadings using rolling window estimates. Berger and Pozzi (2013) also apply ICAPM to measure stock market integration, where country-specific and global risk premiums, and their variances, are estimated from a latent factor decomposition through the use of state space methods that allow for GARCH errors. The recent paper by Bekaert and Mehl (2017) suggest that factor exposures may vary with global shocks and shifts in global risk aversion over time. All these literature illustrates that the ICAPM with constant factor loadings and volatility may be to restricted to successfully model and predict financial integration, especially when the global stock markets are volatile.

In this paper, therefore, we employ an ICAPM framework that allows us to capture short run transitory and long run structural changes in the economy that might affect the measurement of financial integration.[5] We aim to answer the following questions: Do time-varying coefficients and stochastic volatility matter when modelling and predicting financial integration? Has integration increased over time due to the surge of capital flows or other economic and regulatory changes? What drives and predicts the dynamics of financial integration?

[4]The importance of time-varying coefficients and stochastic volatility has also been emphasized in the macroeconomic literature. Using a large macroeconomic dataset of U.S., Stock and Watson (2009) find significant instability in factor exposures around 1984. Del Negro and Otrok (2008) develop a dynamic factor model with time-varying factor loadings and stochastic volatility to measure changes in international business cycles.

[5]Another strand of the literature has relied on cross-country correlations between different stock markets as a measure of integration. However, as argued by Pukthuanthong and Roll (2009), even perfectly integrated stock markets can be weakly correlated and Forbes and Rigobon (2002) suggest that integration drawn from correlations could be biased upward due to conditional heteroskedasticity. Eiling and Gerard (2007) propose that the fraction of return variance explained by the global factors is a better way to measure financial integration than simple correlations. Therefore, we generally adapt this method to measure integration.

To construct our financial integration measure, we begin by using principal components to capture the comovement of the international stock markets for 18 advanced economies over the period 1970-2017. Stock returns then can be explained by a country-specific risk factor and global factors, which are characterized by time-varying factor loadings and stochastic volatility. Our method does not depend upon rolling window or recursive estimates, but explicitly models time-variation in the coefficients and volatility from the data.

Our contribution goes further than developing a measure of financial integration. We investigate the characteristics of cross-country financial integration and assess the general perception that it has increased substantially during the past decades. The flexibility of our method also allows us to analyze which economic elements drive cross-country integration. In particular, we decompose the total return variance into global, local and estimation risk and aim to understand the way in which these three components influence integration. Moreover, by implementing a model combination method, we are able to forecast financial integration using macroeconomic fundamentals including the CBOE volatility index (VIX), which is closely related to the global financial cycle (see, Miranda-Agrippino and Rey (2015), Rey (2015) and Byrne and Fiess (2016)). To the best of our knowledge, ours is the first paper that systematically studies financial integration predictability across countries and the importance of its determinants over time. As greater integration implies less global risk-sharing, out-of-sample predictability has important implications for risk management and portfolio allocation of the international stock markets.

Among papers studying the importance of instabilities of factor loadings and volatility of ICAPM to measure integration, we note contributions by Pozzi and Wolswijk (2012), Berger and Pozzi (2013) and Everaert and Pozzi (2016). However, while they discuss time-variation in the parameters of ICAPM model and its ability to capture changes in integration, they do not explicitly examine the effect of the former upon the latter. Therefore, our study complements theirs, by testing time-varying betas ex ante using the Elliott and Müller (2006) test, and by comparing the difference between constant and time-varying parameter ICAPM with stochastic volatility. As far as we know, our paper is the first study to test time-variation in factor loadings when constructing financial integration. We also extend the analysis in the above papers to examine the origins of changes in integration from the perspectives of decomposition and time series prediction.

To preview our results, we uncover that although financial integration displays a secular upward trend, none of the advanced economies we consider consistently achieve full stock market integration. Importantly, integration typically reaches local maxima during the global financial crisis in 2008. But there exists some country and region specific effects: such as the increasing integration for Hong Kong and Singapore due to the Asia Crisis of 1997 and increased European integration during the European sovereign debt crisis. Essentially, time-variation in factor loadings and stochastic volatility are the key elements to capture dynamics in financial integration. By applying trend and break tests, we confirm that financial integration has experienced a structural change and generally increased for our sample of advanced economies. We also find that instead of a decreasing country-specific effect, increasing global risk is the key element that drives integration. Finally, we provide formal evidence that integration is highly predictable using macroeconomic and financial indicators. In general, the VIX index is the main determinant of financial integration, followed by cross-country trade openness. This is consistent with a global financial cycle that originates in United States, since VIX reflects realised volatility and market-wide risk aversion.

The remainder of the paper is set out as follows. Section 2 lays out the model framework to measure financial integration. Section 3 discusses the data and Section 4 studies the characteristics of our measure of financial integration. Section 5 presents the trend and break tests results. Section 6 analyzes the economic mechanisms that drive integration and Section 7 concludes.

2 Model Framework

Financial integration can be constructed from a dynamic factor model that satisfies the following principles: i) The model should be flexible enough to account for changes in the global factors and country-specific effects; ii) The model should accommodate the volatility of financial markets; iii) The model should be data-driven and the integration measure should be implicitly derived from the estimation process. Therefore, our starting point is a time-varying factor loadings and volatility model which captures the relationship between global factors and country-specific stock returns under a Bayesian state space framework. Financial integration is measured therefore as the evolving proportion of variance explained by the global factors.

2.1 Dynamic Model with Stochastic Volatility

Consider an International CAPM model with $r_{i,t}$ as the excess return for country i at period t:

$$r_{i,t} = \mu_{i,t} + \beta^p_{i,t} r^p_t + \varepsilon_t \sqrt{exp(\ln h_{i,t})} \qquad i = 1, \dots, N, \quad t = 1, \dots, T, \quad \varepsilon_t \sim N(0,1) \tag{1}$$

where $\mu_{i,t}$ is the unobserved country-specific factor, r^p_t are the principal components we obtained which can be treated as the excess return of the world equity portfolio. The superscript p in r^p_t refers to the number of principal components in our model and ε_t denotes normally distributed errors with mean zero and variance one. An important feature of our methodology is that factor exposures on different global factors for each country $\beta^p_{i,t}$ and the idiosyncratic variance $h_{i,t}$ are time-varying.

Denote the time-varying parameter set $B_{i,t} = \{\mu_{i,t}, \beta^p_{i,t}\}$, then for different countries, the time-varying coefficients in Equation (1) follow a random walk process:

$$B_{i,t} = B_{i,t-1} + e_{i,t} \qquad\qquad e_{i,t} \sim N(0, H_i) \tag{2}$$

where $e_{i,t}$ is the error term with mean zero and time-varying variance H_i. Bekaert et al. (2009) argue that flexibility in the modeling of betas is important in capturing underlying structural changes in financial markets. Occasionally, the financial integration literature focuses upon the factor loadings on the global factor (i.e., the betas in our model) as the measure of stock market integration.[6] However, this measure can be problematic, as a fully integrated country which only depends on global factors can also have low loading betas.

We argue that stochastic volatility is also essential to the construction of the financial integration. Here, we assume that the shock to stochastic volatility $h_{i,t}$ in Equation (1) is independent of r_t^p, which is in line with the theoretical literature. The GARCH type models applied in Carrieri et al. (2007) and Berger and Pozzi (2013) do not share this distinctive characteristic. Specifically, the variance of the error term $h_{i,t}$ in Equation (1) evolves as:

$$\ln h_{i,t} = \ln h_{i,t-1} + v_{i,t} \qquad\qquad v_{i,t} \sim N(0, Q_i) \tag{3}$$

where $v_{i,t}$ is the disturbance term with mean zero and time-varying variance Q_i.

This time-varying factor loadings with stochastic volatility model can be estimated by combining the Carter and Kohn algorithm with the Metropolis algorithm in a Bayesian setting (Blake and Mumtaz, 2012). We set an inverse Wishart prior for H_i, where $H_{i,0} = k \times H_{i,ols} \times T_0$. T_0 is the length of training sample and we set $T_0 = 52$, equivalent to the number of weeks in one year. For country i, $H_{i,ols}$ is the

[6] For instance, Baele et al. (2004), Schotman and Zalewska (2006), Kizys and Pierdzioch (2009) and Bekaert and Mehl (2017) take the betas as the integration integration.

OLS estimation of the variance covariance matrix for B_i using the training sample period and k is a small scaling factor. An inverse Gamma prior is set for g such as $p(Q_i) \sim IG(q_0, v_0)$, where the prior scale q_0=0.01 and the prior degree of freedom v_0=1.

Details on implementation of time-varying coefficients with stochastic volatility model is provided in the online appendix. To estimate the model, 50,000 draws are made based on the algorithm above, with the first 45,000 as burn-in draws and the last 5,000 used to construct financial integration.

2.2 Measuring Financial Integration

In this paper, we adapt an ICAPM approach to measure financial integration. Empirical integration measures such as simple correlations can be contaminated because of volatility bias (see e.g., Forbes and Rigobon (2002) and Pukthuanthong and Roll (2009)). Especially, correlations may increase due to increasing common factor variance, rather than increasing factor exposures. We, therefore, measure integration by focusing on the proportion of total variance explained by the global factors for the stock market returns, following among others, Bekaert and Harvey (1997) Pukthuanthong and Roll (2009) and Eiling and Gerard (2014).[7] A time-varying stock market integration $TVI_{i,t}$ for country i at time period t is denoted as:

$$TVI_{i,t} = \frac{V_t(\beta^p_{i,t} r^p_t)}{V_t(r_{i,t})} = \frac{V_t(\beta^p_{i,t} r^p_t)}{V_t(\mu_{i,t} + \beta^p_{i,t} r^p_t + \varepsilon_t \sqrt{exp(lnh_{i,t})})} = \frac{V_t(\beta^p_{i,t} r^p_t)}{V_t(\mu_{i,t} + \beta^p_{i,t} r^p_t) + h_{i,t}} \tag{4}$$

where V_t denotes the variance of corresponding terms, based upon Equation (1).[8]

[7]Even though Pukthuanthong and Roll (2009) claim that the integration measure they apply based on the proportion of a countrys returns that can be explained by global factors, the multi-factor R-square indicator they actually use cannot distinguish whether the explanatory power is truly global or country-specific.

[8]As acknowledged by Pukthuanthong and Roll (2009), when sampling error is admitted, there will be some inevitable variation in the estimated integration measure in Equation 4 even though the true integration is constant. They suggest this is not likely to be a serious problem as factor variation and estimation error are common. We further adjust this bias by relying on longer-term trends using quarterly instead of weekly data and investigate the importance of allowing stochastic volatility in Section 4.3.

The integration measure in Equation (4) lies within zero and one. In extreme, if a country is fully detached from the world, local or regional factors dominate the market while factor exposure $\beta^p_{i,t}$ tends to be zero, and its integration will be negligible. On the contrary, a more integrated country is highly susceptible to the global factors and has an integration index close to one. Our integration measure echos the statement by Bekaert and Harvey (1995): a market is completely integrated if the common world factors can explain its expected returns, whereas segmentation will prevail if these common factors have little power to explain the expected returns.

We argue that the total variance of stock returns can be decomposed into three parts: variance of the global factor, variance of the country effect and stochastic volatility from Equation (1). Therefore, $TVI_{i,t}$ will increase when the risk of global factor $\beta^p_{i,t} r^p_t$ increases, when the risk of the local effect $\mu_{i,t}$ decreases, and/or when the stochastic volatility $h_{i,t}$ decreases. We study the sources of uncertainty of stock returns in Section 6.1 and investigate which components drive the financial integration dynamics.

Compared to other integration measures derived from the ICAPM model, a key innovation of our study is that we accommodate time-varying local effect $\mu_{i,t}$, factor loadings $\beta^p_{i,t}$ and stochastic volatility $h_{i,t}$ in the construction of the financial integration. Whereas, for a model with constant coefficients and volatility, the dynamics in the integration measure will only be driven by time-variation in the global factors r^p_t extracted from individual stock markets, according to Equation (4). This may be unreasonable, especially in a changing world, with changes in economic conditions, *de jure* financial openness and global risk. We further assess ex ante the necessity of time-varying factor loadings using a statistical test and compare our model with the constant loadings and variance model in Section 4.3.

3 Data

We focus on the excess returns using the MSCI index for 18 advanced economies around the world: Australia, Austria, Belguim, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the United States. These countries have a considerable influence on the world financial market and are included in the MSCI developed country index. Moreover, they have the longest data availability on Datastream. Similar to Bekaert et al. (2009), weekly returns data is used to alleviate the problems caused by nonsynchronous trading days and opening hours for different countries at higher frequencies. In total, 2544 weekly observations are obtained over the period 1970:01-2017:01. We present the country-specific MSCI price index and its Datastream mnemonic in the online appendix.

We measure the excess stock returns using continuously compounded returns net of the U.S. risk-free rate:

$$r_{i,t} = (log(\frac{P_{i,t}}{P_{i,t-1}})) * 100 - r_{ft} \tag{5}$$

where $P_{i,t}$ is the price index for country i at time t and r_{ft} is the U.S. weekly risk-free rate at time t. We use the MSCI price index in US dollars, to take the perspective of an international investor.[9] This allows us to take possible reasons, such as exchange rate risk, for comovement variability into account. Regarding r_{ft}, we use the weekly three-month U.S. T-Bill rate provided by Federal Reserve Bank of St. Louis in annualized percentage terms. To convert this annual risk-free rate to a weekly rate, we divide the annualized three-month T-Bill by 52.

[9]The MSCI price index does not include dividends. It would be preferable to use total return index which includes reinvested dividends. However, total return index has shorter data availability. Hence, we use the MSCI price index to investigate longer horizon of international stock returns.

4 Financial Integration

In this section, we first report the global factors obtained by out-of-sample principal component analysis. Then we demonstrate the cross-country financial integration and analyze its distinctive features.

4.1 Out-of-Sample Principal Components and Co-movement

Principal component analysis (PCA) is widely used in the literature and is advantageous in determining the co-movement in different areas as only a few components are needed to summarize the observed variation in the data. For instance, Pukthuanthong and Roll (2009) investigate the evolution of market integration based on the explanatory power of a multi-factor model. Financial integration is then calculated as the adjusted R-square from the regressions of stock market returns on the estimated factors. However, it is not well defined whether the estimated factors are truly global or country-specific. Volosovych (2011) also implements PCA to construct an integration index. He uses the percentage of variance explained by the first principal component as the measure of financial integration in the bond market. Nonetheless, this measure simply generates an identical integration index for all the countries and using a single global factor might not be enough to reveal the important information about integration.

Following Pukthuanthong and Roll (2009), we conduct an out-of-sample principal component analysis to capture global factors in the stock market across countries, where principal components are estimated using the eigenvectors obtained from the previous calendar year. In other words, we first conduct the common PCA for the year 1970. Then the eigenvectors from 1970 will be used on the integration series from 1971. This is repeated in each calendar year until the final available full sample year 2016.[10]

[10] As we implement the out-of-sample PCA, the resulting principal components are not exactly orthogonal. However, the correlations between out-of-sample principal components are small and it

To identify the number of common factors, we use the information criteria (IC) proposed by Bai and Ng (2002), which is suggested to have better power and size properties than the usual AIC and BIC measures.[11] The IC3 criteria selects two principal components. Bai and Ng (2002) indicates that this criteria is more reliable especially in the presence of cross sectional correlation, which is likely in our case.

We calculate the average cumulative proportion of variance explained by the out-of-sample principal components.[12] Among the 18 principal components, the first component explains over 80% of the variance and the first two components explain over 90% of the total variance. This clearly implies the existence of global factors and further confirms the number of common factors selected by the IC3 criteria. The fact that the first component explains over 80% of the variance also reflects the finding of global financial cycle of Miranda-Agrippino and Rey (2015): "one global factor explains an important part of the variance of a large cross section of returns of risky assets around the world." They interpret this global factor as reflecting realized world market volatility of risky assets and the market-wide risk aversion.

4.2 Financial Integration

As acknowledged by Pukthuanthong and Roll (2009), to mitigate the problem that the integration measure will be biased upward when global factor volatility happens to be greater than the total country volatility, it is prudent to use longer-term trends instead of shorter-term variation in the estimated financial integration. We, therefore, use the weekly MSCI return data to estimate quarterly financial integration from

would not be a problem using these components as explanatory variables in regressions.

[11] As acknowledged by Bai and Ng (2002), IC3 criteria is a function of both N and T (the cross-section dimension and the time dimension, respectively) and it can lead to a consistent estimate of numbers of factors. Whereas, the usual AIC and BIC, which are functions of N or T alone, do not work well specially when N and T are large.

[12] We present the figure of percentage variance explained by principal components in the online appendix.

1971Q1 to 2017Q1, to alleviate short-run disturbances.[13]

Table 1: Summary Statistics For Financial Integration

	Mean	Median	Stdev	Min	Max	Skew	Kurt	$\rho(1)$	$\rho(2)$	p_{ADF}
Australia	0.37	0.36	0.13	0.12	0.77	0.45	2.99	0.71	0.59	0.13
Austria	0.32	0.31	0.13	0.07	0.71	0.41	2.79	0.74	0.64	0.09
Belgium	0.19	0.17	0.10	0.05	0.53	0.93	3.67	0.71	0.57	0.02
Canada	0.37	0.36	0.12	0.12	0.74	0.57	3.36	0.67	0.52	0.12
Denmark	0.29	0.26	0.14	0.04	0.80	1.03	4.24	0.64	0.48	0.02
France	0.38	0.33	0.18	0.11	0.92	0.79	2.97	0.73	0.63	0.05
Germany	0.39	0.39	0.13	0.11	0.79	0.30	2.94	0.72	0.61	0.17
Hong Kong	0.67	0.70	0.15	0.15	0.98	-0.92	4.14	0.73	0.62	0.39
Italy	0.44	0.45	0.16	0.15	0.89	0.24	2.44	0.76	0.65	0.15
Japan	0.18	0.15	0.12	0.03	0.61	1.60	5.41	0.69	0.51	0.00
Netherlands	0.40	0.40	0.14	0.12	0.82	0.35	3.06	0.74	0.64	0.18
Norway	0.47	0.48	0.15	0.11	0.87	-0.05	2.87	0.71	0.57	0.16
Singapore	0.50	0.52	0.17	0.15	0.89	-0.02	2.51	0.75	0.66	0.20
Spain	0.53	0.53	0.14	0.15	0.88	-0.17	2.92	0.67	0.56	0.23
Sweden	0.38	0.38	0.14	0.08	0.85	0.42	3.07	0.70	0.57	0.10
Switzerland	0.45	0.44	0.17	0.10	0.90	0.47	2.97	0.71	0.59	0.12
United Kingdom	0.40	0.37	0.17	0.07	0.86	0.52	2.71	0.73	0.63	0.07
United States	0.46	0.47	0.13	0.17	0.83	0.12	2.96	0.63	0.47	0.14

Notes: This table reports the summary statistics for financial integration cross-country. $\rho(1)$ and $\rho(2)$ show autocorrealtion coefficients for one and two lags. p_{ADF} shows the p values of the Augmented Dickey-Fuller test for a unit root with an intercept and a time trend, where the optimal number of lags is determined by Bayesian Information Criterion. The null hypothesis is that there exists a unit root in the financial integration series. The sample period is from 1971Q1 to 2017Q1.

Table 1 shows summary statistics of the estimated integration for our countries of interest, indicating that integration reveals a substantial amount of heterogeneity. Over the whole sample period, Hong Kong has the largest integration index among the 18 advanced economies. Due to almost free port trade, well established and regulated international financial market as well as close ties with mainland China, Hong Kong has the highest degree of economic and financial freedom since 1995 (Heritage, 2017). On the other hand, Japan has the lowest integration compared to others, only with

[13]We first obtain weekly financial integration then convert it to quarterly data by taking means. This transformation is convenient for us to conduct the prediction in Section 6.2 as all the macroeconomic fundamentals are quarterly data. Financial integration starts from 1971Q1 instead of 1970Q1 since we use the first year sample as the training period.

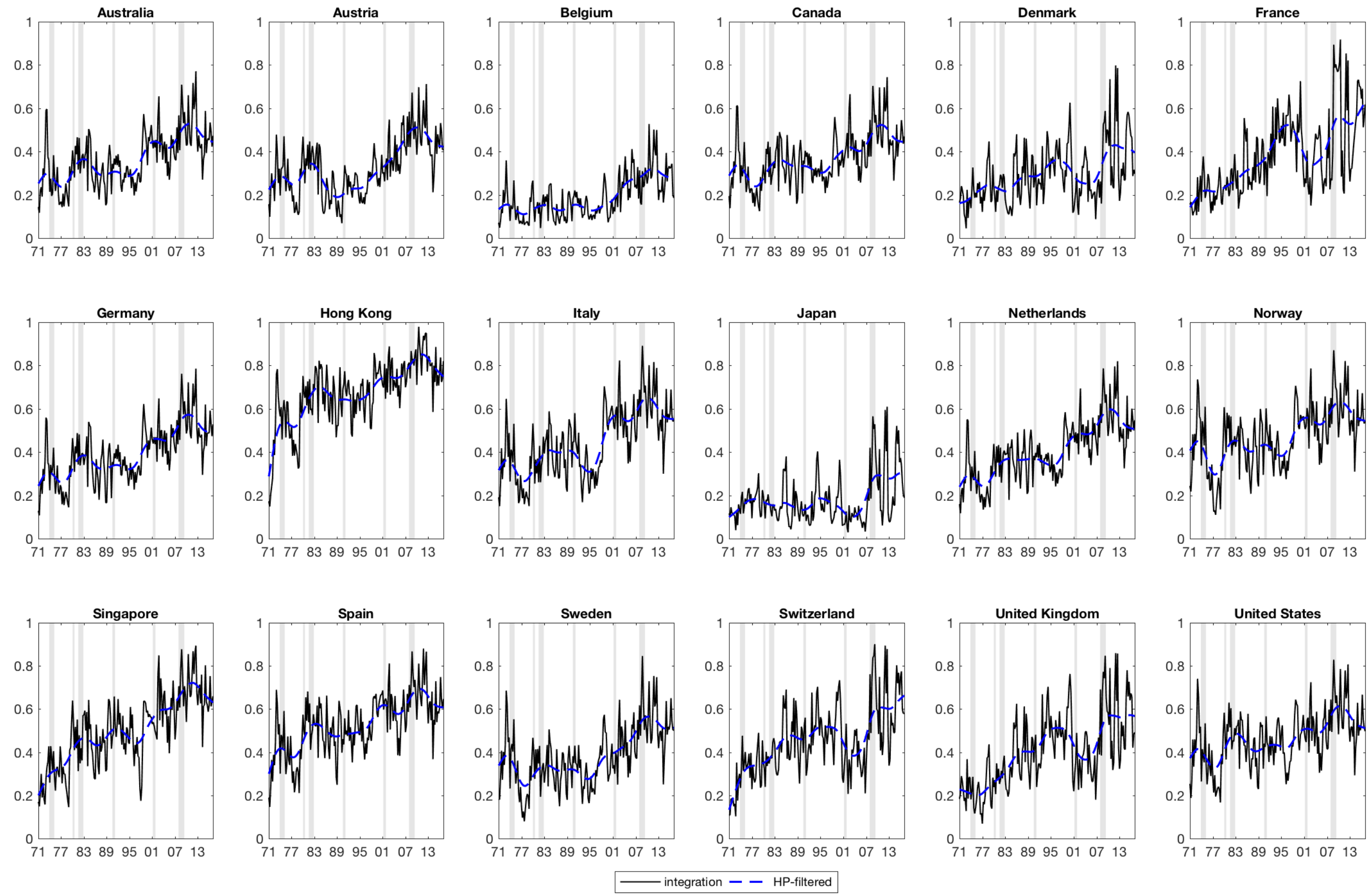
large fluctuations recently. This is in line with earlier findings that the integration of Japan has not increased substantially over time (Berben and Jansen, 2005; Berger and Pozzi, 2013). The United States, as the largest economy in the world, also shows greater integration compared with other countries. In general, the financial integration exhibits serial correlation and we find that for most of the countries we cannot reject the null hypothesis of a unit root, see p_{ADF} in Table 1.

We demonstrate the financial integration for 18 advanced economies in Figure 1. Due to the reversals in the integration series, we also superimpose a plot of the Hodrick-Prescott (H-P) filtered trend series to focus upon the long-term trend.[14] Despite the variability, almost all the countries appear to display an upward time trend. This is consistent with the fact that capital mobility and cross-border financial flows have generally increased from the mid-1980s, and financial liberalization policies can stall and even reverse, causing fluctuations in integration. We further check this argument in Section 5 by applying trend and break tests.

We also find that none of the advanced economies we consider achieve and maintain complete stock market integration, confirming the statement that there still exists some market segmentation and benefits from international diversification. This is not surprising, as even with fully liberalized financial markets, due to the home bias puzzle, individuals and institutions still prefer investing at home rather than abroad. In contrast, according to the popular financial openness measure suggested by Chinn and Ito (2008) and the financial reform index proposed by Abiad et al. (2010), financial markets are entirely open for most of our economies of interest.

[14]By convention, we set the smoothing parameter of the H-P filter to 1600 for quarterly data.

Figure 1: Measure of Financial Integration Based Upon ICAPM Model



Notes: This figure shows the time-varying integration measure we derive based on the fraction of total return variance explained by global factors cross-country. The solid line is the financial integration, the dashed line is the H-P filtered trend of integration and the shaded areas are the NBER recession dates.

As expected, integration of almost all the countries reached their local maxima around 2008, at the peak of the financial crisis. Globally, the surge of cross-border financial flows in the decade before the crisis leads to the excessive growth in credit markets (Lane, 2013). The US is considered to be the epicenter of the crisis due to speculative bubbles and crashes, and then it quickly spread to other countries around the world. This reflects the fact that high level of financial integration during time of stress could cause the international financial markets vulnerable. Additionally, the local maxima of integration around 2008 echoing the argument from Bekaert and Mehl (2017) that "global betas tend to increase significantly in periods of heightened market volatility".

Our financial integration measure also suggests that despite the liberalization of financial markets during recent decades, country-specific risk is still an essential element in interpreting the time variation in expected returns. Hence none of the countries are completely integrated. In particular, Figure 1 sheds light on the importance of cross-country differences in the evolution of financial integration. Examples include increases in integration for Hong Kong and Singapore due to the 1997 Asia financial crisis as well as the decreasing trend of integration for Japan during 1991 to 2007 as a result of the "lost decade" after the Japanese asset price bubble's collapse. For European countries, integration raises rapidly as result of the euro area debt crisis in 2010-2012, then it subsequently fell during the past four years due to implementation of new banking regulations and increasing sovereign risk. Moreover, the degree of financial integration was quite high in some countries (e.g., Australia, Belgium, Canada, Hong Kong, Norway, the United States etc) around the 1973 oil crisis and the fall of the Bretton Woods system. We conclude that the evolution of financial integration over the last five decades has many similarities but also has substantial differences across countries. Our methods capture dynamics not only in the global factors but also in the country-specific financial markets.

4.3 Importance of Time-varying Factor Loadings and Stochastic Volatility

So far we have presented the financial integration measure with time-varying betas and stochastic volatility. But do these conditional terms matter? In this section, we explicitly test why incorporating time-varying betas and stochastic volatility matter when deriving financial integration from our ICAPM model.

We first check whether there is persistent time variation in the factor loadings regardless of the data-generating process. Given a regression with individual stock return as the dependent variable and global factors as explanatory variables, we examine the stability of the regression model. Elliott and Müller (2006) propose an efficient test statistics that allows for many or a few breaks, clustered breaks, frequently occurring breaks, or smooth transitions to variation in the regression coefficients. Moreover, this test has good power and sample size even for models with heteroscedasticity. We therefore apply the Elliott and Müller (2006) test to examine whether we should incorporate time-varying betas ex ante. To the best of our knowledge, our study is the first one to systematically test the importance of time-variation in betas of the ICAPM model.

Table 2: Elliott-Müller Test for Time-varying Factor Loadings

	Test stat.		*Test stat.*
Australia	-57.47***	Japan	-65.42***
Austria	-148.39***	Netherlands	-60.80***
Belgium	-62.12***	Norway	-112.15***
Canada	-67.83***	Singapore	-57.27***
Denmark	-68.40***	Spain	-63.17***
France	-48.90***	Sweden	-115.55***
Germany	-72.28***	Switzerland	-42.56***
Hong Kong	-96.32***	United Kingdom	-43.51***
Italy	-97.43***	United States	-28.06***

Notes: This table reports the Elliott and Müller test statistics to detect time-variation in factor loadings. The null hypothesis is that factor loadings are fixed over the sample period. Hence rejection of the null implies that the parameters are time-varying. The 1%(*), 5%(**) and 10% (***) critical values are -23.42, -19.84 and -18.07 respectively. The sample period is 1971Q1 to 2017Q1.

Table 2 presents the results of the Elliott and Müller (2006) test. We strongly reject the null hypothesis that factor loadings of ICAPM are constant over the whole period for every economy we investigate at the 1% significance level. This implies that there is statistical evidence of time-variation in factor loadings and we should take this feature into account. Otherwise, the inference using standard methods may be misleading.

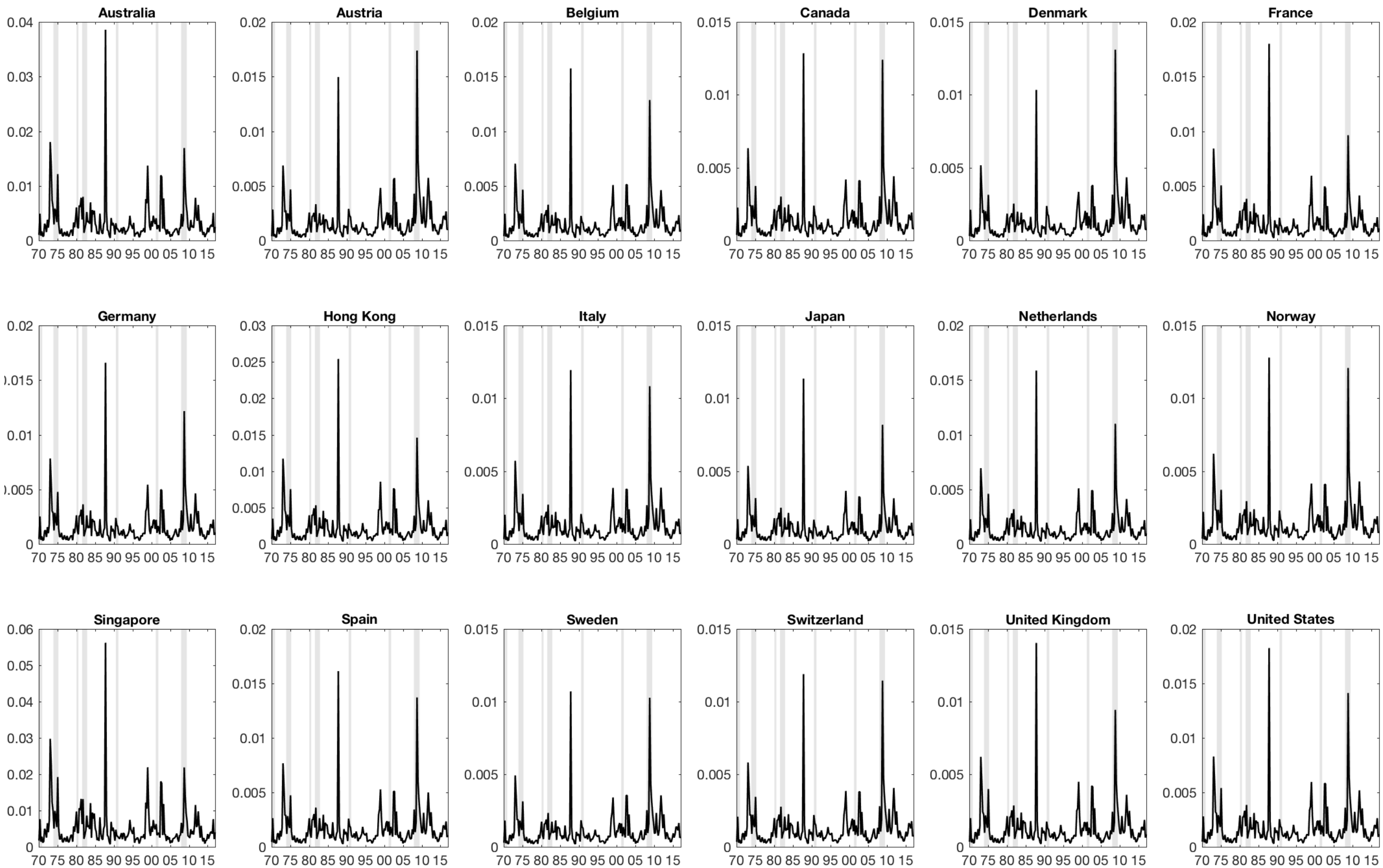
To reinforce our point, after we identify time-variation in factor loadings, we investigate whether it matters when constructing our measure of financial integration. Therefore, we compare our integration measure with the one drawn from constant betas and risk. The simple ICAPM is measured using global factors as explanatory variables and stock return of each country as the dependent variable, with constant coefficients and volatility. Particularly, the variance-covariance matrix of the coefficients are heteroskedasticity robust. The integration is measured in the same way as described in Section 2.2.

Figure 2 shows the simple ICAPM integration measure with constant factor loadings and volatility. Counter-intuitively, there is little evidence of increased financial integration over time and excess sensitivity to outliers: after the initial data-points, financial integration peaks either during the financial crisis in 2008 or during the financial market crash in 1987.[15] Hence, the simple integration measure with constant factor and risk cannot reveal systematic differences cross countries. Importantly, the magnitude of the integration is negligible, with the largest integration being less than 0.05.[16] This negligible degree of integration is unable to explain the dynamics among different financial markets, especially with the development of trade linkages and financial liberalization over the recent decades.

[15] The integration derived from simple ICAPM starts from 1970 as there is no training data.

[16] By using a difference in means test, we confirm that integration measured using simple ICAPM is significantly smaller than that using our ICAPM with time-variation. The test statistics is reported in the online appendix.

Figure 2: Financial Integration Derived from Constant Factor Loading and Risk



Notes: This figure shows the time-varying integration derived from the simple international CAPM, with constant factor loading and constant volatility in Equation 4. The shaded areas are the NBER recession dates.

As discussed in Section 2.2, dynamics in financial integration derived from a constant coefficients and volatility model is, by restriction, only driven by dynamics in the global factors. Whereas, for our integration measure, time-varying coefficients and stochastic volatility also contribute to the changes in integration. We therefore conclude that, integration is mainly driven by the time-variation presented in the factor loadings and the volatility derived simultaneously from Equation (1). Each national stock market locks onto the global factors in a time evolving and contrasting fashion.

5 Trends and Breaks in Financial Integration

In the previous section, we presented evidence of a rising trend in financial integration, therefore, we are interested in whether this time trend is significant. Specifically, for each country, we focus on the regression:

$$TVI_t = a + b \cdot trend + u_t \tag{6}$$

where TVI_t is the financial integration identified in the previous section for each country, $trend$ is a linear time trend, constant parameters are denoted by a and b, while u_t is the error term.

We apply the Perron and Yabu (2009a) test to examine the null hypothesis that $H_0 : b = 0$.[17] The advantage of this test is that it is still effective even without any prior knowledge of whether the series is trend-stationary or contains a unit root.[18] This is exactly our case as some countries are trend-stationary while others contain unit roots,

[17]Perron and Yabu (2009a) assume that $u_t = a \cdot u(t-1) + A(L)(u(t-1) - u(t-2)) + e(t)$ where $e(t) \sim i.i.d.(0, \sigma^2)$.

[18]Bekaert et al. (2009) and Eiling and Gerard (2014) perform the Bunzel and Vogelsang (2005) trend test instead. However, Perron and Yabu (2009a) show that their procedure leads to better size and power properties than the test proposed by Bunzel and Vogelsang (2005) and Harvey et al. (2007). This is because even though their tests are valid with either $I(1)$ or $I(0)$ errors, good properties of these random scaling tests disappear in finite samples. The Perron and Yabu (2009a) test is different from theirs and does not relate to random scaling.

as showed in Table 1. Perron and Yabu (2009a) show that by using the Feasible Quasi Generalized Least Squares, inference on the slope coefficient can be measured using the simple standard Normal distribution with either $I(0)$ or $I(1)$ error components.

Table 3: Financial Integration Trend Tests

	Trend	*t test*		*Trend*	*t test*
Australia	0.15%	4.00***	Japan	0.04%	0.25
Austria	0.14%	0.52	Netherlands	0.19%	4.58***
Belgium	0.11%	2.92***	Norway	0.17%	2.44**
Canada	0.13%	3.06***	Singapore	0.27%	1.63
Denmark	0.12%	3.39***	Spain	0.20%	3.86***
France	0.22%	4.38***	Sweden	0.17%	2.35**
Germany	0.18%	4.26***	Switzerland	0.26%	1.15
Hong Kong	0.34%	4.29***	United Kingdom	0.21%	2.45**
Italy	0.22%	2.86***	United States	0.13%	2.62***

Notes: This table reports the estimated trend coefficients in percentages ("trend") based on the Perron and Yabu (2009a) test in the financial integration series. The null hypothesis is that there is no trend in the integration. Following a normal distribution, and the 1%(*), 5%(**) and 10% (***) critical values of these two-sided tests are 1.65, 1.96 and 2.58 respectively.

Table 3 reports the Perron and Yabu (2009a) test results for financial integration. According to the estimated trend coefficients, all of the countries increasingly integrate with each other during the past few decades. Not surprisingly, integration for Hong Kong increases by 0.34% per year and is the largest among all the countries, due to its status as a world financial center. Additionally, we strongly reject the null hypothesis that there is no time trend at the 5% significance level for most of the countries we are interested in, except for Austria, Japan, Singapore and Switzerland. This suggests that integration has increased significantly for most of the economies we consider.

It is well known that the tests for deterministic trends can be invalidated by shifts or structural breaks. To assess this probability, we apply the Perron and Yabu (2009b) test for breaks in the integration series. This approach is robust for stationary or integrated noise component, and is valid whether the break is known or unknown.

Table 4 shows the test statistics of Perron and Yabu (2009b), the estimated break date and the integration before and after the break dates. The break dates are obtained by minimizing the sum of squared residuals from the regression of the stock market integration on a constant, a deterministic trend, a level-shift dummy and a slope-shift dummy.[19] Interestingly, while Austria, Japan and Switzerland all have significant breaks in their integration measure, these markets lack trends in the integration. This echos our thought that the trend test in Table 3 may be weakened by the breaks. For some of the Eurozone countries such as France and Italy, the break dates are significant around January 1999, the time when the euro was introduced, reflecting its sizable impact upon financial markets. In addition, integration break dates are all around 2008, for the United States, Canada, Germany, Japan, Netherlands and Spain, shedding light on the importance of the global financial crisis on integration.

Table 4: Financial Integration Break Tests

	W_{RQF}	T_{Break}	*Before*	*After*
Australia	1.20	1998Q2	0.30	0.47
Austria	8.40***	1984Q4	0.29	0.34
Belgium	4.85***	2002Q2	0.14	0.28
Canada	1.27	2008Q2	0.34	0.49
Denmark	1.01	2000Q3	0.27	0.33
France	3.00*	2000Q3	0.33	0.47
Germany	1.26	2008Q2	0.36	0.54
Hong Kong	4.11**	1986Q3	0.57	0.73
Italy	2.60*	1998Q2	0.35	0.58
Japan	5.00***	2007Q4	0.15	0.30
Netherlands	1.41	2007Q4	0.36	0.56
Norway	0.57	1979Q1	0.36	0.49
Singapore	1.14	1984Q4	0.37	0.56
Spain	0.75	2008Q2	0.50	0.66
Sweden	2.97*	1996Q4	0.31	0.48
Switzerland	4.22**	2000Q3	0.42	0.52
United Kingdom	3.90**	2000Q3	0.36	0.48
United States	0.71	2008Q2	0.44	0.58

Notes: This table shows the break test of Perron and Yabu (2009b) and the average integration index before and after break dates. W_{RQF} represents Perron and Yabu (2009b) test statistics and T_{Break} shows the dates of the breaks. $Before$ and $After$ represent the level of financial integration before and after its corresponding break dates. The specification of the break test includes a constant and a time trend. The critical values for W_{RQF} are 2.48, 3.12 and 4.47 at the significance level of 10%(*), 5%(**) and 1%(***) respectively.

[19] According to Perron and Zhu (2005), this break date selection generates a consistent estimate regardless whether the noise component is stationary or integrated.

We further exploit the differences of integration before and after the break dates in Table 4. The integration after the break appears to be greater than before. Take Japan as an example, its average integration index jumps to 0.30, twice as large as the level of integration before the estimated break date 2007Q4, around the financial crisis in 2008. Additionally, by applying a simple t test with Newey-West error, we strongly reject the null hypothesis that the mean before the breaks are larger than that after at the 5% significance level across different countries.[20] We conclude that the estimated integration series are of substantially greater magnitude after the break dates. In other words, financial integration has increased structurally among advanced economies and cross-country diversification has decreased around the world. Therefore, the lack of significant trends in cross-country integration for some countries is likely due to the structural breaks, confirming the argument that integration is changing over time and reflecting the setting of time-varying factor exposures and risk in our model.

6 What Drives Financial Integration?

This section focuses on the statistic and economic mechanisms that drive international financial integration. We first decompose the integration measure to investigate trends in the global and local components. Then, we predict the integration measure using macroeconomic fundamentals identified by the literature, in particular the VIX index, and verify which variables are informative about the evolution of integration.

6.1 Decomposing the Integration Measure

After studying the features of our integration measure, we aim to understand the statistic and economic mechanisms behind the cross-country differences and trends in integration. Our method is advantageous as we are able to trace the systematic

[20]We report the test statistics in the online appendix.

risk of global factor, local factor and estimation error over time and examine which components are the drivers of financial integration.

As discussed in Section 2.2, rising financial integration can be caused by increasing risk due to the global factor and/or decreasing risk due to the country factor and estimation error. We present trend tests for these three elements in absolute terms in Table 5, to underscore the channels through which integration has varied across countries. [21] We uncover that the upward trends in financial integration are mainly a result of increasing global risk, with positive and significant trends coefficients of large magnitudes for most of the countries. For instance, in Table 5, Hong Kong has a large trend coefficient for global risk, consistent with it having the greatest degree of integration among the economies we study. Interestingly, for countries such as Australia, Germany and Netherlands on the one hand, the positive effect of increasing global factors is further amplified by decreasing local risk and estimation risk, leading to greater integration. On the other hand, the rest of the countries have sizable local and estimation risk, which reduces financial integration. Importantly, this negative effect is largely offset by the positive effect generated from growing global risk, resulting in the upward trends in integration. Therefore, we conclude that it is mainly the increasing global factors that drive the dynamics of integration. These results highlight the importance of investigating and understanding all determinants of integration.

6.2 Determinants of Financial Integration

To further understand the economic mechanisms that affect integration, our paper provides formal evidence about the predictability of financial integration based upon economic fundamentals. Concerning investors, this attempt to predict integration has potential implications for international diversification and asset allocation. With respect to policymakers, a robust and integrated future financial market contributes

[21] Eiling and Gerard (2014) decompose the emerging equity market comovements, but they focus on the global risk, regional and country-level risk channels.

Table 5: Trend Tests for the Components of Integration Measure

	Global Risk		Country Risk		Estimation Risk	
	Trend	*t test*	*Trend*	*t test*	*Trend*	*t test*
Australia	7.81%	1.91*	-0.43%	-0.60	-2.99%	-3.01***
Austria	4.59%	2.73***	-0.13%	-0.76	0.63%	0.12
Belgium	0.68%	2.07**	-0.04%	-0.90	0.09%	0.12
Canada	5.20%	1.97**	-0.55%	-1.00	0.25%	0.52
Denmark	2.48%	0.21	2.28%	1.07	1.42%	1.53
France	8.45%	0.39	2.82%	1.75*	0.16%	0.08
Germany	5.77%	2.13**	-0.44%	-1.25	-1.99%	-5.08
Hong Kong	140.60%	3.78***	8.32%	1.78*	-1.35%	-1.07
Italy	7.91%	1.98**	0.76%	8.86***	-2.13%	-1.16
Japan	0.44%	0.10	0.31%	9.29***	0.79%	0.08
Netherlands	4.79%	2.41**	-0.20%	-0.80	-0.87%	-4.00***
Norway	9.38%	1.93*	0.95%	8.84***	-1.87%	-1.44
Singapore	11.73%	3.12***	0.40%	5.96***	-2.96%	-1.90*
Spain	18.82%	2.42**	1.08%	5.22***	-2.93%	-4.01***
Sweden	4.13%	1.85*	0.42%	7.89***	-0.22%	-0.17
Switzerland	5.31%	0.16	0.52%	11.52***	-1.26%	-1.88*
United Kingdom	4.80%	0.22	0.55%	14.49***	0.23%	0.11
United States	6.19%	1.89*	0.59%	7.59***	-0.68%	-1.64

Notes: This table reports the trend tests for the variance due to the global factors $\beta^{p}_{i,t}$ (global risk), the country-specific factor $\mu_{i,t}$ (country risk) and the stochastic volatility $h_{i,t}$ (estimation risk) when constructing integration measure. ***, ** and * denote significance at the 1%, 5% and 10% levels. See more details about the trend test in Table 3.

to the smooth transmission of monetary policy. Furthermore, one should be also be aware of the spillovers and contagion risk generated from integrated financial markets. Cerutti et al. (2017) argue that further work on integration could be done by introducing intrinsic dynamics in global financial cycles and evaluating their magnitudes using out-of-sample statistical techniques. This explicitly echos our financial integration prediction exercise. Particularly, by applying a flexible Bayesian forecasting model developed by Dangl and Halling (2012) and Koop and Korobilis (2012), we are able to understand the importance of possible determinants of financial integration over time, and the differences between each country's integration procedure. To the best of our knowledge, this is the first study in the literature that systematically forecasts financial integration using different macroeconomic predictors.

6.2.1 Construction of Macroeconomic Predictors

In this section, we discuss the potential macroeconomic predictors for financial integration. Our first potential determinant of financial integration is international trade. As trade increases economic ties between countries, such as cash flows, this may lead to an increasing link between their equity market. We, therefore, expect trade openness to positively affect financial integration. Usually, the trade channel links to international spillovers or contagion (see, Caramazza et al. (2004) and Baele and Inghelbrecht (2009) for examples). Similar to, among others, Carrieri et al. (2007) and Eiling and Gerard (2014), we measure trade openness as the ratio of imports and exports over nominal GDP in US dollars. Quarterly trade and GDP data are obtained from the IMF.

Second, we consider investment openness. A higher level of investment openness lessens restrictions encountered by investors from foreign countries and leads to greater stock market integration. According to Bekaert et al. (2002), stock market integration tends to lag financial reforms as liberalization always takes time to be effective. Thus, investment openness could be a predictor of integration. We measure investment openness as the ratio of FDI assets plus FDI liabilities over nominal GDP in dollars. FDI data is from the International Financial Statistics database based on the IMF.

Third, following Eiling and Gerard (2014), we assess the relevance of the growth in real per capital GDP as a proxy of economic growth. Real per capital GDP data comes from the IMF, World Bank, Eurostat and the OECD databases. Fourth, as Longin and Solnik (2001) and Forbes and Rigobon (2002) clearly find evidence that linkages between different financial markets increase in time of stress due to heteroskedasticity volatility, we include a business cycle variable: the NBER recession dummy.[22]

Last, we consider VIX, the Chicago Board Options Exchange (CBOE) Volatility Index, which is viewed as a measure of risk aversion and fear in financial markets. Rey (2015) uncovers that there exists a global financial cycle in risky assets around the world, which can be interpreted as the effective risk appetite of the market and realized world market volatility. It is therefore expected that this global cycle is related to the VIX index (Miranda-Agrippino and Rey, 2015; Rey, 2015). In our paper, we extract global factors from stock markets and use these factors to construct financial integration for each economy. We, thus, expect VIX could affect our financial integration measure and we believe that this is the first work that studies the relationship between VIX and financial integration.

For most of the countries, the out of sample period starts from 1990Q1. Exceptions are Singapore, for which the sample starts from 1995Q1, Japan, sample starts from 1996Q1, Hong Kong and Switzerland, sample starts from 1999Q1. Belgium and Austria have short sample periods, beginning from 2002Q1 and 2005Q1 respectively.

[22]We also consider the OECD based recession indicator, which is available for most of the countries except Hong Kong, Singapore and United States. The results are qualitatively similar.

6.2.2 Dynamic Linear Models

In this section, instead of OLS regressions, we set up dynamic linear models following Dangl and Halling (2012) to predict cross-country integration. This is because a large number of researchers have suggested that time-variation in coefficients would improve forecast performance.[23] While dynamic models capture the time-varying nature of financial integration and macroeconomic explanatory variables, constant coefficients ignore the problem of parameter instability. Here we strictly perform an out-of-sample predictive performance, in the sense that we only use available information at/or before time t to forecast the integration at time $t+1$. Particularly, the linkage between integration TVI_{t+1} and its determinants Z_t is captured using the following model:

$$TVI_{t+1} = Z_t'\theta_t + v_{t+1}, \quad v \sim N(0, V) \quad \text{(observation equation)} \tag{7}$$

$$\theta_t = \theta_{t-1} + \omega_t, \quad \omega \sim N(0, W_t) \quad \text{(system equation)} \tag{8}$$

where the vector Z_t contains possible combinations of the predictors, θ_t is the vector of time-varying coefficients which are composed to random shocks with variance matrix W_t and V is the unknown observational variance.

Let $D_t = [TVI_t, TVI_{t-1}, \ldots, Z_t, Z_{t-1}, \ldots]$ denote the information available at time t. The posteriors of the coefficients follow a multivariate t-distribution:

$$\theta_{t-1} \mid D_t \sim T_{n_t}[\hat{\theta}_t, S_t C_t^*] \tag{9}$$

where S_t is the mean of the estimated V at time t and C_t^* is the estimated, conditional covariance matrix of θ_{t-1} normalized by the observational variance. When iteratively

[23]See, for example, Dangl and Halling (2012) in the context of stock returns and Byrne et al. (2018) for exchange rate prediction.

updating the coefficients, they are exposed to Gaussian shocks W_t:

$$\theta_t \mid D_t \sim T_{n_t}[\hat{\theta}_t, R_t], \quad R_t = S_t C_t^* + W_t \tag{10}$$

Instead of specifying W_t, we apply a discount factor approach to ease computational demands:

$$R_t = \frac{1}{\delta} S_t, \quad \delta \in \delta_1, \delta_2, \ldots, \delta_d, \quad 0 < \delta_k \leq 1 \tag{11}$$

Therefore, models with constant coefficients correspond to a specification of $\delta = 1$. Whereas, setting δ below 1 implies coefficients are time-varying. As the choice of degree of variability in coefficients influences the predictive density of the dynamic linear models, we need to choose the range of δ. In general, we assume $\delta \in [0.90, 1]$.[24] When δ=0.99, the variance of the coefficient will increase 18% within five years. Whereas, for δ=0.90, this increase will jump to 88%. The latter case suggests the coefficients change rapidly and, therefore, we set it as the lower bound. We provide more details about dynamic linear models in the online appendix.

6.2.3 Dynamic Model Averaging

Since this is the first study to have examined the predictors of financial integration, there is considerable uncertainty as to which indicators contain useful information. Indeed, even though we introduce dynamics in the linear model, there is still high uncertainty regarding the choice of predictive variables.[25] The online appendix provides more details about the Dynamic Model Averaging (DMA) proposed by Raftery et al. (2010) and Koop and Korobilis (2012).

[24] Specifically, $\delta = [0.90, 0.91, 0.92, 0.93, 0.94, 0.95, 0.96, 0.97, 0.98, 0.99, 1]$

[25] For instance, assume we have m candidate indicators (including the constant), this implies $2^m - 1$ possible linear regression models. Considering d kinds of the presumed variability in the coefficients θ_t leads to a total of $d \cdot (2^m - 1)$ possible dynamic linear models. Following Dangl and Halling (2012) and Koop and Korobilis (2012), we assign diffuse prior for each model at first (i.e., $1/(d \cdot (2^m - 1))$) and the posterior probabilities of these models are updated quarter by quarter according to Bayes rule.

Generally, the DMA allows for the weights attached to each dynamic linear model to change based upon their past forecasting performances in a way that the entire forecasting model is time-varying. In particular, α is the forgetting factor that controls the degree of time-variation in forecasting models, see Raftery et al. (2010), Koop and Korobilis (2012) and Byrne and Fu (2017) for more details. For example, $\alpha = 0.95$ means that forecast performance five years ago only receives 36% weight than that last quarter. When $\alpha = 0.99$ this number increases to 82%. When $\alpha = 1$, DMA shrinks to normal Bayesian model averaging (BMA) and when $\alpha = 0$, each model has the same weight over time. Here we fix $\alpha = 0.99$ with modest change in the forecasting models. In sum, we take the uncertainty of time-variation in coefficients, in addition to the uncertainty of predictors into account when conducting the forecasting practice.

6.2.4 Forecast Results

As mentioned above, we forecast financial integration using trade, FDI, growth, NBER recessions and VIX. We focus on the importance of VIX on predicting integration, since Rey (2015) suggests this is a key driver of the financial cycle. Therefore, we compare forecast results using the DMA which includes VIX as a predictor and the DMA without VIX, while keeping other predictors the same in the predictive regressions.

In terms of forecast evaluation, we first compute the Relative Mean Squared Forecast Error (RMSFE) of DMA compared to driftless Random Walk (RW) to measure forecast performance. Values below one indicate that DMA performs better than RW. The RW is well known to be a strict out-of-sample benchmark. The RW excludes predictors and only includes a constant term with constant coefficient in the regressions. To evaluate the statistical differences in forecast, we employ the Clark and West (2007) (CW) test under the null hypothesis that the MSFE of RW is less than or equal to that of DMA.[26] The last criteria we use is the log Predictive Likelihood difference between DMA and RW (Δlog(PL)). Values above zero imply that this specification has larger predictive likelihood and it has better forecasts in a Bayesian comparison.

Table 6: Forecast Evaluation

	DMA with VIX		DMA without VIX	
	RMSFE	*Δlog(PL)*	*RMSFE*	*Δlog(PL)*
Australia	0.41***	28.72	0.44***	25.02
Austria	0.97	0.00	0.98	-0.04
Belgium	0.99*	-0.52	0.99*	-0.52
Canada	0.56***	21.45	0.67***	13.40
Denmark	0.80**	8.30	0.88*	5.11
France	0.63***	9.81	0.69*	5.61
Germany	0.38***	34.85	0.51***	24.64
Hong Kong	0.89***	2.27	0.89***	2.28
Italy	0.37***	37.50	0.49***	25.88
Japan	0.59**	22.02	0.79*	12.28
Netherlands	0.52***	27.51	0.62***	20.02
Norway	0.53***	18.00	0.68***	10.85
Singapore	0.67***	9.11	0.78***	5.98
Spain	0.68***	12.36	0.74***	10.48
Sweden	0.46***	29.30	0.49***	28.92
Switzerland	0.66***	9.69	0.74***	7.25
United Kingdom	0.79***	10.24	0.82***	8.06
United States	0.70***	12.19	0.80***	7.29

Notes: Forecast evaluation for time-varying integration using different predictors compared to driftless Random Walk (RW), the benchmark model. Specially, we consider two scenarios: DMA including VIX as a predictor and those excluding VIX. Forecast measures include the Relative Mean Squared Forecast Error (RMSFE), p values for Clark and West test and the difference of log Predictive Likelihood (Δlog(PL)). Asterisks (*10%, **5%, ***1%) relate to the Clark and West test under the null hypothesis that the MSFE of the RW is less than or equal to that of the DMA model.

Table 6 shows the forecast performance of the DMA compared to the RW. The overall story is clear: the time-varying integration we derive is highly predictable, as the DMA with VIX and the one without VIX both largely and significantly outperform RW almost for all the countries we consider. Take Italy as an example when VIX

[26] One of the advantages of the CW test is that it still follows an asymptotically standard normal distribution when comparing with the predictive results of nested models. This is exactly our case as RW is nested in our general DMA model.

is considered, the reduction in the RMSFE reaches 63%, with the CW test being rejected at the 1% significance level, and the difference in predictive likelihood 37.50. These findings have important implications for investors due to the fact that increasing integration implies decreasing international diversification. Therefore, investors could manage risk and adjust portfolio allocation, based on the prediction of the financial market integration cross-country.

We also find that although DMA's prediction of integration without VIX can dominate RW, including VIX as a predictor can improve forecast results. In particular, compared to the DMA without VIX, the RMSFE of DMA with VIX for each country is larger and the predictive likelihood of it is smaller. This extends the finding in Miranda-Agrippino and Rey (2015) that VIX interacts with the global factor. We conclude that VIX, which is constructed using the implied volatilities of a wide range of S&P 500 index options, is informative about the movements of financial integration for each country, reflecting the argument that international financial system is more vulnerable to the shocks that originate from the center economies such as the United States.

It is well known that the prediction results can be contaminated if there exists the problem of reverse causality. Therefore, to check whether financial integration reversely predict movements of the VIX index, we further employ the pair-wise Granger causality test between financial integration and VIX index for different countries in the online appendix. Importantly, according to Table A.5, we find that for all the countries we consider, we cannot reject the null hypotheses that integration does not granger cause VIX. Nevertheless, the hypotheses that VIX does not Granger cause integration can be strongly rejected, except for three Asian economies: Hong Kong, Japan and Singapore. This echoes to the finding that Hong Kong and Japan especially have different integration dynamics compared with others and is also in line with the argument that VIX is a powerful predictor for financial integration.

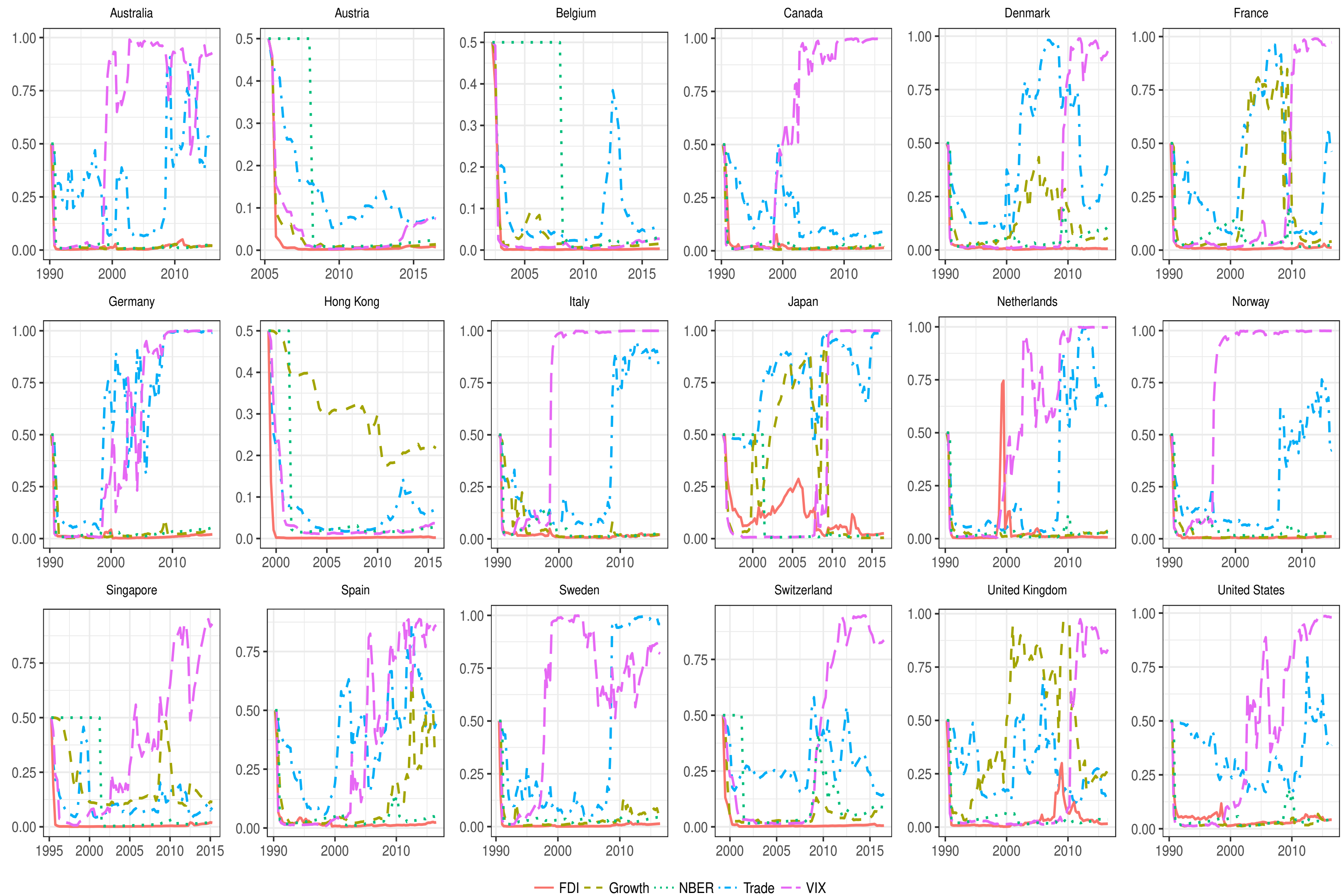
Interestingly, the literature argues that in a perfect and frictionless economy, individual stock prices reflect changes about future cash flows and discount rates. Thus, firm-level stock prices should move together due to economic fundamentals. However, in a world with frictions and irrational investors, comovement in stock prices tend to isolate from fundamentals explained by the "friction-based" and "sentiment-based" theories, see among others Pindyck and Rotemberg (1993) and Boyer (2011). We argue that time-variation in coefficients and in models could account for some degrees of the financial integration from an aggregate stock return perspective. This is analogous to the finding of Chen et al. (2016) that changes in loadings on the fundamentals relieve the evidence of excess comovement for individual stocks.

6.2.5 Time-varying Prediction Inclusion Probabilities

We aim to explain financial integration and why it changes over time. To this end, we present the time-varying posterior inclusion probabilities for each predictor across different countries. Higher inclusion probabilities imply higher predictor importance and demonstrates the different characteristics of integration predictability cross-country.

Figure 3 depicts the time-varying inclusion probabilities for different predictors. The prior of inclusion probability is 0.5 as there is equal chance that this predictor is included or not. While a higher inclusion probability implies a better predictive power, we find that financial integration for different countries has different determinants and their importance evolves over time. Therefore, it would be less appropriate to employ simple pooled cross-sectional time-series regressions and time-series regressions following Carrieri et al. (2007) and Eiling and Gerard (2014).

Figure 3: Time-Varying Inclusion Probabilities for Different Predictors



Notes: The figure shows time-varying inclusion probabilities for different predictors cross-country. The description of the predictors is as follows: FDI refers to investment openness (longdash), Growth refers to real GDP per capita (dashed), NBER refers to NBER recession dummy (dotted), Trade refers to trade openness (solid) and VIX refers to the Chicago Board Options Exchange (CBOE) Volatility Index (dotdash).

We uncover from Figure 3 that VIX becomes increasingly important at the end of the sample period, with its inclusion probability almost one for G7 and European countries. Trade openness is also highly informative about movements for most of the financial integration series. Additionally, we find some evidence suggesting that real GDP per capital affects integration, especially for Denmark, France, Hong Kong, Japan, Singapore, Spain and the United Kingdom. Whereas, investment openness is less crucial as its inclusion probabilities quickly become negligible after the initial data points, except for Japan around 2005, Netherlands around 2000 and the United Kingdom during the recent financial crisis.

Take Japan as an illustration of how the importance of predictors changes over time. Trade openness and real GDP per capital are initially influential. FDI marginally affects integration between 2000 to 2008 and the inclusion probability for NBER over the whole sample period is negligible. The importance of real GDP per capital declines and inclusion probability for investment openness spikes around 2008. From 2010, VIX gains support from the data and is included in the predictive regression. Interestingly, we notice that the inclusion probabilities of all the predictors for Austria are low after the initial data adjustment, reflecting the fact that it is the only country that fails to outperform the RW for the whole sample period.

To summarize the way in which how macro fundamentals affect integration over the whole sample period, we present the average inclusion probabilities for each predictor across countries. We also provide the average inclusion probabilities for G7 countries and for all the countries we consider. Generally, the main determinant of cross-country financial integration is our proxy for market volatility and risk aversion: the VIX index, with overall average inclusion probability of 0.38. Trade openness is the second strong predictor for integration.[27] Miranda-Agrippino and Rey (2015) point out that the gains of international financial integration could be less than the risks due to

[27]This is consist with the finding in Eiling and Gerard (2014) that trade openness affects integration measure.

volatile capital flows driven by extreme events occurred in center economies such as the United States. We confirm this statement as VIX dominates other integration drivers in general. This provides insights that peripheral countries may choose to insulate themselves from global comovements by introducing macro-prudential policies and self-insurance mechanisms.

Table 7: Average Inclusion Probabilities for Different Predictors

	VIX	FDI	Growth	NBER	Trade
Australia	0.60	0.02	0.02	0.03	0.33
Austria	0.05	0.03	0.04	0.14	0.14
Belgium	0.03	0.02	0.04	0.22	0.09
Canada	0.52	0.03	0.02	0.04	0.19
Denmark	0.28	0.02	0.13	0.06	0.42
France	0.25	0.02	0.26	0.06	0.36
Germany	0.45	0.02	0.01	0.04	0.64
Hong Kong	0.05	0.01	0.31	0.08	0.07
Italy	0.67	0.02	0.06	0.05	0.36
Japan	0.38	0.11	0.31	0.14	0.76
Netherlands	0.43	0.04	0.03	0.04	0.29
Norway	0.75	0.02	0.03	0.05	0.26
Singapore	0.37	0.01	0.19	0.16	0.12
Spain	0.35	0.02	0.12	0.05	0.38
Sweden	0.60	0.01	0.04	0.04	0.40
Switzerland	0.38	0.02	0.05	0.13	0.28
United Kingdom	0.18	0.04	0.47	0.05	0.28
United States	0.43	0.05	0.03	0.05	0.35
G7	0.41	0.04	0.17	0.06	0.42
overall average	0.38	0.03	0.12	0.08	0.32

Notes: This table presents the average inclusion probabilities for different predictors over the corresponding sample periods. The higher the inclusion probabilities, the more important the predictors are on predicting integration. The description of the predictors is as follows: FDI refers to investment openness, Growth refers to real GDP per capita, NBER refers to NBER recession dummy, Trade refers to trade openness and VIX refers to the Chicago Board Options Exchange (CBOE) Volatility Index. We also summarize the average inclusion probabilities for G7 countries and for all the countries we consider.

7 Conclusion

It is crucial to accurately measure financial integration both for academic research and policy making. A natural approach to measure integration is by an applying International CAPM model (ICAPM), in the sense that if the stock returns of different countries can be fully explained by the same global factors, they are perfectly integrated. However, a common assumption of using ICAPM to measure integration is that both the factor loadings and the stochastic volatility in the factor model are constant over time, and consequently it is unable to capture short run transitory and long run structural changes in the integration measure.

In this paper, therefore, we incorporate time-variation in factor exposures and volatility within an ICAPM model to construct financial integration. Specifically, we first apply principal component analysis to capture the financial market global factors. We then set up a model which decomposes stock returns into country-specific effects and global factors using time-varying coefficients and stochastic volatility. The time-varying financial integration is then calculated as the percentage of total return variance explained by the global factors.

We uncover that the financial integration is generally increasing, although that financial liberalization policies can stall and reverse. In contrast to other *de jure* financial openness measures such as Chinn and Ito (2008) and Abiad et al. (2010), none of the advanced economies in our sample consistently achieve full financial integration, as even for fully liberalized markets, investors still prefer investing at home due to the home bias puzzle. Financial integration reaches local maxima during the financial crisis in 2008. However, while global factors are relevant in explaining time variation of cross-market integration, the country-specific effect still prevails.

Importantly, we find that time-varying factor loadings and stochastic volatility matter when measuring integration. In particular, by testing time-variation in the factor loadings and comparing our integration measure to that drawn from constant factor loadings and risk under the ICAPM framework, we show that factor loadings are time-varying and simple ICAPM cannot reveal the linkages between different financial markets. We further check whether time trends and/or breaks exist in the time-varying integration and find that financial integration increased structurally in recent decades, consistent with the perception that financial markets are more connected due to the development of financial liberalization and capital mobility.

Finally, we illustrate that the upward trend in integration is mainly driven by increasing global comovement instead of decreasing local effects. Furthermore, integration is highly predictable by combining different dynamic linear models using macroeconomic predictors. The importance of each predictor evolves distinctly across different markets. Generally, the VIX index is highly informative about movements of integration for most economies. This is consistent with the view that financial integration is predominantly driven by extreme events originating from the United States.

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Appendices

A Detailed Estimation of The Time-varying Coefficients Model with Stochastic Volatility

Following Blake and Mumtaz (2012), we implement our time-varying coefficients model with stochastic volatility based on Metropolis-Hastings algorithm and Carter and Kohn (1994) algorithm.

- Step 1 Time 0

  Conditional on g and B_t sample h_0, the initial value of h_t from the log normal density

$$f(h_0 \mid h_1) = h_0^{-1} exp\Big(\frac{-(\ln h_0 - \mu_0)^2}{2\sigma_0}\Big) \tag{A.1}$$

  where $\mu_0 = \sigma(\frac{\overline{\mu}}{\overline{\sigma}} + \frac{\ln h_1}{g})$ and $\sigma_0 = \frac{\overline{\sigma} g}{\overline{\sigma} + g}$.

- Step 1 Time 1 to T-1

  Conditional on g and B_t draw a new h_t for each time period $t = 1$ to $T - 1$ from the candidate density

$$q(\Phi^{G+1}) = h_t^{-1} exp\Big(\frac{-(\ln h_t - \mu)^2}{2\sigma_h}\Big) \tag{A.2}$$

  where $\mu = \frac{\ln h_{t+1} + \ln h_{t-1}}{2}$ and $\sigma_h = \frac{g}{2}$. Calculate the acceptance probability

$$\alpha = \min\left(\frac{h_{t,new}^{0.5} exp(\frac{-\varepsilon_t^2}{2h_{t,new}})}{h_{t,old}^{0.5} exp(\frac{-\varepsilon_t^2}{2h_{t,old}})}, 1\right) \tag{A.3}$$

  Draw $u \sim U(0,1)$. If $u < \alpha$, set $h_t = h_{t,new}$. Otherwise retain the old draw $h_{t,old}$.

- Step 1 Time T

For $t = T$, $\mu = \ln h_{t-1}$ and $\sigma_h = g$. Draw $h_{t,new}$ from the candidate density

$$q(\Phi^{G+1}) = h_t^{-1} exp\Big(\frac{-(\ln h_t - \mu)^2}{2\sigma_h}\Big) \tag{A.4}$$

Calculate the acceptance probability

$$\alpha = \min\left(\frac{h_{t,new}^{0.5} exp(\frac{-\varepsilon_t^2}{2h_{t,new}})}{h_{t,old}^{0.5} exp(\frac{-\varepsilon_t^2}{2h_{t,old}})}, 1\right) \tag{A.5}$$

Draw $u \sim U(0,1)$. If $u < \alpha$, set $h_t = h_{t,new}$. Otherwise retain the old draw $h_{t,old}$.

- Step 2 Given a draw for h_t, compute $v_t = \ln h_t - \ln h_{t-1}$. Draw g from the following inverse Gamma distribution

$$g \sim IG(\frac{v_t' v_t + g_0}{2}, \frac{T + v0}{2}) \tag{A.6}$$

- Step 3 Conditional on h_t and Q, sample B_t using Carter and Kohn (1994) algorithm.

- Step 4 Conditional on B_t, sample Q from the inverse Wishart distribution with scale matrix $(B_t - B_{t-1})'(B_t - B_{t-1}) + Q_0$ and degrees of freedom $T_0 + T$.

- Step 5 Repeat step 1 to step 4 50,000 times. We keep the last 5,000 draws of h_t, g, B_t and Q to compute the marginal posterior distributions.

B Dynamic Linear Model

We set a natural conjugate g-prior specification of the prior information for observational variance and coefficients:

$$V \mid D_0 \sim IG[\frac{1}{2}, \frac{1}{2} S_0] \tag{B.1}$$

$$\theta_0 \mid D_0, \quad V \sim N[0, gS_0(Z'Z)^{-1}] \tag{B.2}$$

where

$$S_0 = \frac{1}{N-1} TVI^{'}(I - Z(Z'Z)^{-1}Z')TVI \tag{B.3}$$

This is a noninformative prior under the null-hypothesis of no-predictability and where g is the scaling factor that measures the confidence attached to the null-hypothesis. We perform the prediction procedure with g=50.

The posteriors of unobservable coefficients $\theta_{t-1} \mid D_t$ and the observational variance $V \mid D_t$ are of the following forms

$$V \mid D_t \sim IG[\frac{n_t}{2}, \frac{n_t S_t}{2}], \quad n_{t+1} = n_t + 1 \tag{B.4}$$

$$\theta_{t-1} \mid D_t, V \sim N[\hat{\theta}_t, VC_t^*] \tag{B.5}$$

where S_t is the mean of the observational variance V at time t, n_t is the degree of freedom and C_t^* is the conditional covariance of θ_{t-1} normalized by V. Vector of coefficients θ_t is updated using Kalman filter

$$\theta_{t-1} \mid D_t \sim T_{n_t}[\hat{\theta}_t, S_t C_t^*] \tag{B.6}$$

$$\theta_t \mid D_t \sim T_{n_t}[\hat{\theta}_t, R_t], \quad R_t = S_t C_t^* + W_t \tag{B.7}$$

where

$$\hat{\theta}_{t+1} = \hat{\theta}_t + R_t Z_t Q_{t+1}^{-1} e_{t+1} \tag{B.8}$$

$$R_{t+1} = \frac{1}{\delta}(R_t - R_t Z_t Q_{t+1}^{-1} Z_t' R_t') \tag{B.9}$$

$$e_{t+1} = TVI_{t+1} - \widehat{TVI}_{t+1} \tag{B.10}$$

$$Q_{t+1} = Z_t' R_t Z_t + S_t \tag{B.11}$$

and we assume the estimate of the observational variance S_t is constant. The predictive density is given by

$$
\begin{aligned}
f(TVI_{t+1} \mid D_t) &= \int_0^\infty [\int_\theta \varphi(TVI_t; Z_t'\theta, V)\varphi(\theta; \hat{\theta}_t, VC_t^* + W_t)d\theta] \times IG(\frac{n_t}{2}, \frac{n_t S_t}{2})dV \\
&= \int_0^\infty \varphi(TVI_t; Z_t'\hat{\theta}_t, Z_t'(VC_t^* + W_t)Z_t') + V) \times IG(\frac{n_t}{2}, \frac{n_t S_t}{2})dV \\
&= t_{n_t}(TVI_{t+1}; \widehat{TVI}_{t+1}, Q_{t+1})
\end{aligned}
\tag{B.12}
$$

C Dynamic Model Averaging

The choices of different predictors and different time-variation in coefficients crucially affect the predictive density of the individual models. We conduct the Dynamic Model Averaging following Koop and Korobilis (2012). Denote M_j^t as a certain selection of predictors from the m variables at t, and δ_k^t as a certain choice from the possible set $\{\delta_1, \delta_2, \ldots, \delta_d\}$ at time t. Given model M_j^t and $\delta = \delta_k^t$, we rewrite the estimate of TVI_{t+1} as

$$
\widehat{TVI}_{t,j}^{k} = \mathbb{E}(TVI_{t+1} \mid M_j^t, \delta_k^t, D_t) = Z_t'\hat{\theta}_t \mid M_j^t, \delta_k^t, D_t \tag{C.1}
$$

For the initial weight of each individual model, we set a diffuse conditional prior $P(M_j^0 \mid \delta_k^0, D_0) = 1/(2^m - 1)\forall i$. The posterior probabilities for model updating equation are obtained through Bayes' rule

$$
P(M_j^t \mid \delta_k^t, D_t) = \frac{f(TVI_t \mid M_j^t, \delta_k^t, D_{t-1})P(M_j^t \mid \delta_k^t, D_{t-1})}{\sum_m f(TVI_t \mid M_j^t, \delta_k^t, D_{t-1})P(M_j^t \mid \delta_k^t, D_{t-1})} \tag{C.2}
$$

where the prediction equation is

$$P(M_j^t \mid \delta_k^t, D_{t-1}) = \frac{P(M_j^{t-1} \mid \delta_k^{t-1}, D_{t-1})^\alpha}{\sum_m P(M_j^{t-1} \mid \delta_k^{t-1}, D_{t-1})^\alpha} \tag{C.3}$$

The conditional density is

$$f(TVI_t \mid M_j, \delta_k, D_{t-1}) \sim \frac{1}{\sqrt{Q_{t,j}^k}} t_{n_{t-1}} \left(\frac{TVI_t - \widehat{TVI}_{t,j}^k}{\sqrt{Q_{t,j}^k}} \right) \tag{C.4}$$

where $t_{n_{t-1}}$ is the density of a student t distribution with degrees of freedom n_{t-1}, and $Q_{t,j}^k$ is the variance of the predictive distribution of model M_j given time variation in coefficients δ_k. Average all the possible models, the return prediction given $\delta = \delta_k$ is

$$\widehat{TVI}_t^k = \sum_{j=1}^{2^m-1} P(M_j^t \mid \delta_k^t, D_t) \widehat{TVI}_{t,j}^k \tag{C.5}$$

$$P(M_j^t, \delta_k^t \mid D_t) = P(M_j^t \mid \delta_k^t, D_t) P(\delta_k^t \mid D_t) \tag{C.6}$$

We also perform Bayesian model averaging over different values of time-variation in coefficients δ. A diffuse prior probability of $1/d$ is assigned to each δ. Then the posterior probability of a certain δ at time t is given by

$$P(\delta_k^t \mid D_t) = \frac{f(TVI_t \mid \delta_k^t, D_{t-1}) P(\delta_k^t \mid D_{t-1})}{\sum_\delta f(TVI_t \mid \delta_k^t, D_{t-1}) P(\delta_k^t \mid D_{t-1})} \tag{C.7}$$

where

$$P(\delta_k^t \mid D_t) = \frac{P(\delta_k^t \mid D_{t-1})^\alpha}{\sum_d P(\delta_k^t \mid D_{t-1})^\alpha} \tag{C.8}$$

and we can tell that the time-variation in coefficients is supported by the data.

Besides, the posterior probability of a certain model given a choice of predictor and

δ is denoted as

$$P(M_j^t, \delta_k^t \mid D_t) = P(M_j^t \mid \delta_k^t, D_t) P(\delta_k^t \mid D_t) \tag{C.9}$$

Finally, the unconditional prediction of integration is

$$\widehat{TVI}_{t+1} = \sum_{k=1}^{d} P(\delta_k^t \mid D_t) \widehat{TVI}_{t+1}^{k} \tag{C.10}$$

Table A.1: MSCI Data Description and DataStream Mnemonic

Country	**Index identification**	**DataStream mnemonic**
Australia	MSCI Australia U$ - Price Index	MSAUST$
Austria	MSCI Austria U$ - Price Index	MSASTR$
Belguim	MSCI Belgium U$ - Price Index	MSBELG$
Canada	MSCI Canada U$ - Price Index	MSCNDA$
Denmark	MSCI Denmark U$ - Price Index	MSDNMK$
France	MSCI France U$ - Price Index	MSFRNC$
Germany	MSCI Germany U$ - Price Index	MSGERM$
Hong Kong	MSCI Hong Kong U$ - Price Index	MSHGKG$
Italy	MSCI Italy U$ - Price Index	MSITAL$
Japan	MSCI Japan U$ - Price Index	MSJPAN$
Netherlands	MSCI Netherlands U$ - Price Index	MSNETH$
Norway	MSCI Norway U$ - Price Index	MSNWAY$
Singapore	MSCI Singapore U$ - Price Index	MSSING$
Spain	MSCI Spain U$ - Price Index	MSSPAN$
Sweden	MSCI Sweden U$ - Price Index	MSSWDN$
Switzerland	MSCI Switzerland U$ - Price Index	MSSWIT$
United Kingdom	MSCI UK U$ - Price Index	MSUTDK$
United States	MSCI USA U$ - Price Index	MSUSAM$

Notes: Country-specific MSCI price index and its DataStream mnemonic. All index values are converted in to the U.S. dollar. For each country, data starts from 31-Dec-1969 to 11-Jan-2017. 2445 weekly observations are obtained.

Table A.2: Trend and Break Tests of H-P Filtered Financial Integration

	Trend Test		Break Test			
	Trend	*t test*	W_{RQF}	T_{break}	*Before*	*After*
Australia	0.10%	1.09	1.54	1998Q2	0.30	0.46
Austria	0.11%	0.71	1.59	1985Q4	0.28	0.34
Belgium	0.07%	0.70	1.41	2002Q1	0.14	0.28
Canada	0.08%	1.87*	1.37	2007Q4	0.34	0.48
Denmark	0.13%	1.81*	0.43	2000Q4	0.26	0.34
France	0.26%	2.22**	1.05	2000Q1	0.32	0.47
Germany	0.13%	1.53	2.29	1998Q2	0.32	0.49
Hong Kong	0.25%	2.33**	8.22***	1986Q2	0.57	0.73
Italy	0.13%	0.90	1.12	1998Q3	0.36	0.58
Japan	0.11%	1.27	1.67	2007Q1	0.15	0.28
Netherlands	0.15%	1.54	3.45**	2007Q4	0.37	0.56
Norway	0.07%	0.71	1.19	1998Q1	0.40	0.56
Singapore	0.23%	2.35**	3.93**	1984Q3	0.36	0.56
Spain	0.17%	2.00**	2.58*	2008Q3	0.50	0.65
Sweden	0.10%	0.85	1.87	1997Q1	0.31	0.47
Switzerland	0.29%	2.38**	1.06	2000Q2	0.41	0.53
United Kingdom	0.18%	1.45	0.60	2000Q3	0.35	0.49
United States	0.08%	1.46	1.84	2007Q4	0.44	0.57

Notes: See detailed notes in table 3 and 4.

Table A.3: Test for Differences in Means Between Integration Derived from Constant Parameters and Our Integration Measure

	Test stat.		*Test stat.*
Australia	-38.43***	Japan	-20.82***
Austria	-33.18***	Netherlands	-39.64***
Belgium	-25.91***	Norway	-43.65***
Canada	-41.81***	Singapore	-40.16***
Denmark	-29.13***	Spain	-51.31***
France	-27.82***	Sweden	-36.54***
Germany	-40.38***	Switzerland	-37.14***
Hong Kong	-60.48***	United Kingdom	-31.81***
Italy	-37.36***	United States	-48.46***

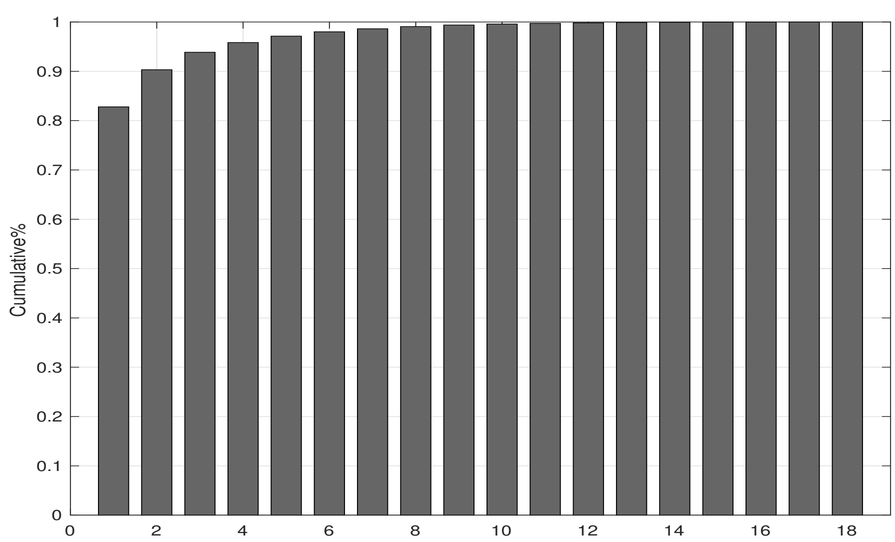
Notes: This table reports t statistics with Newey-West correction for a one-sided test based on the null hypothesis that the mean of the integration derived from constant parameters is higher than our integration measure for the corresponding country. The 1%(*), 5%(**) and 10% (***) critical values are 2.33, 1.65 and 1.28 respectively.

Table A.4: Test for Differences in Means of Integration Before and After Breaks

	Test stat.		*Test stat.*
Australia	-11.59***	Japan	-5.56***
Austria	-2.18**	Netherlands	-9.83***
Belgium	-11.36***	Norway	-4.41***
Canada	-7.94***	Singapore	-8.69***
Denmark	-2.90***	Spain	-7.88***
France	-4.62***	Sweden	-9.45***
Germany	-9.20***	Switzerland	-3.89***
Hong Kong	-6.52***	United Kingdom	-4.61***
Italy	-13.88***	United States	-6.41***

Notes: This table reports t statistics with Newey-West correction for a one-sided test based on the null hypothesis that the mean of the integration before the breaks is higher than that after the breaks. The 1%(*), 5%(**) and 10% (***) critical values are 2.33, 1.65 and 1.28 respectively.

Figure A.1: Average Cumulative Percentage of Variance Explained by the Out-of-sample Principal Components



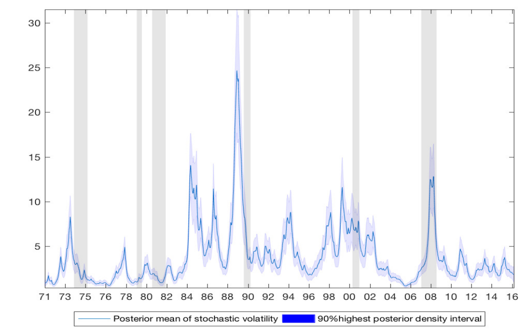
Notes: The figure shows the average cumulative percentage of variance explained by all the 18 out-of-sample principal components.

Table A.5: Pair-Wise Granger Causality Test Between Integration and VIX

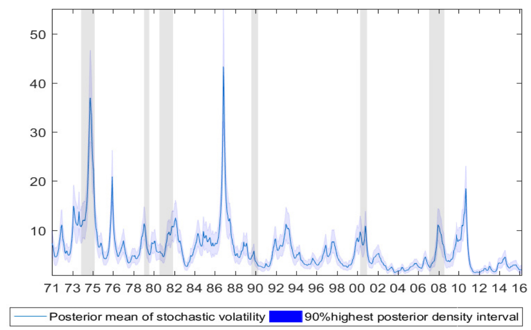
Country	Null Hypotheses	F stat	Prob
Australia	Integration does not Granger cause VIX	0.04	0.84
	VIX does not Granger cause integration	4.55	**0.01*****
Austria	Integration does not Granger cause VIX	0.03	0.87
	VIX does not Granger cause integration	3.82	**0.03****
Belgium	Integration does not Granger cause VIX	0.86	0.36
	VIX does not Granger cause integration	2.83	**0.06***
Canada	Integration does not Granger cause VIX	0.27	0.61
	VIX does not Granger cause integration	5.31	**0.01*****
Denmark	Integration does not Granger cause VIX	1.27	0.26
	VIX does not Granger cause integration	5.35	**0.02****
France	Integration does not Granger cause VIX	1.65	0.20
	VIX does not Granger cause integration	2.94	**0.01*****
Germany	Integration does not Granger cause VIX	0.07	0.79
	VIX does not Granger cause integration	3.43	**0.00*****
Hong Kong	Integration does not Granger cause VIX	1.56	0.20
	VIX does not Granger cause integration	0.53	0.72
Italy	Integration does not Granger cause VIX	0.18	0.67
	VIX does not Granger cause integration	4.21	**0.02****
Japan	Integration does not Granger cause VIX	0.10	0.75
	VIX does not Granger cause integration	0.16	0.69
Netherlands	Integration does not Granger cause VIX	0.04	0.84
	VIX does not Granger cause integration	4.22	**0.02****
Norway	Integration does not Granger cause VIX	0.22	0.64
	VIX does not Granger cause integration	4.79	**0.01*****
Singapore	Integration does not Granger cause VIX	0.07	0.80
	VIX does not Granger cause integration	1.62	0.20
Spain	Integration does not Granger cause VIX	0.31	0.58
	VIX does not Granger cause integration	3.34	**0.04****
Sweden	Integration does not Granger cause VIX	0.03	0.86
	VIX does not Granger cause integration	3.81	**0.03****
Switzerland	Integration does not Granger cause VIX	0.25	0.62
	VIX does not Granger cause integration	5.42	**0.01*****
United Kingdom	Integration does not Granger cause VIX	0.17	0.68
	VIX does not Granger cause integration	4.78	**0.03****
United States	Integration does not Granger cause VIX	0.17	0.68
	VIX does not Granger cause integration	3.44	**0.04****

Notes: This table reports F statistics and p values for the granger causality test between financial integration and VIX for different countries. The order of the granger causality test is optimally selected by the AIC and BIC criterion.

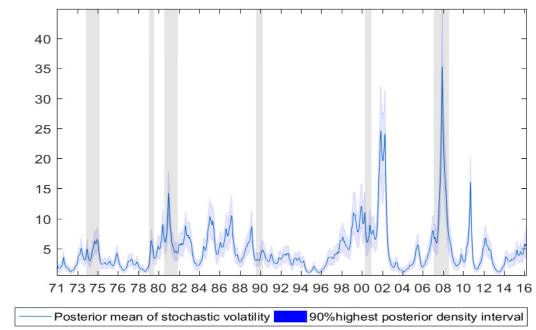
Figure A.2: Stochastic Volatility



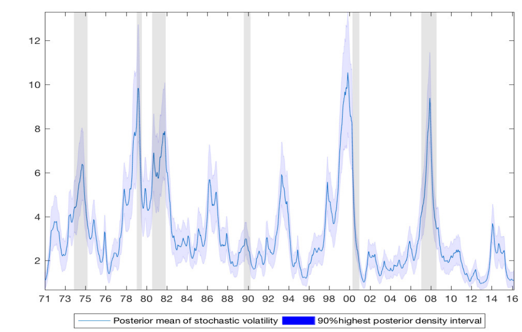
(a) Australia



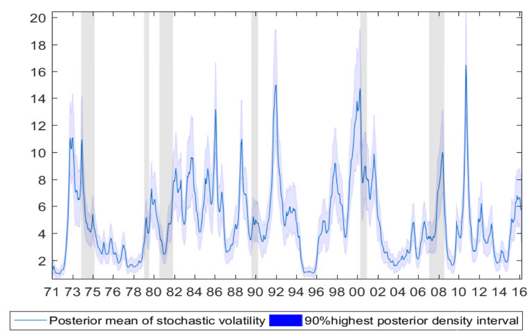
(b) Austria



(c) Belgium



(d) Canada



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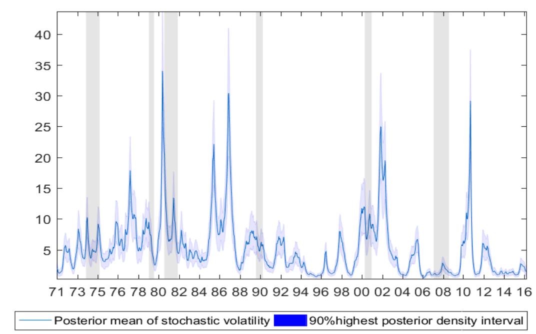
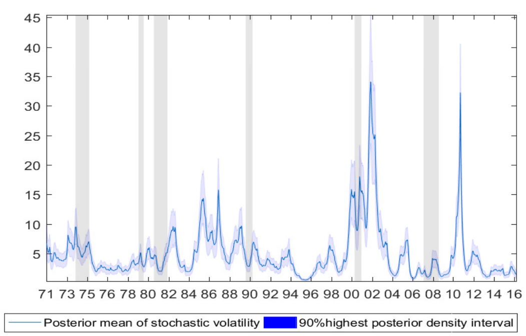
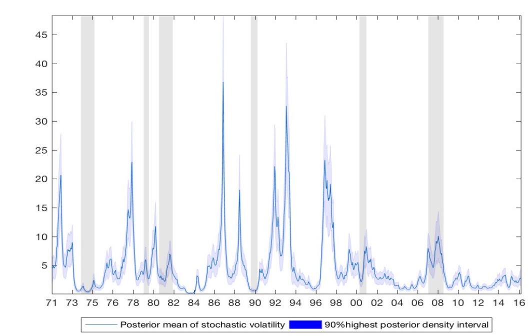


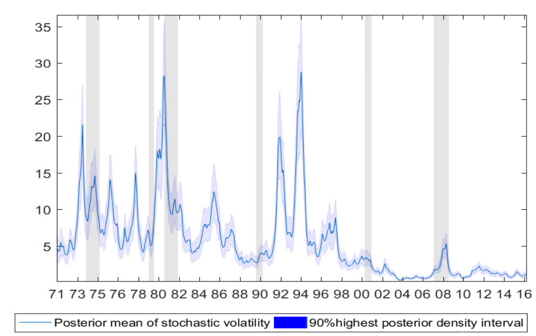
(f) France



(g) Germany

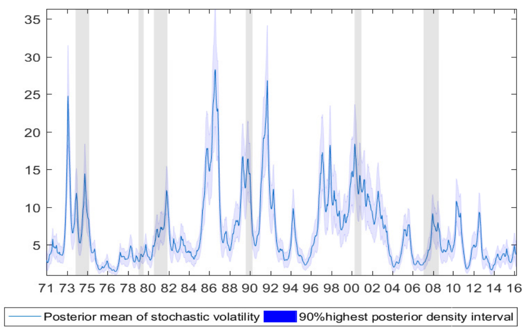


(h) Hong Kong

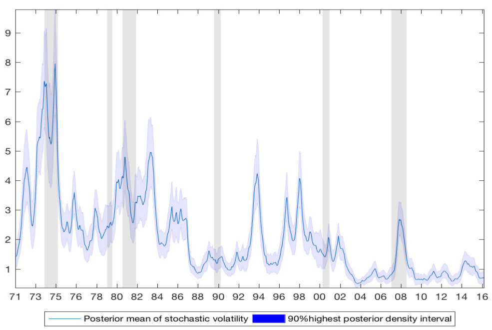


(i) Italy

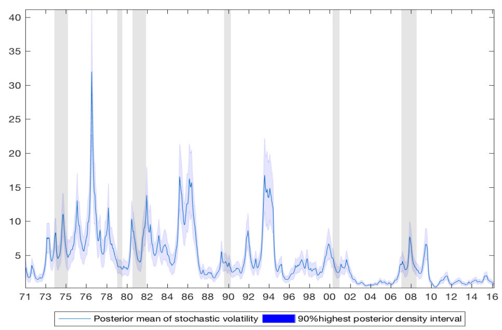
Figure A.2 (Cont.): Stochastic Volatility



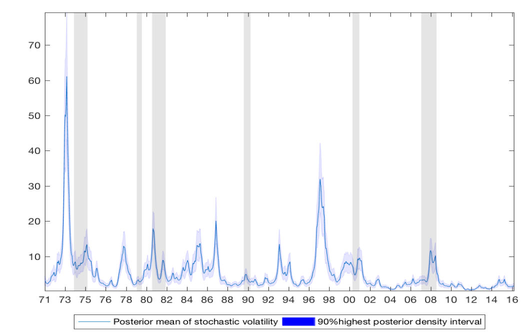
(a) Japan



(b) Netherlands



(c) Norway



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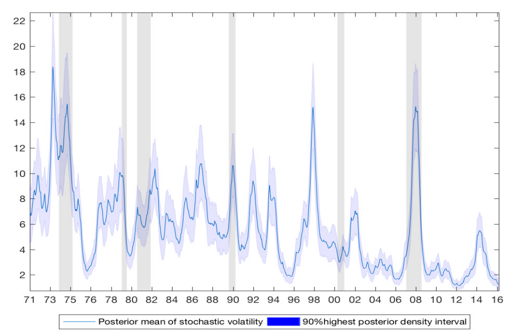
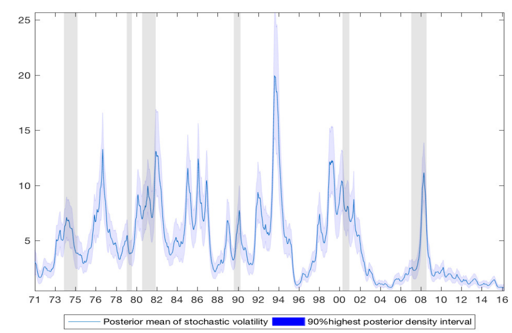
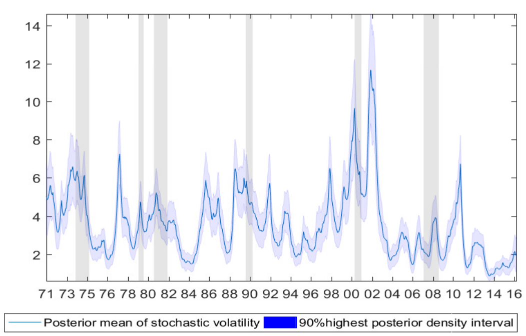


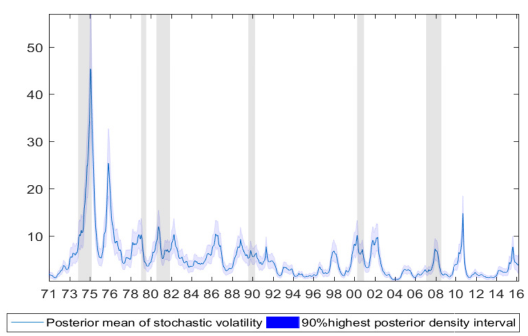
(e) Spain



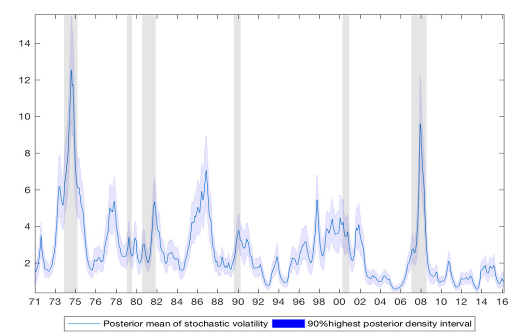
(f) Sweden



(g) Switzerland



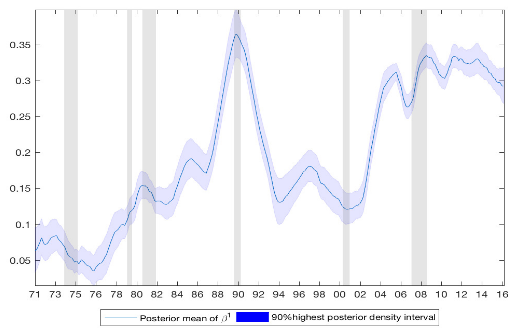
(h) United Kingdom



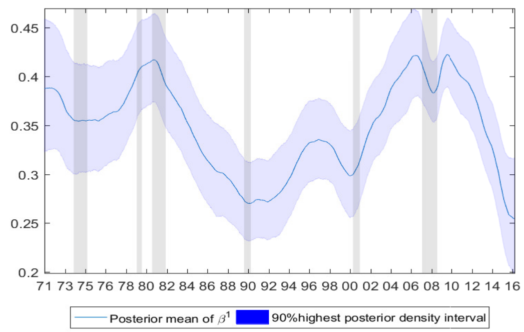
(i) United States

Notes: This figure shows the stochastic volatility $h_{i,t}$ in Equation (1) for different countries. The shaded area is the NBER recession dates.

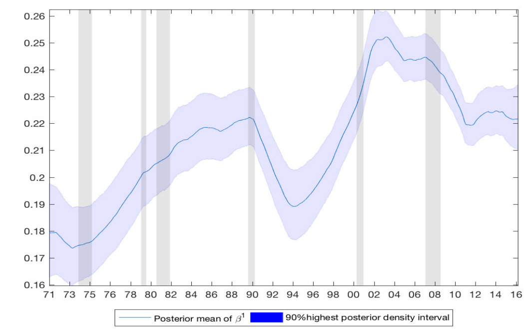
Figure A.3: Factor Loading on The First Global Factor



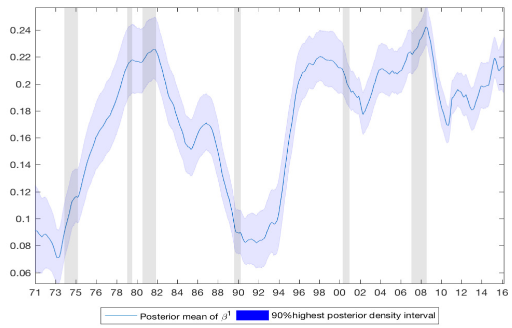
(a) Australia



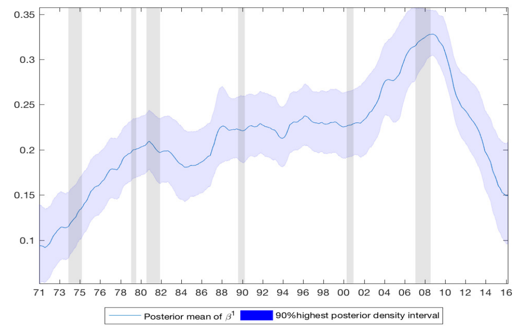
(b) Austria



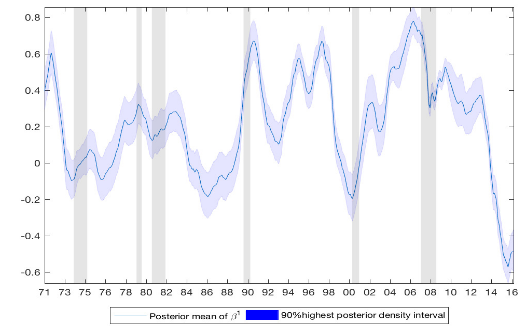
(c) Belgium



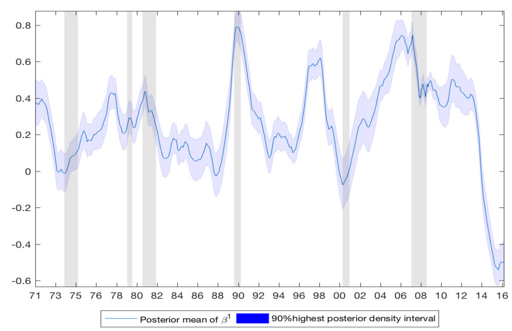
(d) Canada



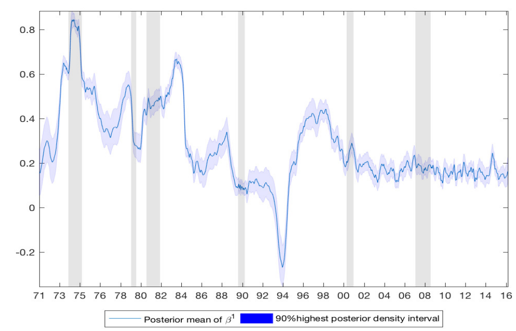
(e) Denmark



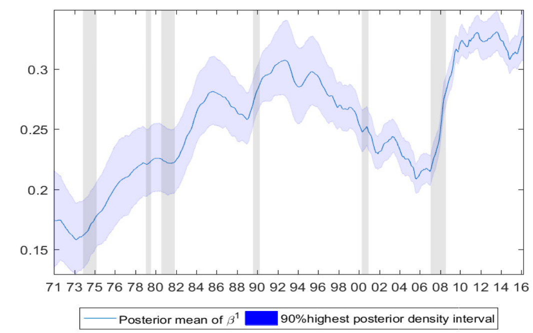
(f) France



(g) Germany

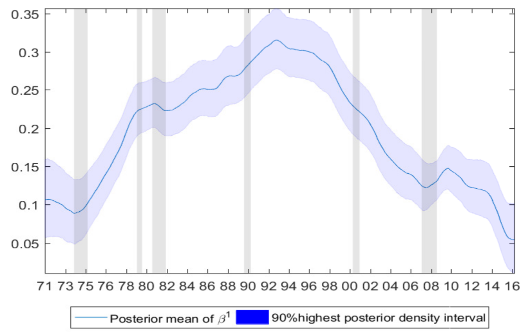


(h) Hong Kong

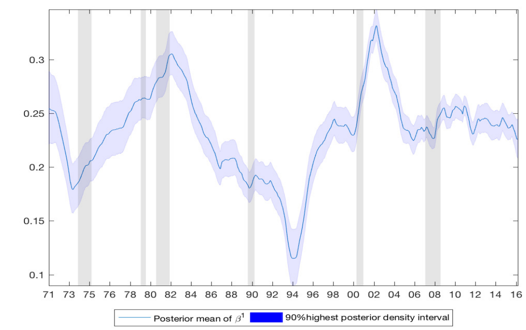


(i) Italy

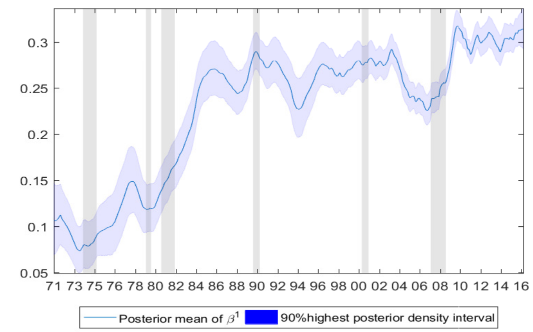
Figure A.3 (Cont.): Factor Loading on The First Global Factor



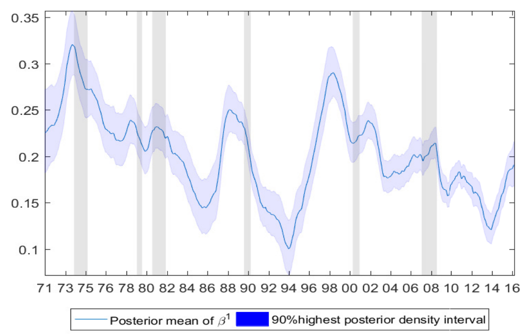
(a) Japan



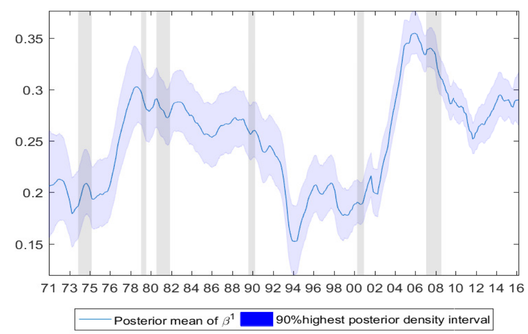
(b) Netherlands



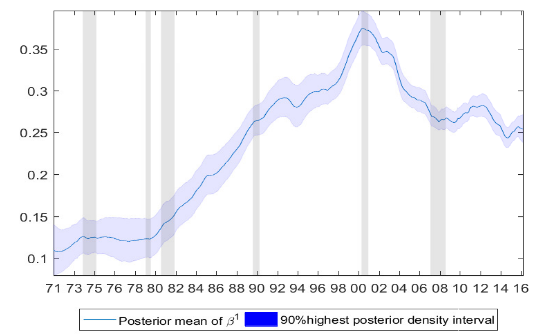
(c) Norway



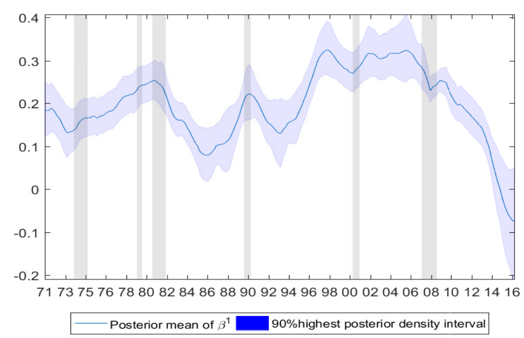
(d) Singapore



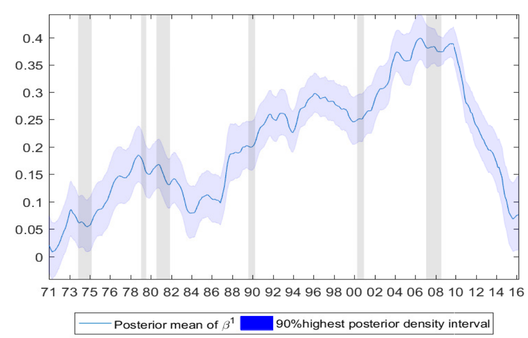
(e) Spain



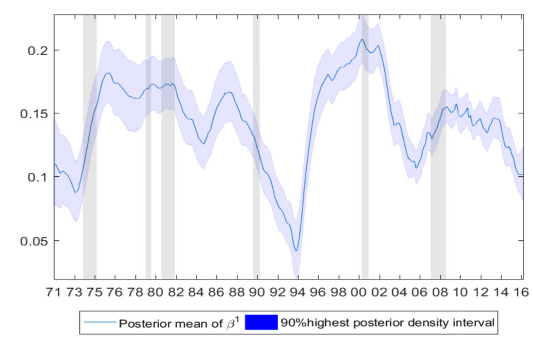
(f) Sweden



(g) Switzerland



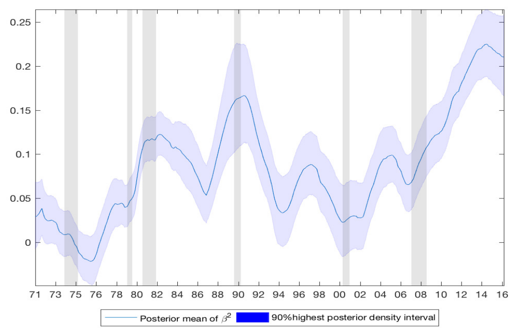
(h) United Kingdom



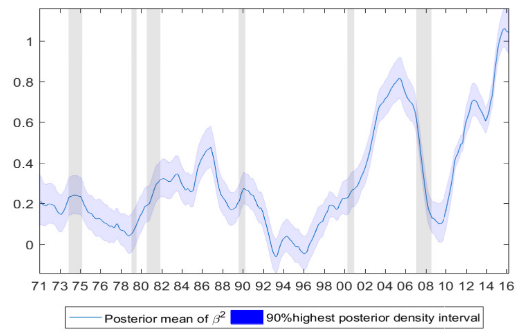
(i) United States

Notes: This figure shows the factor loading on the first global factor $\beta^1_{i,t}$ in Equation (1) for different countries. The shaded area is the NBER recession dates.

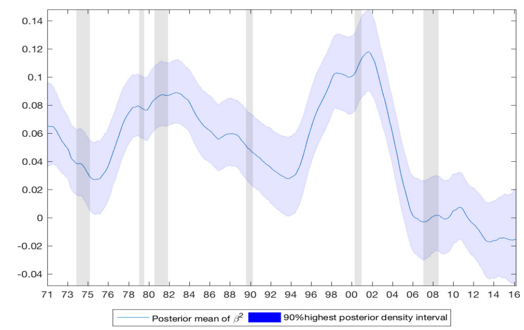
Figure A.4: Factor Loading on The Second Global Factor



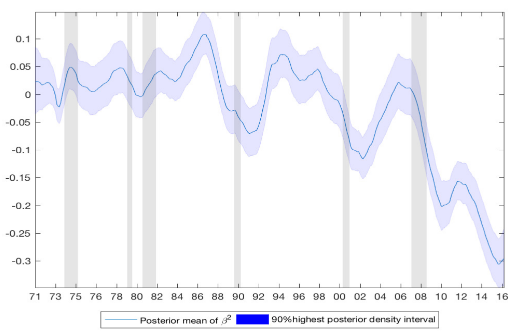
(a) Australia



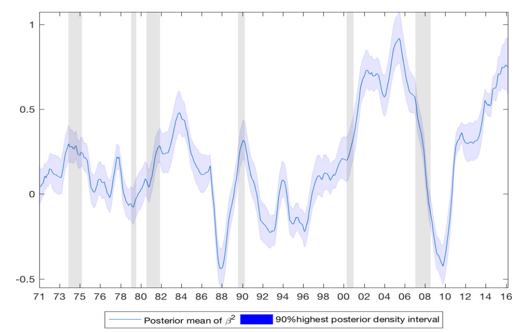
(b) Austria



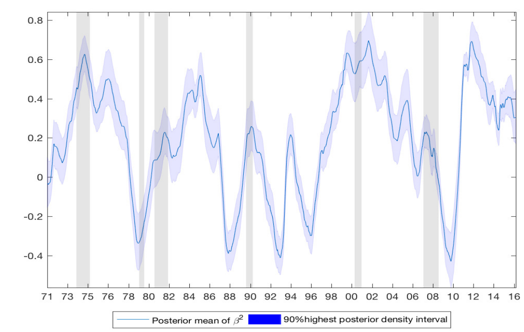
(c) Belgium



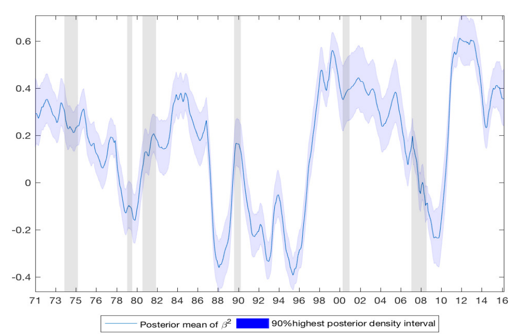
(d) Canada



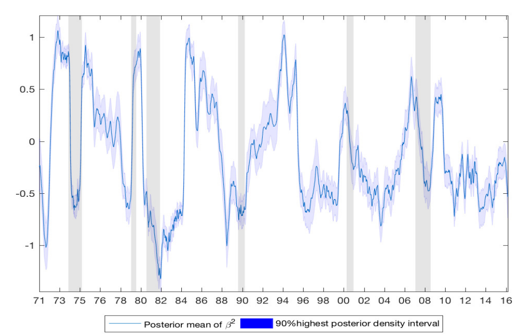
(e) Denmark



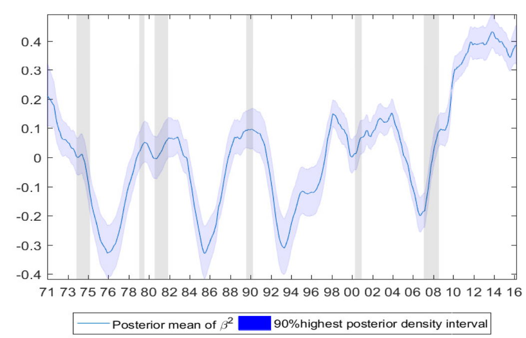
(f) France



(g) Germany

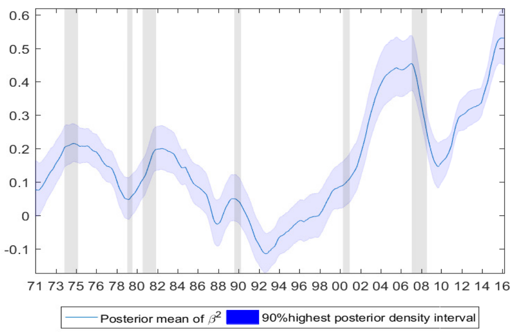


(h) Hong Kong

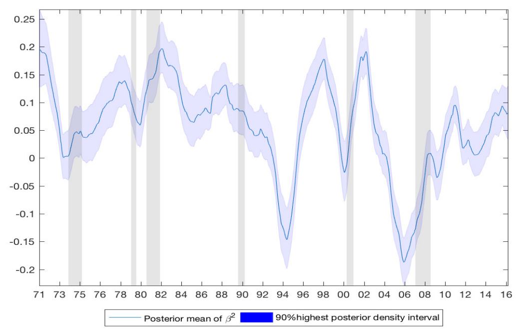


(i) Italy

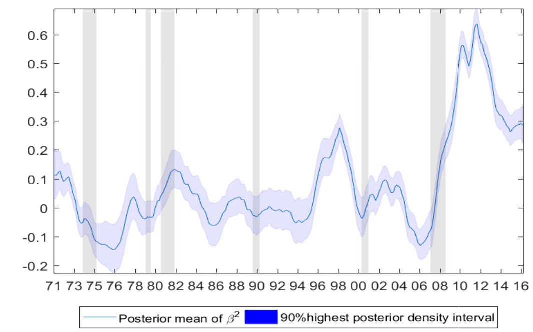
Figure A.4 (Cont.): Factor Loading on The Second Global Factor



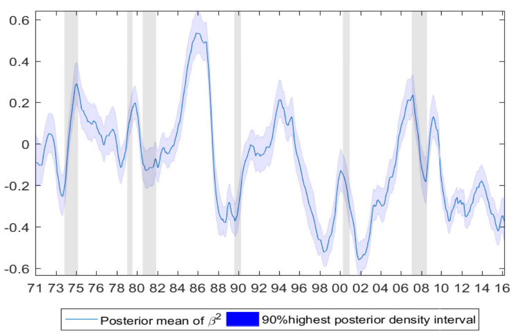
(a) Japan



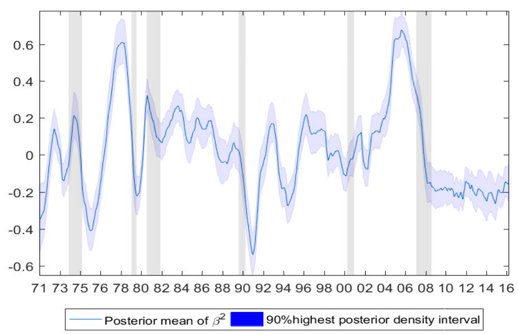
(b) Netherlands



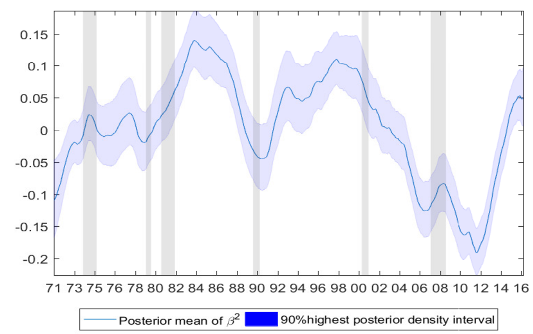
(c) Norway



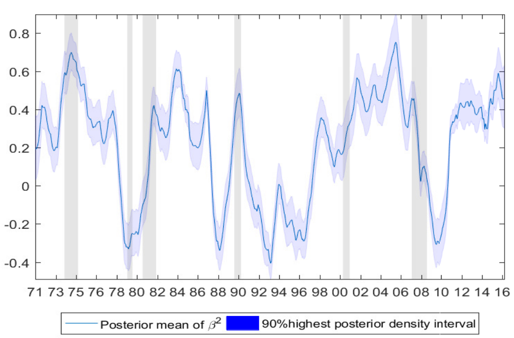
(d) Singapore



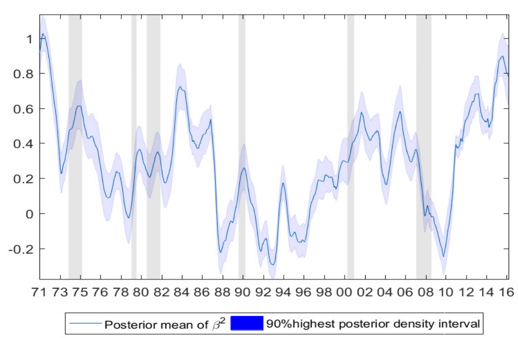
(e) Spain



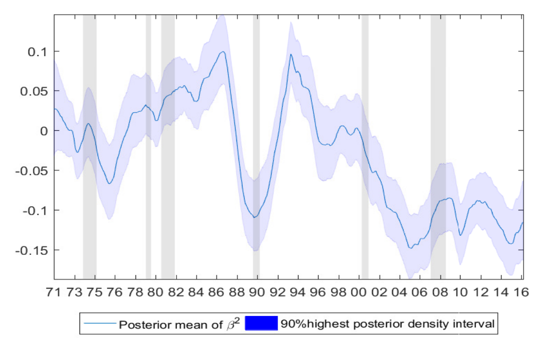
(f) Sweden



(g) Switzerland



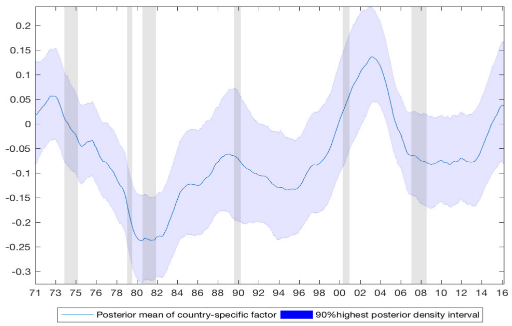
(h) United Kingdom



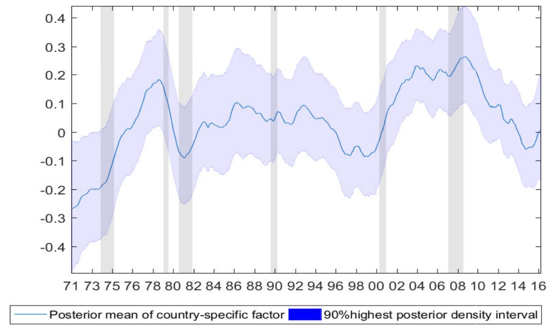
(i) United States

Notes: This figure shows the factor loading on the second global factor $\beta^2_{i,t}$ in Equation (1) for different countries. The shaded area is the NBER recession dates.

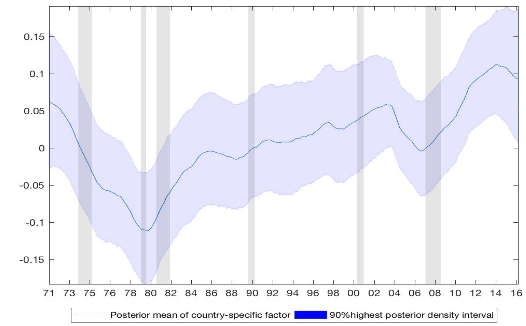
Figure A.5: Country-specific Factor



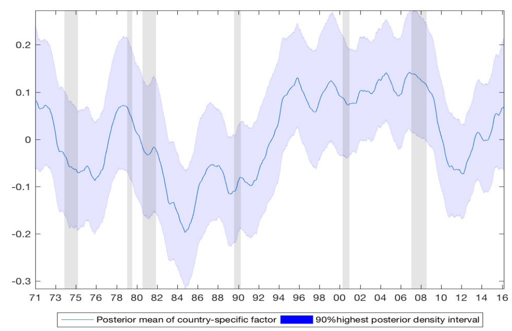
(a) Australia



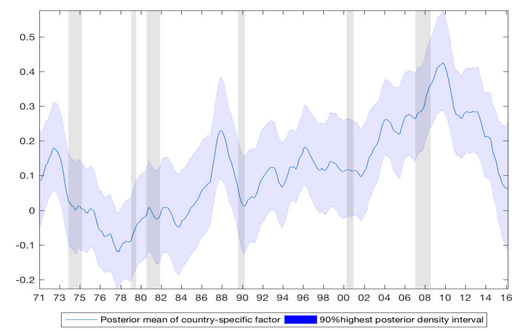
(b) Austria



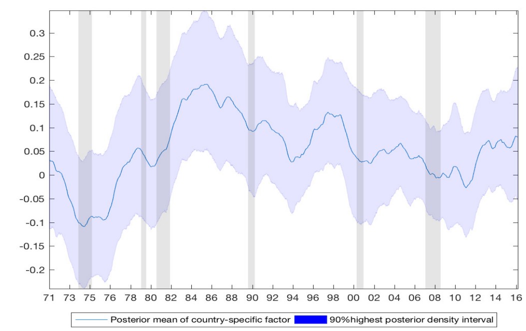
(c) Belgium



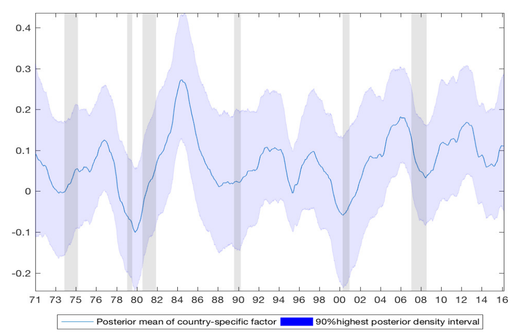
(d) Canada



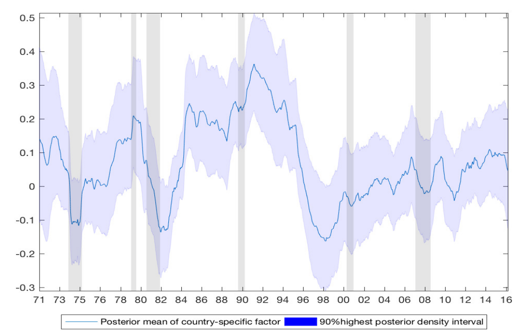
(e) Denmark



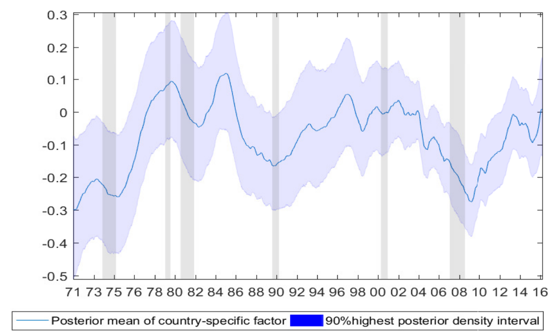
(f) France



(g) Germany

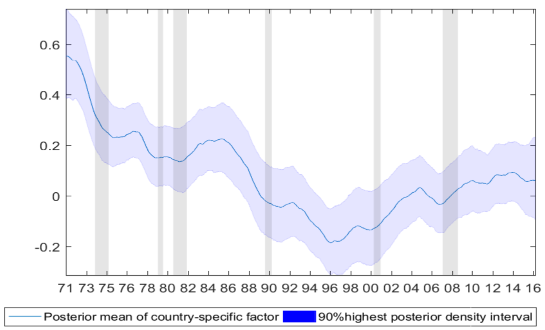


(h) Hong Kong

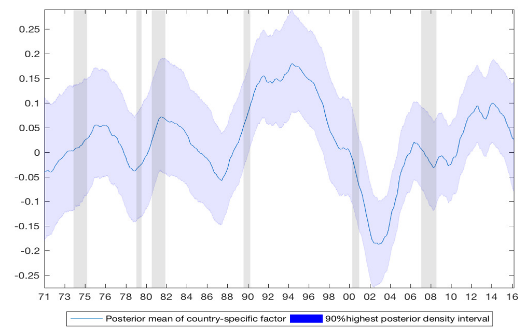


(i) Italy

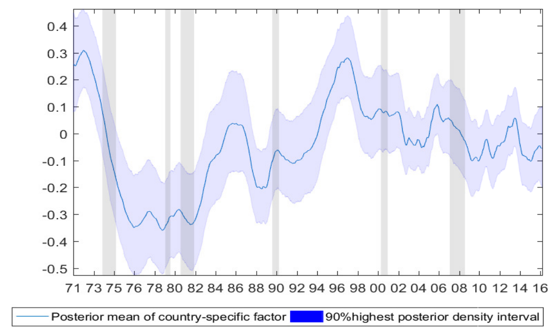
Figure A.5 (Cont.): Country-specific Factor



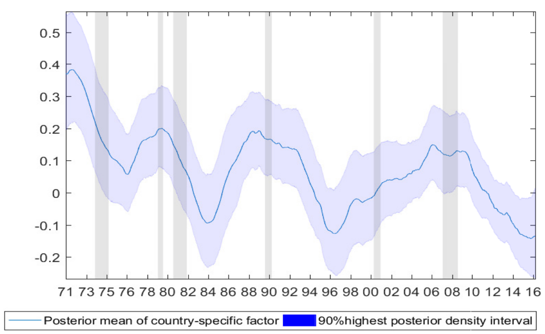
(a) Japan



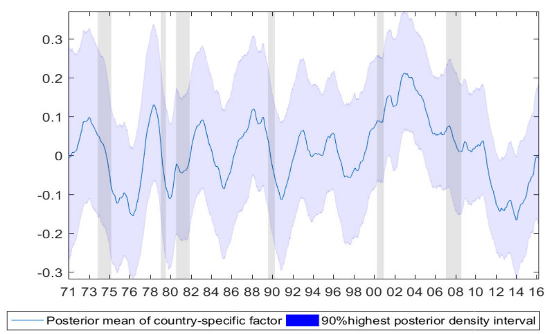
(b) Netherlands



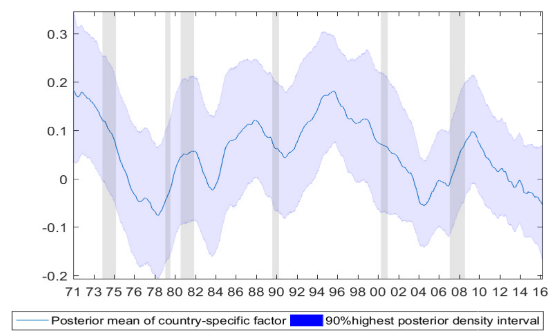
(c) Norway



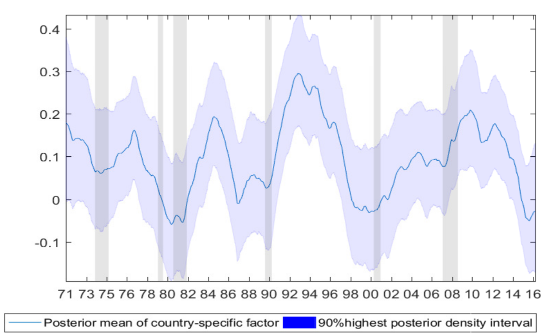
(d) Singapore



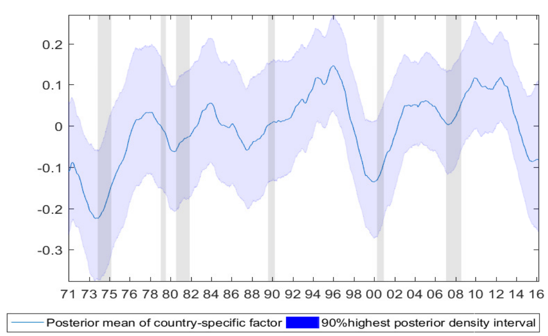
(e) Spain



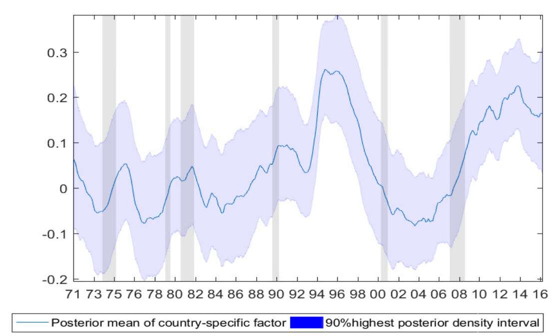
(f) Sweden



(g) Switzerland



(h) United Kingdom



(i) USA

Notes: This figure shows the country-specific factor $\mu_{i,t}$ in Equation (1) for different countries. The shaded area is the NBER recession dates.