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WORKING PAPER

A new model-based approach to measuring time-varying financial market integration

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A new model-based approach to measuring time-varying financial market integration

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Abstract

We investigate financial market integration by looking at the stock market linkages of five developed countries (France, Germany, Japan, the UK, and the US) over the period 1970:1-2010:8. We measure the time-varying degree of world stock market integration of each country through the conditional variance of the country-specific premium in equity excess returns. The country-specific premiums are derived theoretically from an international CAPM with market imperfections. They are estimated from the latent factor decomposition implied by the theory through the use of state space methods that allow for $GARCH$ errors. Our empirical results suggest that stock market integration has increased over the period 1970:1-2010:8 in all countries but Japan. And while there is a structural increase in stock market integration in four out of five countries, all countries also exhibit several shorter periods of disintegration (reversals), i.e. periods in which country-specific shocks play a more dominant role. Hence, stock market integration is measured as a dynamic process that is fluctuating in the short run while gradually increasing in the long run.

JEL Classification: G15, C32

Keywords: financial markets, integration, factor model, unobserved component, GARCH

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1 Introduction

The question of whether the integration between the financial markets of different countries changes over time has been at the forefront of both academic research and policy making. Knowledge of the degree of financial market integration is important for different reasons. Increased financial market integration may reduce the possibility of risk diversification by decreasing the volatility of the country-specific or idiosyncratic component of asset returns. Financial integration, by reducing the portfolio home bias of investors (i.e. the tendency of investors to overweight domestic assets in their portfolios), may increase market efficiency. Increased financial market integration may also imply that domestic shocks spill over to other countries, thereby making the entire international financial system sensitive to country-specific shocks. Finally, the process of globalization and increased financial market integration may be responsible for diverging global current account positions.

Although the general perception exists that financial market integration has increased during the past decades the empirical literature is less clear on this.[1]

For stock markets Roll (1989) reviews different papers from the 1980s and argues that cross-country correlations of equity returns in the 1980s are only marginally higher than in the 1970s. King et al. (1994) argue that estimates pointing toward increased integration in the late 1980s are confusing transitory increases in stock market return correlations (i.e. due to the 1987 crash which had a global impact) with permanent ones. Bekaert and Harvey (1995) find that stock market integration in the 1970s, 1980s, and the early 1990s has increased in some emerging countries while decreasing in others. Ramchand and Susmel (1998) and Ball and Torous (2000) find that correlations among major stock markets are time-varying but they do not find evidence of a structural increase in stock market integration.[2] Longin and Solnik (1995), on the other hand, find an important increase in cross-country correlations between the stock markets of seven countries (France, Germany, Switzerland, UK, Japan, Canada, US) over the period 1960-1990. Ammer and Mei (1996) find stronger linkages between the stock markets of the UK and the US after the abandonment of the Bretton Woods currency arrangement. Berben and Jansen (2005a) find that

[1] Given the large literature on the topic the literature overview that follows is unavoidably incomplete. First, we mention only studies that explicitly tackle time-variation in integration. Second, the studies mentioned focus on asset returns. We do not discuss papers that study integration through asset indices/prices. Third, we focus on time-variation in integration occurring during the past three to four decades. For a long-run perspective on equity market integration see e.g. Goetzmann et al. (2005).

[2] Some authors (see Brooks and Del Negro (2002) and citations therein) study the relative impact on equity returns of country-specific factors versus industry factors. Brooks and Del Negro (2002) find no evidence of a systematic global increase of industry effects relative to country factors suggesting that there is no real increase in global financial market integration. They report the opposite conclusion for Europe however suggesting that EMU is promoting greater integration across European stock markets. Similarly, Adjaoute and Danthine (2004 and citations therein) point to evidence suggesting that industry factors have become more important than country factors in the euro area.

the correlations between German, UK, and US equity returns have doubled over the period 1980-2000 while remaining unchanged in Japan. Carrieri et al. (2007) find that the evolution towards more stock market integration is apparent for eight emerging economies over the period 1977-2000 though the integration process is also characterized by temporary reversals. For European countries Baele et al. (2004), Hardouvelis et al. (2006), and Cappiello et al. (2006) document an increase in stock market integration of countries joining the European Monetary Union.[3] The impact of monetary unification on the degree of stock market integration is not always unambiguous however as Berben and Jansen (2005b) argue that European stock market integration was largely independent of monetary unification.

For government bond markets Barr and Priestley (2004) reject time-variation in the degree of integration of Canada, Germany, Japan, the UK, and the US in the world government bond market. Focusing on Europe however Baele et al. (2004), Berben and Jansen (2005b), Cappiello et al. (2006), and Pozzi and Wolswijk (2010) document an increase in government bond market integration of countries joining the European Monetary Union.

In this paper we present a new empirical approach to investigate the time-varying integration of the stock markets of five developed countries (France, Germany, Japan, the UK, and the US). The approach combines a number of advantages which are seldom or never simultaneously achieved by the existing methodolgies. First, the method is model-based. Second, the estimation method employed takes into consideration all countries simultaneously as opposed to an approach based on correlations between only two countries at a time. Third, the specification used to capture the time-varying degree of integration can simultaneously capture short run transitory and long run structural changes in integration.[4] Fourth, the approach is data-based as it exploits the typical characteristics of financial market data to construct a measure of financial market integration. Fifth, the approach avoids the use of, potentially low-quality, instruments and conditioning variables to proxy country-specific and common risk premiums in returns data and/or to calculate the degree of integration.[5] Sixth, the approach is widely applicable.

These advantages are clarified by discussing the contribution of the paper to the literature which is threefold.

First, we study financial market integration in a specific theoretical context. We consider an

[3]Further studies that document an increase in stock market integration related to the start of EMU include Fratzscher (2002), Kim et al. (2005), Kearney and Poti (2006), and Christiansen (2010).

[4]In the literature some papers use a markov switching specification for the degree of integration which is well suited to capture transitory changes while other papers use deterministic specifications like time trends which are better suited to capture structural changes.

[5]Often the inclusion of certain instruments is based solely on their performance in other datasets and studies. As a result, instruments may be of poor quality and the conditioning information may be inadequate to accurately estimate country-specific and common equity risk premiums and/or the degree of financial market integration.

international version of the Capital Asset Pricing Model (CAPM) with market imperfections (e.g. liquidity risk) as presented by Acharya and Pedersen (1995). In this framework, considered previously by Pozzi and Wolswijk (2010), a representative global investor invests in the equity markets of different countries. The investor takes the costs of impediments encountered on the equity market of each individual country into account. These impediments can include transaction and information costs investors face as well as various legal restrictions and investment barriers applied to foreign investors. Excess returns of each country are then driven by a country-specific or idiosyncratic factor on top of the standard risk factor that is common across countries. We define financial market integration as a decrease in the country-specific risk factor. Full integration of a country's stock market with the stock markets of the other countries is achieved when its country-specific risk factor equals zero. In that case the model collapses to Harvey's (1991) standard international CAPM. This approach of considering an international version of Acharya and Pedersen's (2005) CAPM with market imperfections leads to a somewhat different framework to study time-varying financial market integration than the one put forward by Bekaert and Harvey (1995). In their framework integration or disintegration is the movement between two *polar* asset pricing models (a fully segmented national CAPM versus a fully integrated international CAPM). In our framework integration or disintegration is the movement between two *nested* asset pricing models: an international CAPM with impediments to invest in the local asset markets which encompasses a standard international CAPM. The main implication is that the excess returns in our model are at all times affected by the global risk factor whereas this is not the case in Bekaert and Harvey's (1995) set-up.

Second, we use state space methods to estimate the latent factor decomposition of the excess returns as implied by the theoretical model. A state space system approach makes it possible to consider all countries simultaneously and is naturally well-suited to capture the dynamics of the integration process as it easily allows for time-variation in the variances of the factors as well as in the parameters of the system. State space methods have the additional advantage that stochastic processes can be assumed for the unobserved factors (i.e. the country-specific premium and the common risk factor). These factors are then filtered out of the excess returns data with the Kalman filter. Hence, neither the country-specific premiums nor the return on the global portfolio need to be obtained through the use of conditioning variables.

Third, our framework exploits the typical characteristics of financial data to construct a measure of stock market integration. In particular, stock market excess returns are characterized by time-varying and persistent conditional variances which are well captured by (integrated) generalized autoregressive conditional heteroskedasticity or $(I)GARCH$ processes (see Tsay, 2005, p.113-120, and Enders, 2004, p.140-141). Since stock market integration depends on the (volatility of the) country-specific factor in the excess returns we can measure the degree of stock market integration with an indicator that is constructed from the estimated time-varying conditional variance series of the country-specific factor. Additionally, a conditional variance analysis of the excess returns is possible which offers yet another way to measure the degree of stock market integration. Importantly, both measures can capture the potential long run structural trend in stock market integration as well shorter run transitory movements.

While our application investigates the integration of stock markets in five developed countries, the methodology can easily be applied to different countries (e.g. developing or emerging countries), to larger groups of countries (e.g. all OECD countries, all euro area countries), or to different types of assets (e.g. bonds).

Using monthly data on stock market excess returns of France, Germany, Japan, the UK, and the US our results suggest that stock market integration has increased over the period 1970:1-2010:8 in all countries but Japan. By the end of the sample period the common factor in stock market excess returns accounts for well above 65% of the overall fluctuations in excess returns of France, Germany, the UK, and the US. France and Germany are the most integrated markets. They are followed by the UK and the US which are also relatively well integrated in the world financial markets. The integration of Japan with the other countries under consideration is relatively low and has not increased over the sample period. The result for Japan confirms earlier findings by Kaltenhaeuser (2003) and Berben and Jansen (2005a).

Besides the structural increase observed in stock market integration in four out of five countries, all countries also exhibit several shorter periods of disintegration, i.e. reversal periods in which country-specific shocks play a more dominant role. Hence, financial market integration is measured as a dynamic process that is fluctuating in the short run while gradually increasing in the long run.

The remainder of the paper is structured as follows: Section 2 presents the theory, Section 3 outlines the empirical specification and elaborates on the estimation methodology, Section 4 explains the data and presents the estimation results, while Section 5 concludes.

2 Theory

Pozzi and Wolswijk (2010) consider an international version of Acharya and Pedersen's (2005) CAPM with market imperfections. While their model focuses on government bonds, in this paper we analyze equity returns. A utility maximizing representative international investor invests in the equity markets of N different countries ($i = 1, ..., N$), in a risk-free asset, and in an international portfolio. The period t excess returns on stocks of country i ($\forall i$) and the period t excess return on the global portfolio are denoted by R_{it} ($\forall i$) and W_t respectively. When investing in equity of country i the investor takes into account the costs of impediments encountered on the stock market of country i which are captured by the variable I_{it}. These costs are purely country-specific or idiosyncratic and reflect the compensation that the investor asks to be willing to invest in country i. Excess returns are expressed in local currency imlying that investors perfectly hedge against exchange rate risk (see e.g. Ilmanen 1995). Hence exchange rate risk is not priced in the model and is not incorporated into I_{it}.[6] This model leads to the following equation,

$$R_{it} = I_{it} + W_t \beta_{it} + \eta_{it} \tag{1}$$

where the country-specific time-varying impact of the global excess return or the international risk factor W_t on the country-specific excess return R_{it} is given by $\beta_{it} = \frac{cov_{t-1}[W_t(R_{it} - I_{it})]}{V_{t-1}[R_{wt}]}$ with V_{t-1} denoting the variance conditional on period $t-1$ information and cov_{t-1} denoting the covariance conditional on period $t-1$ information. The error term is given by $\eta_{it} = (R_{it} - E_{t-1}[R_{it}]) - (I_{it} - E_{t-1}[I_{it}]) - \beta_{it}(W_t - E_{t-1}[W_t])$ with E_{t-1} denoting the expectation conditional on period $t-1$ information. Note that $E_{t-1}[\eta_{it}] = 0$. It is straightforward to show that $cov_{t-1}(W_t, \eta_{it}) = 0$ and $cov_{t-1}(I_{it}, \eta_{it}) = 0$. Since the error term η_{it} is uncorrelated with the (variables from the) structural model, it can be interpreted as pure measurement error.

We define financial market integration as a decrease in the local impediments to invest in a specific country. In terms of the model this means that a fall of I_{it} towards 0 implies that country i's stock market becomes more integrated with the stock markets of the other countries under consideration. Conversely, an increase in I_{it} implies stock market disintegration for country i. Under full stock market integration of country i in period t we have $I_{it} = 0$ and eq.(1) becomes,

$$R_{it} = W_t \beta_{it} + \eta_{it} \tag{2}$$

with $\beta_{it} = \frac{cov_{t-1}[R_{wt}, R_{it}]}{V_{t-1}[R_{wt}]}$ and where $\eta_{it} = (R_{it} - E_t[R_{it}]) - \beta_{it}(W_t - E_{t-1}[W_t])$ with $E_{t-1}[\eta_{it}] = 0$. Eq.(2) is Harvey's (1991) standard international CAPM (without market imperfections).

[6] An alternative approach would be to consider common currency returns (e.g. USD returns). This would require the incorporation of an additional premium in the model (see Dumas and Solnik 1995). Since this exchange rate risk premium would be country-specific, a factor decomposition would not be able to distinguish it from the premium related to illiquidity and other market imperfections. A cleaner measurement of integration is obtained by considering local currency returns since financial market integration affects the latter premium rather than the former. I.e. in our empirical application exchange rate premiums would not vanish even if asset markets were perfectly integrated (the only exception being the currency risk between Germany and France which vanished in 1999).

3 Empirical specification and estimation method

3.1 Empirical specification

We estimate the following system for $i = 1, ..., N$ countries where R_{it} are excess returns (in deviations from their country-specific sample means),

$$R_{it} = I_{it} + W_t \beta_{it} + \eta_{it} \tag{3}$$

$$I_{it} = \pi_i I_{it-1} + \varepsilon_{it} \tag{4}$$

$$W_t = \pi_w W_{t-1} + \varepsilon_{wt} \tag{5}$$

$$\beta_{it} = f(\Gamma_{it-1}) \tag{6}$$

Eq.(3) was derived in the previous section. Note that we consider excess returns R_{it} in deviations from their country-specific sample means. The reason is that, when estimating a factor model, we cannot attribute the mean of R_{it} to the unobserved components I_{it} and W_t in a non-arbitrary way. Hence, we investigate financial market integration only with respect to the variance of the excess returns, not with respect to the means. As noted in the last section, the error terms η_{it} are uncorrelated with the structural model, so they can be interpreted as pure measurement error and we can assume that they are *i.i.d.* as there is no reason for them to be subject to $GARCH$ effects (see Harvey et al., 1992, p. 138). Hence we assume that $\eta_{it} \sim i.i.d(0, \sigma^2_{\eta i})$ where $\sigma^2_{\eta i}$ is the unconditional variance of η_{it} $(\forall i)$.

In eq.(4) we model the idiosyncratic factors I_{it} as $AR(1)$ processes with AR parameters π_i for which $-1 < \pi_i < 1$. The error terms ε_{it} are white noise and follow a $GARCH(1,1)$ process,

$$\varepsilon_{it} = [h_{it}]^{\frac{1}{2}} \, v_{it} \tag{7}$$

where $v_{it} \sim i.i.d(0,1)$ and where the conditional variances h_{it} of ε_{it} are given by,

$$h_{it} = \delta^a_i + \delta^b_i \varepsilon^2_{it-1} + \delta^c_i h_{it-1} \tag{8}$$

with parameter restrictions $\delta^a_i > 0$, $0 < \delta^b_i < 1$, $0 < \delta^c_i < 1$, and $0 < \delta^b_i + \delta^c_i < 1$. The unconditional variance of ε_{it} is given by $\sigma^2_{\varepsilon i} = \delta^a_i/(1 - \delta^b_i - \delta^c_i)$.

As can be seen in eq.(5) we assume that the common factor W_t follows an $AR(1)$ process with AR parameter π_w for which $-1 < \pi_w < 1$. The error term ε_{wt} is a white noise term that follows a $GARCH(1,1)$ process,

$$\varepsilon_{wt} = [h_{wt}]^{\frac{1}{2}} \, v_{wt} \tag{9}$$

where $v_{wt} \sim i.i.d(0,1)$ and where the conditional variance h_{wt} of ε_{wt} is given by,

$$h_{wt} = \delta^a_w + \delta^b_w \varepsilon^2_{wt-1} + \delta^c_w h_{wt-1} \tag{10}$$

with parameter restrictions $\delta^a_w > 0$, $0 < \delta^b_w < 1$, $0 < \delta^c_w < 1$, and $0 < \delta^b_w + \delta^c_w < 1$. The unconditional variance of ε_{wt} is given by $\sigma^2_{\varepsilon w} = \delta^a_w/(1 - \delta^b_w - \delta^c_w)$.

In eq.(6) the factor loadings β_{it} are modelled as a function f of information available at time $t-1$ as captured by Γ_{it-1}. The reason is that, as shown in the previous section, β_{it} is the ratio of a covariance that is conditional on time $t-1$ information and a variance that is also conditional on time $t-1$ information, i.e. $\beta_{it} = \frac{cov_{t-1}[W_t,(R_{it}-I_{it})]}{V_{t-1}(W_t)} = \frac{cov_{t-1}[W_t,W_t\beta_{it}]}{V_{t-1}(W_t)}$(where the last step follows from eq.(3) and $cov_{t-1}(W_t, \eta_{it}) = 0$). Any assumed specification for β_{it} should be consistent with the last expression. To this end β_{it} can only depend on information up to time $t-1$. Since, in the context of the estimation of a factor model, the factor loadings need to be positive (see section 3.2.2) we use an exponential function for f. More specifically, we estimate a specification for β_{it} of the form,

$$\beta_{it} = \exp\left[\gamma^a_i + \sum_{j=1}^{m_1} \gamma^b_{ji} R_{it-j} + \sum_{j=1}^{m_2} \gamma^c_{ji} R^2_{it-j}\right] \tag{11}$$

The lagged information Γ_{it-1} thus consists of m_1 lags of the excess returns R_{it} and m_2 lags of the squared excess returns R^2_{it}. We include these variables because both the mean and the variance of past returns may contain country-specific information that could affect a country's exposure to international risk. The numbers m_1 and m_2 are to be determined through the use of specification tests.

In the theoretical model discussed in the last section we define full financial market integration of country i in period t as the situation where $I_{it} = 0$, i.e. full integration of a country's stock market with the stock markets of the other countries is achieved when its country-specific risk factor equals zero. In that case the model collapses to Harvey's (1991) standard international CAPM which holds for perfectly integrated markets. From this definition and from the empirical specification discussed in this section we suggest the following time-varying indicator for the degree of financial market integration in country i,

$$\psi_{it} = -\left[h_{it}\right]^{\frac{1}{2}} \tag{12}$$

i.e. the negative of the conditional standard deviation of the shock to the idiosyncratic factor. Note that h_{it} is specified in eq.(8). For values of π_i equal or close to 0 then if $\psi_{it} \approx 0$ country i is close to being fully integrated in the global financial markets since this implies $I_{it} \approx 0$. The more negative the value of ψ_{it} the further the country is from full integration. An alternative indicator suggested by Levine and Zervos (1998) is $-|I_{it}|$, the negative of the absolute value of I_{it}. This variable is obviously a better indicator if π_i is far from 0. The disadvantage of this indicator is that it depends on $|v_{it}|$ which makes it a noisy indicator. Since our estimations suggest that the parameters π_i $(\forall i)$ are not statistically significantly different from 0 we present estimates of ψ_{it} rather than estimates of $-|I_{it}|$.

The dynamic factor model with time-varying conditional variances further allows us to quantify the time-varying degree of stock market integration by means of a conditional variance decomposition. From eq.(3) the conditional variance of R_{it} is given by,

$$\begin{aligned} V_{t-1}(R_{it}) &= V_{t-1}(I_{it}) + \beta_{it}^2 V_{t-1}(W_t) + V_{t-1}(\eta_{it}) \\ &= h_{it} + \beta_{it}^2 h_{wt} + \sigma_{\eta i}^2 \end{aligned} \tag{13}$$

The fraction of the conditional variance which is explained by the idiosyncratic factor is then captured by the indicator χ_{it}, where

$$\chi_{it} = -\frac{V_{t-1}(I_{it})}{V_{t-1}(R_{it})} \tag{14}$$

The variable χ_{it} is defined between -1 and 0 where a value close to 0 indicates a high degree of financial market integration.[7]

[7]Defining χ_{it} to be between -1 and 0 is for convenience since then an increase in χ_{it} means higher financial market integration (similar to the other indicator ψ_{it}).

3.2 Estimation method and identification

3.2.1 Method

We obtain estimates for the unobserved states I_{it} and W_t, for the conditional variance series h_{it} and h_{wt}, for the factor loadings β_{it}, for the financial integration indicator series ψ_{it}, and for the parameters in the model by putting the model described in section 3.1 in state space form. In particular, we estimate a *conditionally* Gaussian linear state space system including time-varying conditional variances (see Harvey et al., 1992, and Kim and Nelson, 1999, chapter 6). In Appendix 2 we report the state space representation of the model. Estimates of the state vector are obtained with the Kalman filter and smoother. Given the assumption of stationarity the initialization of the filter is non-diffuse. The parameters in the system are estimated by maximum likelihood.

The time-varying conditional variances complicate the otherwise standard state space framework. To deal with this we follow the approach by Harvey et al. (1992) and augment the state vector with the shocks ε_{it} and ε_{wt}. The Kalman filter then provides estimates of the conditional variance of the shocks, i.e. estimates for h_{it} and h_{wt}. We refer to the Appendix 2 for more details on the approach followed.

To deal with potential computational difficulties that are caused by the relatively large dimension of the observation vector we follow the univariate approach to multivariate filtering and smoothing as presented by Koopman and Durbin (2000) and Durbin and Koopman (2001, chapter 6). A major advantage of this approach is that we can avoid taking the inverse of the variance matrix of the one-step-ahead prediction errors. We refer to Koopman and Durbin (2000) for the filtering and smoothing recursions and for the calculation of the likelihood.

3.2.2 Identification

For the empirical model to be identified we impose the following restrictions. First, note that we can multiply and divide the term $W_t\beta_{it}$ by a constant q and obtain a different decomposition of R_{it}, i.e. $R_{it} = I_{it} + (W_t/q)(\beta_{it}q) + \eta_{it} = I_{it} + W_t^*\beta_{it}^* + \eta_{it}$. To obtain a unique decomposition of R_{it} and hence to uniquely identify the factor loadings β_{it} on the common factor W_t, we impose an unconditional variance of unity on the shock to the common factor ε_{wt}, i.e. $\sigma^2_{\varepsilon w} = 1$. This amounts to setting $\delta^a_w = 1 - \delta^b_w - \delta^c_w$ in the $GARCH$ specification of the common factor. Second, the signs of the factor loadings β_{it} and of the common factor W_t are not identified since the likelihood remains the same if we multiply both W_t and β_{it} for all i by -1. Therefore, we impose the restriction $\beta_{it} > 0$ in the estimations. This restriction is automatically imposed when we model β_{it} as an exponential function of lagged information as in eq.(11). Third, to separately identify η_{it} and I_{it}, when - as we report in table 3 - we find estimates $\pi_i \approx 0$, we need shocks η_{it} that follow a different process than the shocks to the idiosyncratic factors ε_{it}. This condition is fulfilled since we assume (and find) that the shocks ε_{it} follow $GARCH(1,1)$ processes while, as explained earlier, the shocks η_{it} can safely be assumed to be *i.i.d.*

4 Data and estimation results

4.1 Data

We use monthly data from 1970:1 until 2010:8 on the excess returns for five countries: France, Germany, Japan, the UK, and the US. Equity returns are calculated from a country-specific equity return index. Excess equity returns are obtained by subtraction of a risk free rate. As a measure for equity returns we use the MSCI equity return index provided by Morgan Stanley. For the risk free rate we use short-term interest rates provided by Global Financial Data. More details on the data and on how excess returns are calculated are given in Appendix 1.

As a starting point of the empirical analysis it is worth looking at some descriptive statistics of the data. Table 1 displays the unconditional cross-country correlations of excess returns over the full sample and over three subperiods. These simple correlations highlight two features of the data. First, excess returns are highly correlated across the countries considered. Second, the correlations are steadily increasing in each of the subsamples. The average correlation in the first subsample, i.e. 1970:1-1979:12, is 0.38 and it increases to 0.76 in the subsample 2000:1-2010:8. While the increase in the unconditional correlations can be interpreted as an indication of increasing linkages among global equity markets, a specific correlation pattern is a measure of comovement between two countries only and thus is not necessarily informative about the integration of all markets. Furthermore, the increasing correlation may be driven by some rare events such as times of financial turmoil. Hence a more thorough empirical investigation is needed, the results of which are presented in the next section.

4.2 Estimation results

This section presents the results from the estimation of the model given by equations (3) - (11) for five countries (France, Germany, Japan, the UK, and the US) over the period 1970:1-2010:8.[8]

[8]Note that 3 observations are lost due to the fact that we include a maximum of 3 lags of the excess returns in the specification for β_{it} (see table 2). The remainder of the empirical analysis in the paper is therefore based on the effective sample period 1970:04-2010:08 (i.e. $T = 485$).

The functional form for β_{it}, as given by equation (11), includes two lags of the excess returns but no squared returns, i.e. $m_1 = 2$ and $m_2 = 0$. This particular specification is favoured over specifications with alternative lag structures - including the constant β model - by the Akaike information criterion (AIC). Table 2 shows the AIC for up to three lags for m_1 and m_2.

In Table 3 we present tests for autocorrelation, heteroscedasticity, and normality conducted on the estimated one-step ahead (standardized) prediction errors obtained from the estimation of the state space model. We refer to Durbin and Koopman (2001, p.34) for a discussion of these tests. First, from the Ljung-Box tests for autocorrelation conducted at different lag lengths (1, 4, and 12) we note that the null hypothesis of no autocorrelation is never rejected (except for the UK when lag length 4 is used). This suggests that the empirical specification given by eqs.(3)-(11) is well specified and that a sufficient number of lags has been included in the different processes of the system. Second, we test for heteroskedasticity by conducting Ljung-Box tests for autocorrelation on the *squared* prediction errors. The results of these tests show that the null of no autocorrelation in the squared errors is never rejected. Hence the $GARCH$ processes incorporated in the state space model do a good job of capturing the time-varying conditional heteroskedasticity that is present in the data. Third, normality of the prediction errors is strongly rejected. This is due to the presence of $GARCH$ effects which render the unconditional distributions of the error terms in the state space system non-Gaussian. While the model is assumed to be conditionally Gaussian, it is clearly unconditionally non-Gaussian.

In Table 3 we further present the parameter estimates obtained from the estimation of the state space model. First, the estimates of the AR parameters π are small and insignificant (at the 10% level) for all countries. The common factor has a small positive and significant AR parameter. Both results suggest that the dependency structure of the excess returns R_{it} is very similar across countries. Second, significant $GARCH$ effects are present both in the country-specific factors and in the common factor. The estimated $GARCH$ parameters δ^c are always rather large and larger than the estimated $ARCH$ parameters δ^b while their sum is close to 1 indicating that the conditional variance series are very persistent.[9] Hence, time variation in the variances is very outspoken and this, as we will see, is reflected in our measure for stock market integration ψ_{it} which depends on the conditional variance of the idiosyncratic shocks. Third, the estimated variances of the measurement error term σ^2_η are all very small and insignificant. Hence, country-specific fluctuations in the excess returns are explained solely by the idiosyncratic factors. Finally, the estimated parameters γ^a from

[9]Near-integrated or integrated $GARCH$ is a typical feature of financial market data and causes no specific inference problems. An $IGARCH$ model can be estimated like any other $GARCH$ model (see Enders 2004, p.140-141).

the specification for the factor loadings β_{it} indicate that returns in France and Germany have the largest average exposure to international risk, while Japan has the lowest average exposure over the sample period. Also, as already reported when discussing Table 2, a time-varying function for β_{it} is favoured by the data. The positive and significant parameter estimates for γ_1^b suggest that higher returns lead to a higher exposure to international risk in subsequent periods. We do not find a similar result for the squared returns however which suggests that the volatility of past returns does not affect the exposure to international risk.

In Figure 1 we present the estimated common factor W_t and its conditional variance h_{wt}. Over the sample period the global financial markets experienced several periods of financial turmoil. The shaded areas in both figures indicate times of financial turmoil. The first notable crisis is the period 1973-75. Financial instability due to the end of the Bretton Woods era, the oil crisis, and the recession created a sharp fall in global stock prices. Due to the high oil prices in this period, inflation and thus interest rates on treasury bills were high. This combination led to a sharp decline in the excess returns of all countries. The next major downturn occurred in October 1987 when stock markets around the world crashed. In the period 1997-2003 several events were affecting financial markets leading to a period of financial turmoil in many countries, i.e. the crisis in Asia, Argentine and Russia, the failure of the LTCM hedge fund, and the dot com bubble burst. Finally, there was the recent financial crisis of 2007-2009 which had its origin in the US banking system but rapidly spread across the world. Since all these crises had strong effects on the global financial markets, they are captured by the common factor.

Figure 2 displays the time-varying factor loadings β_{it} for all countries. The time variation in these factor loadings can be explained by one lag of the excess returns. Further lags of the excess returns and lags of squared excess returns have no predictive power for the loadings suggesting that the variation in the loadings is rather limited. In fact, while a time-varying function for β_{it} is preferred over a constant β_{it} model (see Table 2), the difference between both models is rather small.

Figure 3 shows the estimated idiosyncratic factors I_{it} for all countries together with the excess returns R_{it}. Figure 4 shows the estimated time-varying conditional variance series h_{it} of these idiosyncratic components. From both figures a number of country-specific shocks can be identified. In France in May 1981 excess returns dropped sharply after the election of the socialist president Franï¿½ois Mitterrand. The idiosyncratic factor for Germany displays one major negative shock in January 1987 which is likely to be the market response to the West German federal election on

January 25th 1987. In contrast, the idiosyncratic factor in Japan exhibits several peaks and troughs indicating a dominant role for country-specific shocks. When taking a closer look at Japanese stock market history this does not come as a surprise. The 1980s period in Japan provides one of the most striking examples of an asset price bubble in world stock market history. During this period the average stock returns in Japan were more than 10% above the returns in the US (see Siegel 2008, p.165). From 1989 on the bubble gradually collapsed which lead to a sizable decline in asset prices and in the volatility of asset prices. The Japanese bubble and its collapse explain the important role of the idiosyncratic factor observed in Japan until the mid 1990s. When turning to the UK, we note that country-specific shocks in the UK had a large impact in the mid 1970s. In addition to the global crisis the period 1973-75 in the UK was characterized by a crash in property prices which resulted in a banking crisis. The crisis ended after the rent freeze - which had been imposed in 1971 by the Heath government - was lifted in December 1974. This resulted in the sharp increase of stock prices in January 1975 which can be observed in Figure 3. For the US the idiosyncratic shocks often coincide with global shocks as captured by the common factor. When looking at the conditional variance series h_{it} for the US and comparing it to the conditional variance series of the common factor h_{wt} we find that, to a certain extent, both capture similar shocks. This finding is not surprising since the US market is the dominant market in the world. Large shocks in the US, although of country-specific origin (e.g. the recent financial crisis), are more likely to affect other markets and are therefore identified as shocks to the common factor.

Figure 5 then depicts our country-specific time-varying indicators of stock market integration ψ_{it}. From this figure we draw a number of conclusions. First, no market is fully integrated at any moment in time (i.e. $\psi_{it} < 0$ for all i and t). Second, in all countries but Japan ψ_{it} is larger in 2010 as compared to 1970. For France, Germany, the UK, and the US a structural increase in stock market integration can clearly be observed from the figure. Third, although the relative importance of the idiosyncratic factor is diminishing over time in all countries except Japan, there are short periods in which financial markets are more disintegrated. Since the indicator for financial market integration is the negative of the conditional standard error of the idiosyncratic factor, the country-specific shocks that we identified above are affecting the degree of stock market integration. Periods of high country-specific stock market volatility translate in a temporarily lower degree of stock market integration. Hence, financial market integration is a dynamic process that is fluctuating in the short run while it is gradually increasing in the long run. Fourth, we find that the recent 2007-2009 financial crisis has almost no impact on the degree of stock market integration of France, Germany, and the UK, i.e. ψ_{it} hardly falls in these countries during that period. For these countries the impact of the crisis on the stock market is only felt through the impact of the common factor.[10] In Japan and the US, on the other hand, we clearly observe a fall in ψ_{it} during the 2007-2009 crisis.

A similar picture emerges from Figure 6 which displays the conditional variance decompositions of the excess returns. The variance share of the idiosyncratic component (i.e. the indicator $-\chi_{it}$) shows a downward trend for all countries but Japan. In both France and Germany the idiosyncratic factor accounts for less than 10% of the fluctuations in excess returns towards the end of the sample period. The variance decomposition for Japan highlights the important role of country-specific factors. Common shocks account for only about 30% of the overall variance in the last years of the sample period. In the UK the variance share of the idiosyncratic component is about 80% in the early 1970s and fluctuates considerable, particularly since the late 1990s, but accounts for less than 25% of the overall variance in more recent periods. The picture for the US is similar. The variance share of the idiosyncratic component steadily decreases over time and averages 45% over the last few years of the sample. To conclude, by the end of the sample period we find that France and Germany are the most integrated markets. They are followed by the UK and the US which are also rather well integrated in world financial markets. The integration of Japan with the other countries under consideration is relatively low.

5 Conclusions

Our investigation of the world stock market integration of five developed countries (France, Germany, Japan, the UK, and the US) over the period 1970:1-2010:8 suggests that stock market integration has increased over the period 1970:1-2010:8 in all countries but Japan. By the end of the sample period the common factor in stock market excess returns accounts for well above 65% of the overall fluctuations in excess returns of France, Germany, the UK, and the US. And while there is a structural increase in stock market integration in four out of five countries, all countries also exhibit several shorter periods of disintegration, i.e. reversal periods in which country-specific shocks play a more dominant role. Hence stock market integration is measured as a dynamic process that is fluctuating in the short run while gradually increasing in the long run.

The approach used to measure the time-varying degree of financial market integration is new. It is based on the estimated conditional variances of the country-specific premiums in equity excess returns. Country-specific premiums are derived theoretically from an international CAPM with

[10] This seems to suggest that once a certain degree of integration is achieved, temporary falls in the degree of integration become less likely.

market imperfections. Rather than being estimated from large sets of conditioning variables or instruments they are estimated from the latent factor decomposition implied by the theory. For estimation we use of state space methods that allow for $GARCH$ errors. The obtained measures of financial market integration capture both the long run structural trend in stock market integration as well short run transitory changes. The approach can easily be applied to larger groups of countries. Since the approach is based on standard asset pricing theory it can also be applied to other assets (e.g. bonds). It therefore provides a useful alternative framework to study time-variation in financial market integration that can complement existing methodologies, both the model-based ones and the purely econometrical.

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Appendix 1: Data

In order to calculate monthly excess returns in % we calculate continuously compounded returns from a stock market index and subtract the risk free rate, i.e.

$$R_t = \left(\ln\left(\frac{S_t}{S_{t-1}}\right) - \ln\left(\frac{B_t}{B_{t-1}}\right)\right) \cdot 100$$

where S_t is the value of the stock market index at time t and B_t is the value of the treasury bills index at time t. As a measure for S_t we use the country-specific MSCI equity return index provided by Morgan Stanley in local currency taken from Datastream. It covers 90-95% of the investable market capitalization. On a monthly basis these data are available from 1969. As a measure for B_t we use the total return bill index in local currency as reported by *Global Financial Data* which is based upon the yields on 3-month treasury bills. For countries that do not issue treasury bills, either the central bank discount rate or commercial paper yields have been used as a substitute for the yields on treasury bills. The MSCI index as well as the treasury bills index as calculated by *Global Financial Data* are widely used in the literature.

Appendix 2: State space representation

The state space system with state vector Ω_t is,

$$y_t = Z_t \Omega_t + \eta_t$$

$$\Omega_t = T_t \Omega_{t-1} + K_t \varepsilon_t$$

with

$$\eta_{t|t-1} \sim N(0, G)$$

$$\varepsilon_{t|t-1} \sim N(0, Q_t)$$

$$\Omega_1 \sim N(A_1, P_1)$$

For $N = 5$ we have $y_t = \begin{bmatrix} R_{1t} & R_{2t} & R_{3t} & R_{4t} & R_{5t} \end{bmatrix}'$,

$\Omega_t = \begin{bmatrix} I_{1t} & I_{2t} & I_{3t} & I_{4t} & I_{5t} & W_t & \varepsilon_{1t} & \varepsilon_{2t} & \varepsilon_{3t} & \varepsilon_{4t} & \varepsilon_{5t} & \varepsilon_{wt} \end{bmatrix}'$,

$\eta_t = \begin{bmatrix} \eta_{1t} & \eta_{2t} & \eta_{3t} & \eta_{4t} & \eta_{5t} \end{bmatrix}'$,

$\varepsilon_t = \begin{bmatrix} \varepsilon_{1t} & \varepsilon_{2t} & \varepsilon_{3t} & \varepsilon_{4t} & \varepsilon_{5t} & \varepsilon_{wt} \end{bmatrix}'$,

$$Z_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & \beta_{1t} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & \beta_{2t} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & \beta_{3t} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & \beta_{4t} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & \beta_{5t} & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

where $\beta_{it} = f(\Gamma_{it-1})$ (for $i = 1, ..., 5$) where Γ_{it-1} is a set of variables dated time $t-1$ and earlier,

$$T_t = \begin{bmatrix} \pi_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \pi_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \pi_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \pi_4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \pi_5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \pi_w & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$K_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}',$$

$$diag(G) = \begin{bmatrix} \sigma^2_{\eta 1} & \sigma^2_{\eta 2} & \sigma^2_{\eta 3} & \sigma^2_{\eta 4} & \sigma^2_{\eta 5} \end{bmatrix}',$$

$$diag(Q_t) = \begin{bmatrix} h_{1t} & h_{2t} & h_{3t} & h_{4t} & h_{5t} & h_{wt} \end{bmatrix}'$$

where $h_{it} = \delta^a_i + \delta^b_i \varepsilon^2_{it-1} + \delta^c_i h_{it-1}$ (for $i = 1, ..., 5$) and $h_{wt} = \delta^a_w + \delta^b_w \varepsilon^2_{wt-1} + \delta^c_w h_{wt-1}$ with $\delta^a_w = 1 - \delta^b_w - \delta^c_w$,

$$A_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}',$$

$$P_1 = \begin{bmatrix} \frac{\sigma^2_{\varepsilon 1}}{1-\pi_1^2} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 1} & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{\sigma^2_{\varepsilon 2}}{1-\pi_2^2} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{\sigma^2_{\varepsilon 3}}{1-\pi_3^2} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 3} & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{\sigma^2_{\varepsilon 4}}{1-\pi_4^2} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 4} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{\sigma^2_{\varepsilon 5}}{1-\pi_5^2} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 5} & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{\sigma^2_{\varepsilon w}}{1-\pi_w^2} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon w} \\ \sigma^2_{\varepsilon 1} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 1} & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{\varepsilon 2} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{\varepsilon 3} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 3} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{\varepsilon 4} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 4} & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 5} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon 5} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon w} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon w} \end{bmatrix}$$

where $\sigma^2_{\varepsilon i} = \delta_i^a/(1-\delta_i^b-\delta_i^c)$ (for $i = 1, ..., 5$) and $\sigma^2_{\varepsilon w} = \delta_w^a/(1-\delta_w^b-\delta_w^c) = 1$.

Technical notes:

The $GARCH$ effects imply time-varying conditional variances h_{it} and h_{wt} and complicate the state space framework. To deal with this we follow the approach by Harvey et al. (1992) and we include the shocks ε_{it} and ε_{wt} in the state vector. We note then that h_{it+1} (for $i = 1, ..., 5$) and h_{wt+1} and therefore Q_{t+1} are functions of the unobserved states ε_{it} and ε_{wt}. Harvey et al. (1992) replace h_{it+1} and h_{wt+1} in the system by $h^*_{it+1} = \delta_i^a + \delta_i^b \varepsilon^{*2}_{it} + \delta_i^c h^*_{it}$ and $h^*_{wt+1} = \delta_w^a + \delta_w^b \varepsilon^{*2}_{wt} + \delta_w^c h^*_{wt}$ where the unobserved ε^2_{it} and ε^2_{wt} are replaced by their conditional expectations $\varepsilon^{*2}_{it} = E_t\varepsilon^2_{it}$ and $\varepsilon^{*2}_{wt} = E_t\varepsilon^2_{wt}$. Note that $E_t\varepsilon^2_{it} = [E_t\varepsilon_{it}]^2 + \left[E_t(\varepsilon_{it} - E_t\varepsilon_{it})^2\right]$ and $E_t\varepsilon^2_{wt} = [E_t\varepsilon_{wt}]^2 + \left[E_t(\varepsilon_{wt} - E_t\varepsilon_{wt})^2\right]$ where the quantities between square brackets are period t Kalman filter output (conditional means and variances of the states ε_{it} and ε_{wt}). Thus, given h^*_{it} and h^*_{wt} (which are initialized by the unconditional variances of ε_{it} and ε_{wt}, i.e. $\sigma^2_{\varepsilon i}$ and $\sigma^2_{\varepsilon w}$) and given the Kalman filter output from period t, namely $E_t(S_t)$ and $V_t(S_t)$, we can calculate h^*_{it+1} and h^*_{wt+1} and the system matrix Q_{t+1} which makes it possible to calculate $E_t(S_{t+1})$, $V_t(S_{t+1})$ and $E_{t+1}(S_{t+1})$, $V_{t+1}(S_{t+1})$, and so on... .

It should be noted that in the presence of $GARCH$ effects the model is not strictly conditionally Gaussian. The reason is that knowledge of past observations does not imply knowledge of the past disturbances ε_{it} and ε_{wt} and thus ε^2_{it} and ε^2_{wt} since the latter need to be replaced by ε^{*2}_{it} and ε^{*2}_{wt}. Following Harvey et al. (1992) we proceed as though the model *is* conditionally Gaussian. This implies that the Kalman filter is *quasi*-optimal and the likelihood is an approximation. Monte Carlo simulations conducted by Harvey et al. (1992) suggest that this method works rather well for the sample size that is at our disposal.

Tables and figures

Table 1: Unconditional correlations of excess returns

	France	Germany	Japan	UK	US
Full sample 1970:1 - 2010:8					
France	1				
Germany	0.687279	1			
Japan	0.415317	0.411529	1		
UK	0.593888	0.512760	0.386708	1	
US	0.594166	0.573576	0.423189	0.632631	1
First subsample 1970:01 - 1979:12					
France	1				
Germany	0.439620	1			
Japan	0.289123	0.380170	1		
UK	0.492006	0.315512	0.298204	1	
US	0.416152	0.310923	0.351985	0.483510	1
Second subsample 1980:01 - 1989:12					
France	1				
Germany	0.555926	1			
Japan	0.344499	0.294271	1		
UK	0.492861	0.481124	0.399311	1	
US	0.524458	0.470487	0.377978	0.691771	1
Third subsample 1990:01 - 1999:12					
France	1				
Germany	0.779867	1			
Japan	0.437604	0.387666	1		
UK	0.701534	0.617831	0.408057	1	
US	0.593541	0.570363	0.384089	0.643698	1
Fourth subsample 2000:01 - 2010:08					
France	1				
Germany	0.937957	1			
Japan	0.620725	0.560290	1		
UK	0.887021	0.825503	0.606588	1	
US	0.844727	0.820145	0.621092	0.865850	1

Table 2: AIC specification tests on the β function (1970:1-2010:8)

	m_1/m_2									
	0/0	1/1	2/2	3/3	1/0	2/0	3/0	0/1	0/2	0/3
$AICcr^{(a)}$	-17.555	-17.546	-17.541	-17.528	-17.558	-17.559	-17.552	-17.543	-17.558	-17.550

[(a)] AICcr is the Akaike information criterion with a correction term for sample size. Smaller values of AICcr are preferred.

Table 3: Maximum likelihood estimation of the state space system eq.(3)-(11), 1970:1-2010:8

	Country-specific parameters$^{(a)}$					Common parameters$^{(a)}$
	France	Germany	Japan	UK	US	
π	0.046	0.025	0.060	-0.087	-0.092	0.116
	(0.062)	(0.058)	(0.056)	(0.055)	(0.060)	(0.048)
δ^a	1.5E-7	1.6E-5	3.9E-5	3.8E-5	2.0E-5	0.058
	(1.7E-7)	(1.3E-5)	(1.5E-5)	(1.3E-5)	(8.0E-6)	(0.024)
δ^b	0.150	0.141	0.073	0.315	0.075	0.096
	(0.041)	(0.046)	(0.023)	(0.064)	(0.034)	(0.031)
δ^c	0.852	0.845	0.911	0.678	0.906	0.845
	(0.041)	(0.051)	(0.023)	(0.062)	(0.030)	(0.038)
σ^2_η	6.2E-7	1.2E-6	3.5E-6	7.4E-7	3.2E-6	
	(7.5E-7)	2.5E-6)	(9.7E-6)	(1.2E-6)	(1.6E-5)	
γ^a	0.044	0.047	0.027	0.034	0.032	
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	
γ^b_1	0.104	0.080	0.363	0.159	0.088	
	(0.032)	(0.026)	(0.105)	(0.065)	(0.054)	
γ^b_2	1.596	0.332	2.932	2.551	0.948	
	(0.960)	(0.203)	(3.043)	(1.825)	(0.742)	
	Country-specific Ljung-Box test for autocorrelation$^{(b),(c)}$					
lag 1	0.752	0.342	0.042	0.060	9.6E-8	
	[0.386]	[0.559]	[0.841]	[0.806]	[1.000]	
lag 4	5.911	1.659	2.830	11.046	2.332	
	[0.206]	[0.798]	[0.587]	[0.026]	[0.675]	
lag 12	11.875	11.530	7.948	17.416	9.018	
	[0.456]	[0.484]	[0.789]	[0.135]	[0.701]	
	Country-specific Ljung-Box test for heteroscedasticity $^{(b),(d)}$					
lag 1	0.671	2.485	1.643	0.408	0.469	
	[0.413]	[0.115]	[0.200]	[0.522]	[0.493]	
lag 4	1.996	5.361	3.907	4.526	0.941	
	[0.737]	[0.252]	[0.419]	[0.340]	[0.919]	
lag 12	9.397	15.712	12.400	8.596	9.003	
	[0.669]	[0.205]	[0.414]	[0.737]	[0.703]	
	Country-specific test for normality $^{(b),(e)}$					
	28.513	12.246	31.775	19.802	25.518	
	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	

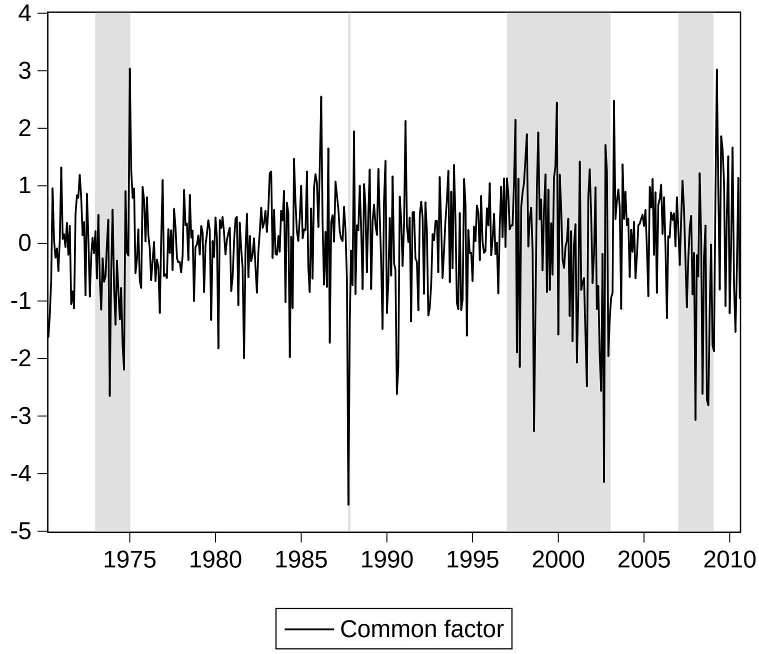
(a) Standard errors are in parentheses. (b) p-values are in square brackets.

(c) The null hypothesis is no autocorrelation in the one-step-ahead prediction errors.

(d) The null hypothesis is homoscedasticity in the one-step-ahead prediction errors.

(e) The null hypothesis is normality of the one-step-ahead prediction errors.

Figure 1: The common factor W_t and its conditional variance h_{wt}



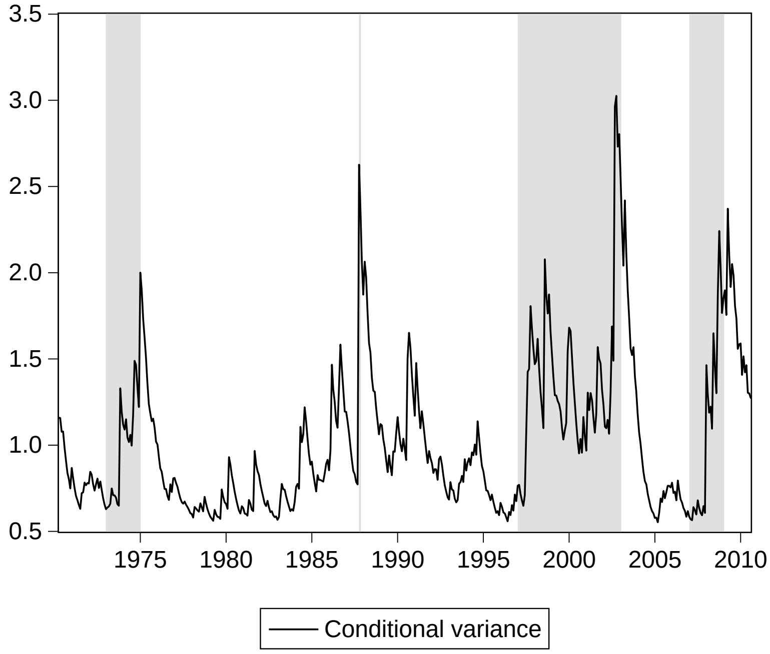


Figure 2: The time-varying factor loadings β_{it}

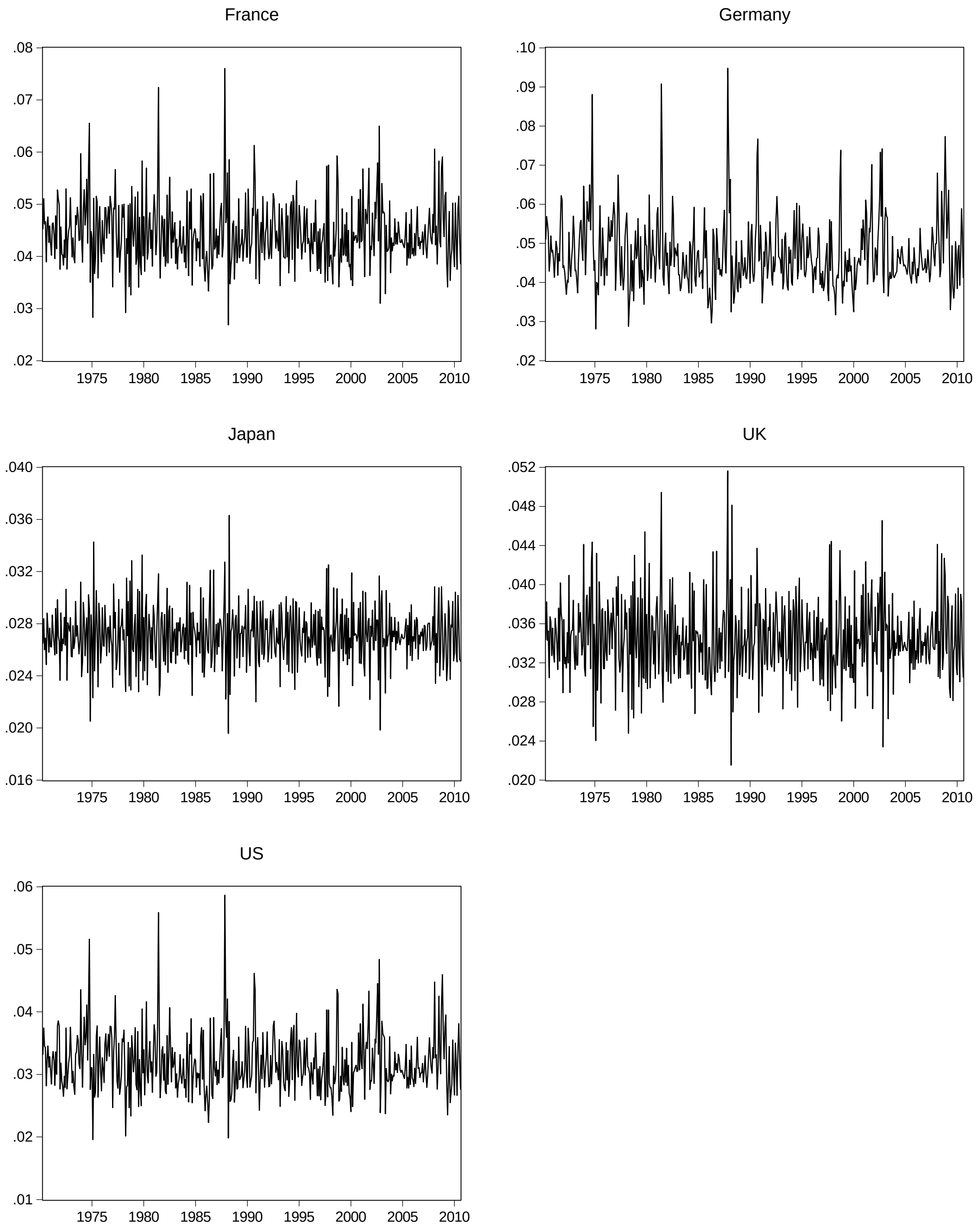


Figure 3: The idiosyncratic factors I_{it} and the excess returns R_{it}

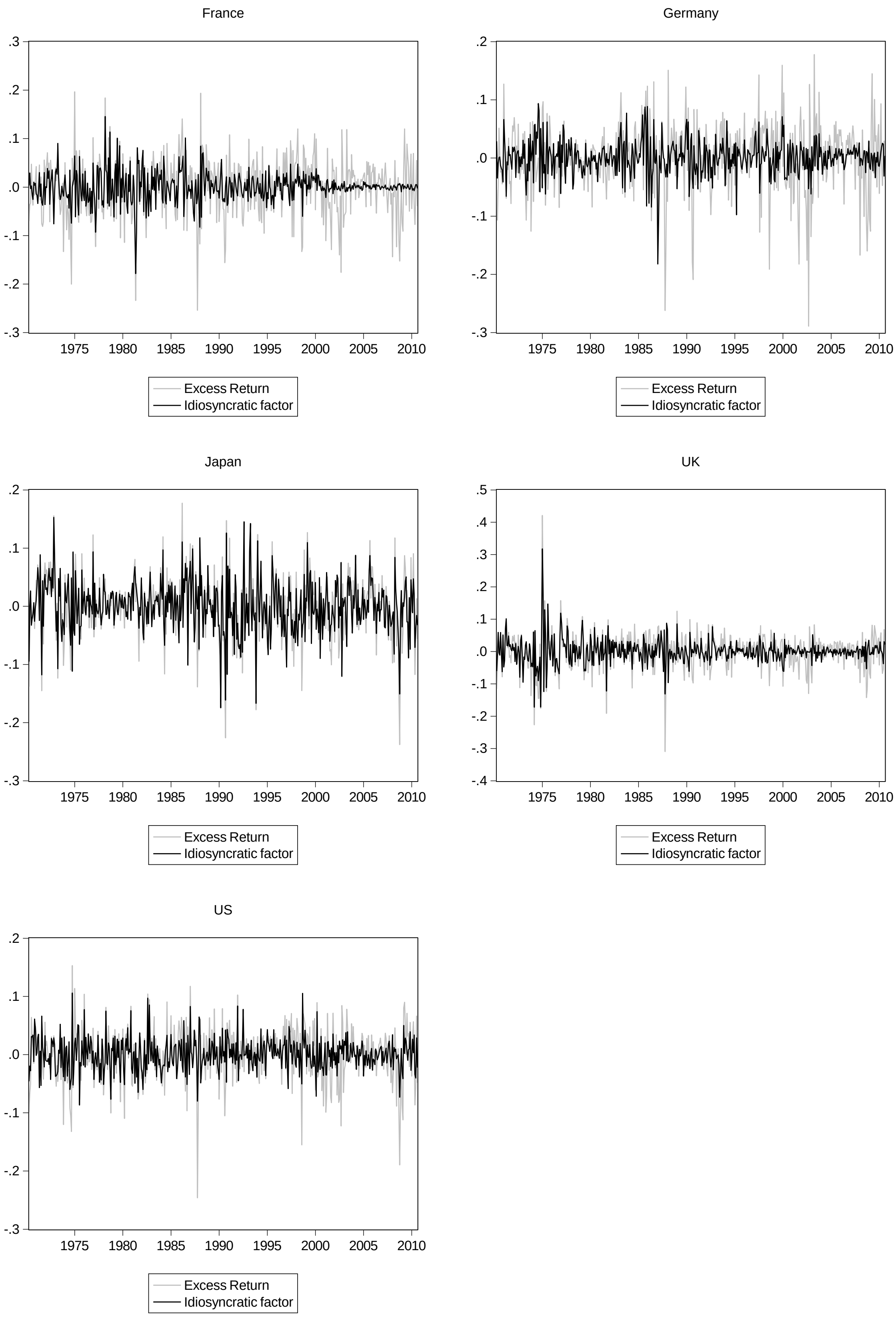


Figure 4: The conditional variances of the idiosyncratic factors h_{it}

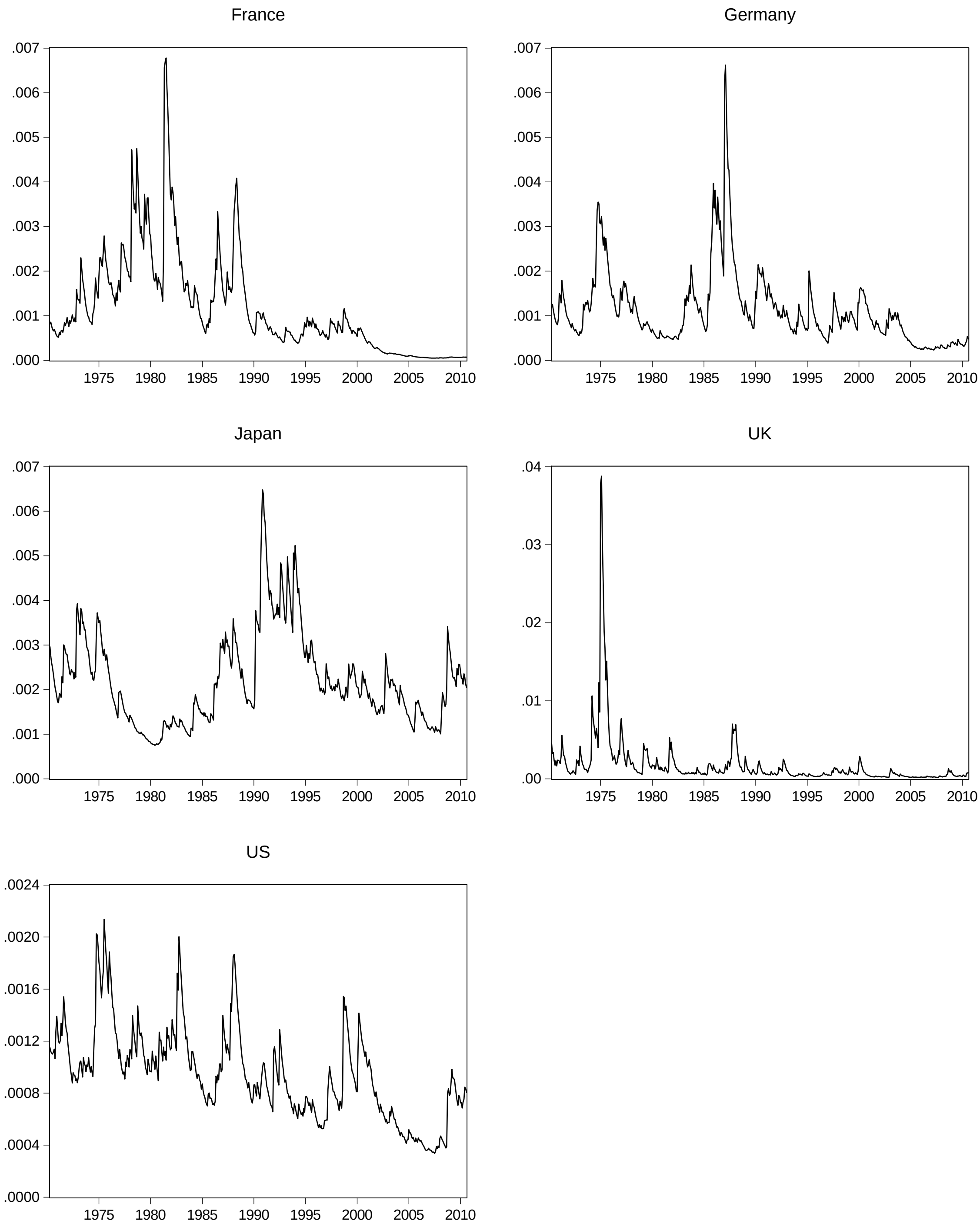


Figure 5: The time-varying indicators of stock market integration ψ_{it}

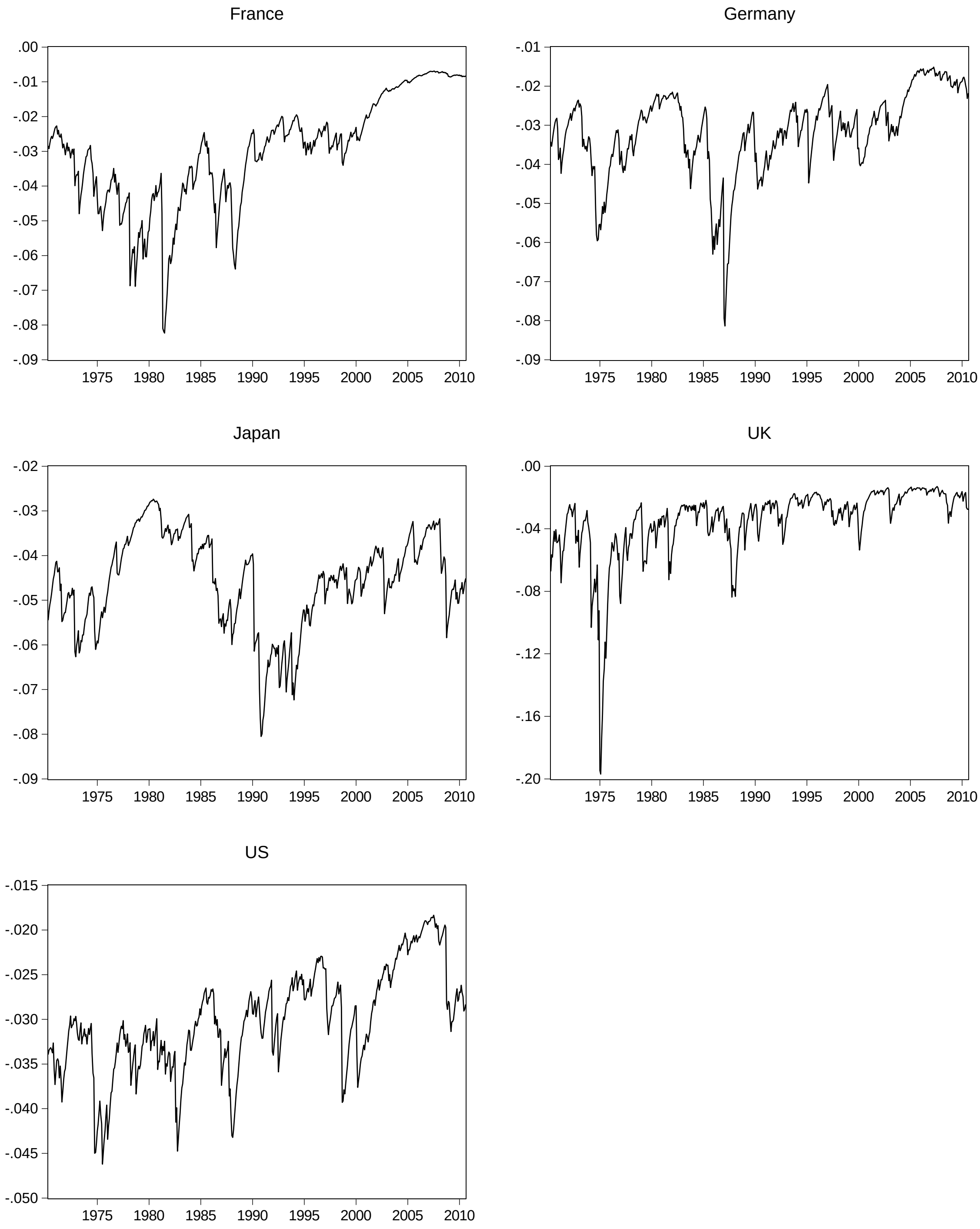


Figure 6: The variance share of the idiosyncratic component χ_{it}