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Time varying integration between countries and industries

Name student: Maurice van Oeveren

Student ID number: 453573

Supervisor: dr. H.J.W.G. Kole

Second assessor: T. van der Zwan

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Abstract

We investigate the financial integration between industries and between countries for stock returns over time. We use monthly returns of seven market sectors for six European countries and three non-European countries in the period 1990 till 2021. We use multiple integration measures, such as correlation measures, a multivariate DCC GARCH model, a CAPM model, principal component methods and a regime switching model. These integration measures shows that the integration has either a positive trend or a constant highly integrated pattern. Crises periods decrease the integration, but this does not result into a turning point towards segmentation. The integration shows that investors can lower their risk by diversifying their portfolios.

Keywords: financial integration, correlation, PCA, DCC GARCH, CAPM, regime switching, diversification benefits

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Contents

1 Introduction

Stocks have become very popular over the last time. Nowadays, the interest rates on the saving accounts are almost zero or negative. Together with increasing stock prices, the stock markets are interesting for investors. However, the global stock markets have changed over time. Since a couple of decades the financial integration between the markets of different countries are increasing over time. This means that the stock markets of European countries move together in and out bull and bear markets. This increase in financial integration between countries can have negative consequences for investors, who want diversified portfolios by investing in stocks in these different countries.

However after the credit crisis, the question arises whether the stock markets of European countries move or do not move together anymore, and whether a split between northern and southern European stock markets arises. This split can be an indicator that the financial integration varies over time. Most of the studies about financial integration are focused on the integration between countries, however it is also possible that financial integration differs between industries. There can be recent factors that have an impact on the integration. For example, the COVID-19 outbreak has some influence. Pardal et al. (2020) and Borgioli et al. (2020) study the integration during the COVID-19 pandemic and find that the integration is high, but there is a decrease in integration around this period. The decrease in integration can also have some impact between the industries because some industries were shut down and for some industries the demand for specific products increased. The COVID-19 crisis can have other permanent consequences for an industry, while other industries are not affected by the crisis. Therefore, we should not only consider country level integration, but we should also consider the integration on industry level.

This gives rise to the question whether there exist variations or patterns in the financial integration between countries and in a country between industries over time. We investigate whether stocks for a specific country and industry are correlated with stocks for other countries or with stocks for different industries for the same country. In order to do this we investigate the financial integration on country and on industry level in the stock market. In this way, our investigation towards financial integration for different industries and countries helps investors by creating diversified portfolios and hedging positions. We focus on industry level integration and on country level, because it is possible that a country is not integrated with the world market but some industries of that country are integrated and vice versa. This is an indicator for investors to diversify their portfolio based on industries instead of different countries or to diversify their portfolio based on countries instead of different industries.

In our research we investigate the movement of the financial integration over time. In order to do this we use stock price indices of seven different industries in nine different countries. The countries that we use are mostly inside Europe, but we also focus on the effects of countries outside Europe, such as the US, Canada or Japan. The price indices that we use are monthly based from December 1988 till June 2021. In this way we consider the latest developments in the stock markets, such as the effect of the COVID-19 crisis, which has a negative impact on the stock market worldwide. In order to use these data to measure the integration, we transform the price indices into simple returns. However, to overcome the time varying exchange rates between different currencies, the price indices have to be in the same currency. We use these exchange rates to transform the price indices of different currencies into Euros, because most of the price indices are in Euros and our research is based on European investors where the foreign countries are used to measure the effect on European investors.

We use different methods to measure the financial integration on industry and country level based on the measures used in Billio et al. (2017). We use a moving window of 60 months to measure the integration over time. First, we use the standard correlation between industries or countries as a measure for the integration. This is one of the simplest way to measure the integration. We can adjust this simple correlation by a factor which is higher in more volatile periods and lower in stable periods. This method corrects for the heteroskedasticity in the correlation. This correlation measure is the Forbes and Rigobon (2002) correlation.

After this correlation measure we consider other models such as the CAPM model to measure the correlation. This model has an asset pricing perspective and measures the correlation of the expected return of a stock with the expected return of the world market, used in De Santis and Gerard (1998). Furthermore, we use GARCH models to model the variance of the returns conditional on all the information of the past. We use a multivariate GARCH model, namely the dynamic conditional correlation (DCC) GARCH model of Engle (2002). This DCC GARCH model which we use is also used in the CAPM model to model the variance.

Another method to measure the integration is by a principal component approach. Therefore we only consider factors that explain most of the variance. We use two different measures of the principal component approach. First, we use the R^2 from a regression of the returns on the first three factors of the principal component analysis. Second, we use the variance explained by the first principal component as a measure for the integration.

The last approach to measure the integration is with the regime switching model of Bekaert and Harvey (1995). Therefore we use a model which has two regimes, where one regimes is an integrated market and the other regime denotes a segmented market. For this model we use the Markov property that the probability of being in a regime in the future only depends on the regime now and not on the past. We use the Hamilton (1989) filter and the Kim (1994) smoother in order to estimate the parameters in a regime.

The integration measures indicate that the integration has two patterns. The correlation measures, which are the cross correlation, Forbes-Rigobon correlation, the DCC GARCH model and the CAPM model, show an increasing trend over time for the integration between the European countries. The other measures, which are the R^2 method, the first principal component method and the regime switching models show an almost constant but highly integrated pattern, with some troughs towards segmentation. Furthermore, the integration between the European countries is the highest in the financial sector and the lowest in the food industry.

When we also include the three non-European countries, the integration has the same patterns as for the integration between the European countries. However, the integration is lower for the integration between all the countries. Another difference is that the highest integration is for the industrial sector instead of the financial sector for the European integration. The food industry has still the lowest integration in both groups.

We also consider the integration between different industries for specific countries. This integration has a different pattern for the correlation measures in comparison with the integration between countries. The integration has alternating periods of decreasing and increasing integration over time instead of the increasing integration over time for the integration between the European countries. For the integration between industries, the integration between Japanese and American industries are the highest and the lowest integration is between the industries of Belgium and the Netherlands.

In the period 1989 to 2021 there are some crises, for example the Dot com bubble, the credit crisis and the COVID-19 pandemic. These crises have a negative effect on the integration, for all the countries and industries the integration decreases around these periods. However, this decrease in integration is for a short period over time and does not result in a turning point towards segmentation. In the recent years there is an increase in integration for most of the countries and industries.

We calculate the diversification benefits with two integration measures. First, we use the cross correlation measure, which indicated that a lower integration results into a larger reduction in variance. This means that investors have the largest reduction in variance by investing into different countries in the food industry or into different industries of Belgium or the Netherlands. Investing into all the assets of all the countries and industries reduce the variance of at least 40%. Second, we use the regime switching model to calculate the diversification benefits. The largest reduction in variance is for investing into different countries in the food industry or into different industries of the Netherlands. The reduction in variance for investing into all the assets is around the 60% for the regime switching model. This indicates that investors can reduce their risk by diversifying their portfolios.

Investing in the food industry reduce the variance of the investors by approximately 70% over time. The integration between the countries for the industries is increasing over time, except for the food industry which remains around the same level over time. This give us the expectation that the integration between the countries for the other industries increases even more, which means that the reduction in variance become less. There are also diversification benefits for investing in the different industries of a country, but the reduction in variance is less in comparison with investing in the countries in the food industry. Furthermore, there is an increase in integration between the industries for each country in the recent years, which means that the reduction in variance become less.

In summary, the integration varies over time. The integration between the countries has an increasing pattern over time, while the integration between the industries has an alternating pattern of decreasing and increasing periods. There are some crisis periods that decrease the integration, but these decreases are for a short period and do not result in a turning point from integration to segmentation. The integration can be used to create diversified portfolios, which reduce the variance for investors. Our contribution to the literature is that the integration between industries differs from the integration between countries over time and therefore plays also an important role for investors in the financial markets. We observe that for most countries the integration between the industries is close to each other and the integration shows that there in general are more diversification benefits for investing in the different industries of a country.

This report is organised as follows. Section 2 discusses the literature on the financial integration. Section 3 describes the data that we use. Section 4 presents the methods for measuring the integration and diagnostic tools. Section 5 presents the results and Section 6 concludes the report.

2 Literature

In order to answer the research questions, we use different models and techniques from other studies. There are multiple methods to measure the integration in financial markets. Billio et al. (2017) uses different techniques and compare them to each other. They find that in the long run the different techniques give the same effect of integration, which is based on country level.

We can divide the different integration measures that we use in groups. One of the most used and easiest method to measure the integration is the cross correlation. This is for example used in Hilliard (1979), who find that the intra-continental prices move simultaneously but the inter-continental prices not. However, the data they used is not recent anymore. A more recent study is the study of Quinn and Voth (2008). They find that open countries have a higher correlation than closed countries. Johnson and Soenen (2003) investigate the integration and comovements in countries in Latin America with the stock market of the US.

The following measure that we use is with the use of a common component. This measure is based on principal component analysis. This is for example used in Chen and Woo (2010), who measure the integration with PCA in the Asia Pacific region. Their PCA method measures an increase in integration from 1990 till 2000 and an increase after 2003.

Another method to measure the integration is with the use of GARCH models. Fratzscher (2002) use a GARCH model to study the integration of the European stock market with the role of the EMU and find empirical evidence of integration in European equity markets. This multivariate GARCH model is used in more researches to estimate the financial integration. For example, by Chambet and Gibson (2008) for emerging stock markets and conclude that the emerging countries are more segmented and the level of integration has been slowed down by the financial crisis in 1990.

The last measure that we use is with the use of asset pricing models to measure the integration. Bekaert and Harvey (1995) use a conditional CAPM model, in which they account for time varying integration. They use a regime switching model between an integrated and a segmented market, and find that the integration between different countries increase over time. De Santis and Gerard (1998) combine the CAPM model with a multivariate GARCH model and find that components of the risk premium vary over time and across markets. However, the integration does not always vary over time. Barr and Priestley (2004) measure the integration for the international bond market with an asset pricing model and conclude that the integration in this market does not vary over time.

However, most of the research of financial integration is based on country level. We also study the financial integration on industry level. One of the studies that investigate the integration on countries and global industries is the research of Carrieri et al. (2004). They find that integration based on country level does not preclude segmentation on industry level and that investors can gain portfolio performance by using both country and industry diversification. Rouwenhorst (1998) investigates the industry factor momentum and find that international momentum returns are correlated with the US.

3 Data

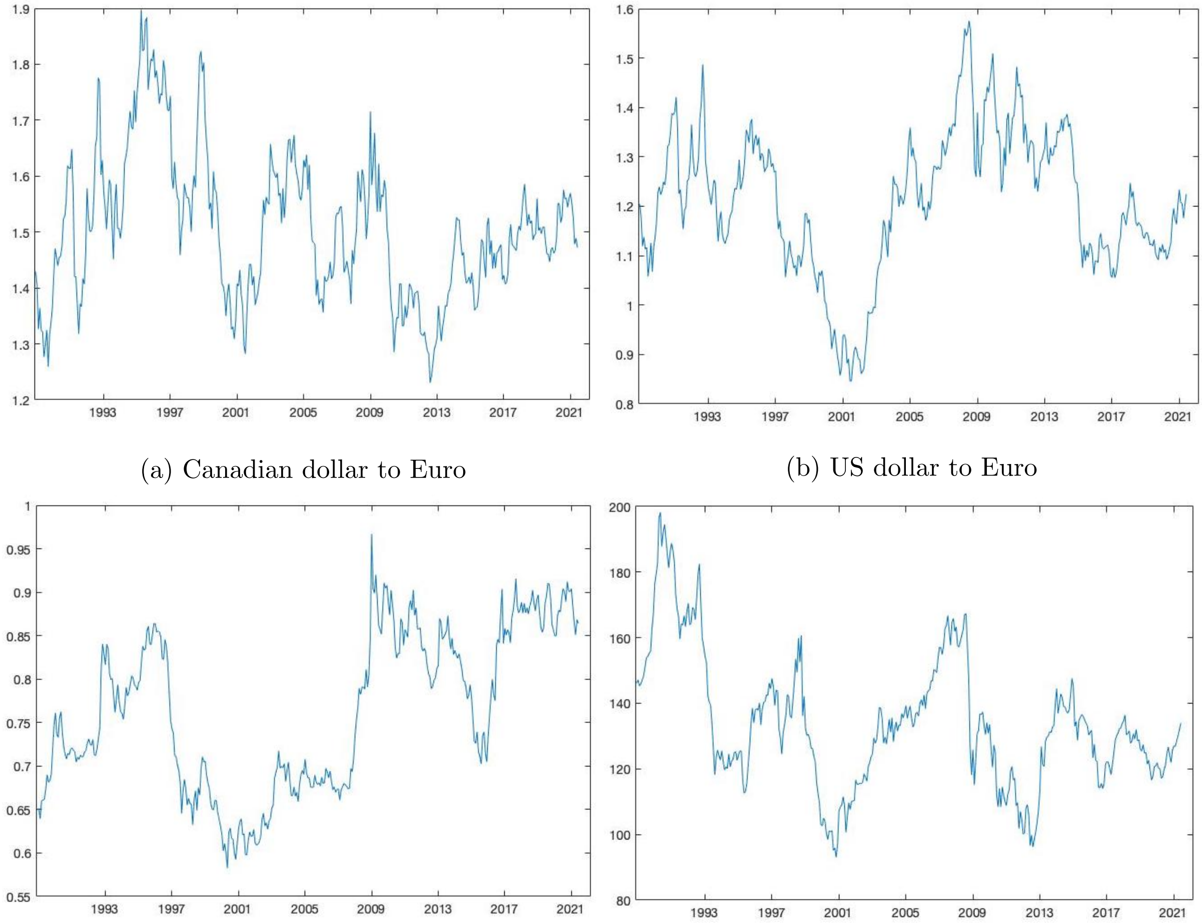
In order to investigate the integration, we use monthly price indices from December 1988 till June 2021. We use the stock prices from different sectors in different countries.

We consider seven of the eleven main sectors, namely Technology, Financials, Basic Materials, Industrials, Food producers, Health Care and Consumer Discretionary. We use nine different countries around the world. The countries in Europe are the Netherlands, Germany, Italy, United Kingdom, France and Belgium. In order to measure the effects of integration from other continents on the European countries we also use the countries United States, Canada and Japan. The data is obtained from Thomson Reuters Datastream. They define the price indices as

$$I_t = I_{t-1} \frac{\sum_{i=1}^{n} (P_t N_t)}{\sum_{i=1}^{n} (P_{t-1} N_t f_t)},$$

where I_t is the price index at time t and $I_0 = 100$. They define P_t as the unadjusted share price on day t and N_t as the number of shares issued on day t. f_t is an adjustment factor for a capital action occurring on day t and n is the number of constituents in the index.

We transform the price indices to returns. This give us a total of 390 observations per sector per country. Figure 1 denotes the exchange rates for the Canadian dollar, the US dollar, the British pound and the Japanse yen relative to the Euro. We observe that these exchange rates vary a lot over time, for example the ratio US dollar to Euro has a range between 0.85 and 1.6. For this reason we adjust the price indices by the exchange rates, such that all the price indices are in Euros. The data for the exchange rates are obtained from the Bank of England.



(a) Canadian dollar to Euro

(b) US dollar to Euro

(c) British pound to Euro

(d) Japanese yen to Euro

Figure 1: The exchange rates for the different currencies (a)-(d) to the Euro.

Figure 2 denotes the natural logarithm of the price indices for the different countries on the financial sector. We observe that the movement of the price indices are more or less the same between the countries, this can be an indication of possible integration. For example, we observe that the price indices of the different countries go down in December 2008, during the global credit crisis, and after that they are increasing. However, there are some differences between the countries. For example, the price index of Japan decreases in the first ten years while the price indices of the other countries increase.

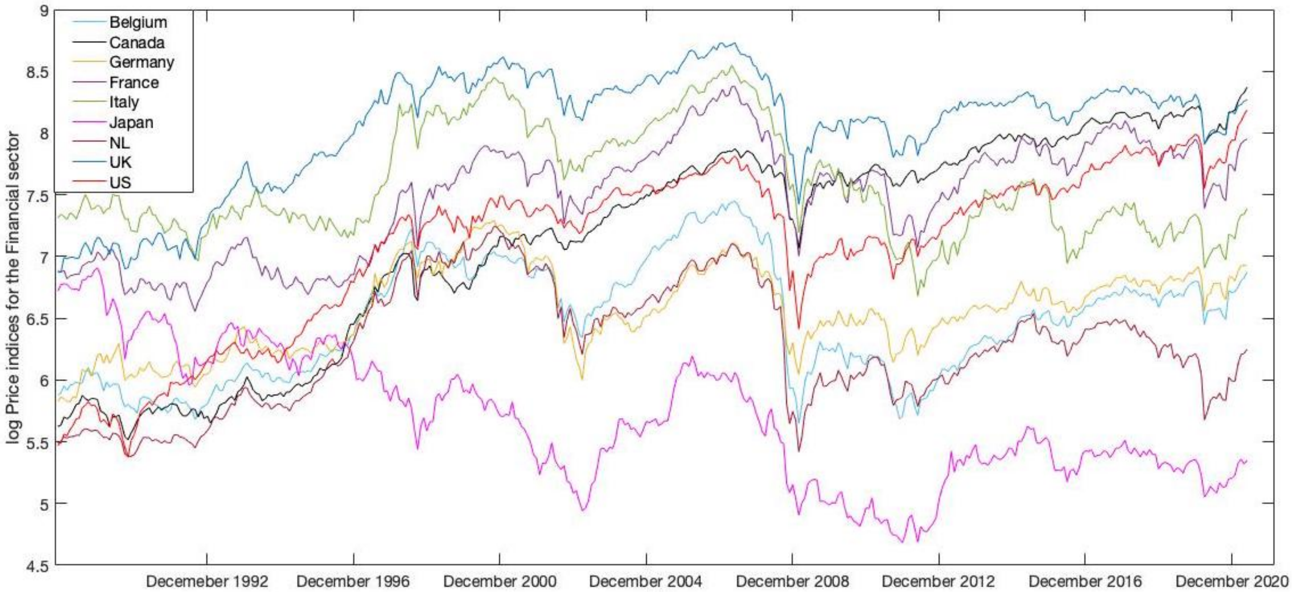


Figure 2: The log price indices for the different countries on the financial sector

In Figure 3 we denote the log price indices for the different industries for one specific country, in this figure we choose the Netherlands as an example. The price indices for the industries have a different pattern over time than the price indices for the countries in Figure 2. The price indices for the industries in the Netherlands have an increasing pattern over time for almost all the industries. However, we observe that the global credit crisis in 2008 has for some industries a larger impact than for others. Table 1 denotes the correlation between the countries in the financial sector over the whole sample. The correlations are all higher than 0.5, except the correlations of all the countries with Japan. Table 2 denotes the correlation between the different industries in the Netherlands. The industries are positively correlated with each other and the lowest correlation is with the health and food industries.

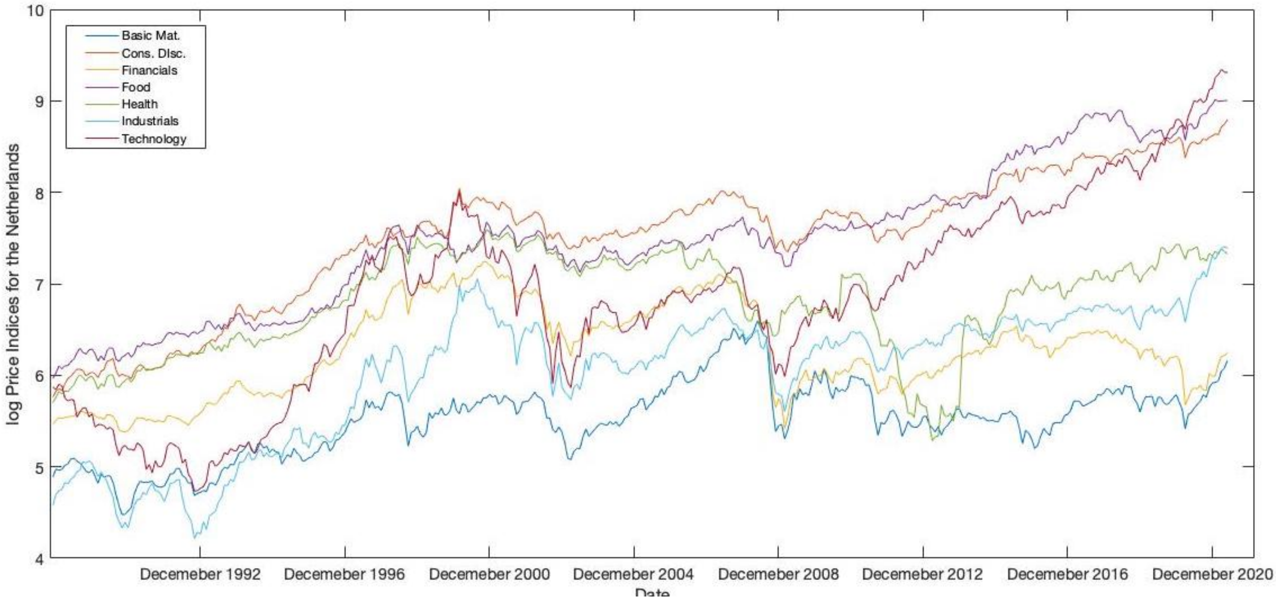


Figure 3: The log price indices for the different sectors for the Netherlands

Table 1: Correlation between the different countries in the Financial sector

Financials	**Belgium**	**Canada**	**Germany**	**France**	**Italy**	**Japan**	**NL**	**UK**	**US**
Belgium	1								
Canada	0.61	1							
Germany	0.76	0.57	1						
France	0.83	0.63	0.80	1					
Italy	0.74	0.52	0.72	0.80	1				
Japan	0.28	0.39	0.29	0.32	0.26	1			
NL	0.87	0.65	0.80	0.84	0.74	0.34	1		
UK	0.77	0.70	0.72	0.78	0.66	0.40	0.80	1	
US	0.62	0.78	0.59	0.64	0.50	0.39	0.66	0.74	1

Table 2: Correlation between the different industries of the Netherlands

NL	**Basic Mat.**	**Cons. Dis.**	**Financials**	**Food**	**Health**	**Industrials**	**Tech**
Basic Mat.	1						
Cons. Dis.	0.56	1					
Financials	0.71	0.58	1				
Food	0.43	0.44	0.48	1			
Health	0.22	0.25	0.30	0.31	1		
Industrials	0.65	0.62	0.65	0.36	0.22	1	
Tech	0.52	0.56	0.57	0.26	0.16	0.71	1

4 Methodology

We first follow the framework of Billio et al. (2017) in Section 4.1 to measure the integration over time. In order to estimate the integration over time we use a rolling window of 60 months. After that we use a regime switching model in Section 4.2 to measure the integration over time. We calculate the integration for this model over the whole sample and with a rolling window of 120 months. Finally, we discuss some diagnostic tools for the integration in Section 4.3.

4.1 Integration measures

We can use factor models to model the returns. We can use a k factor model for the returns which is given as

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{B}_t \boldsymbol{f}_t + \boldsymbol{v}_t, \tag{4.1.1}$$

where $\boldsymbol{B}_t$ denotes a $N \times k$ matrix of factor sensitivities, $\boldsymbol{f}_t$ a $k \times 1$ vector of factors and $\boldsymbol{v}$ a $N \times 1$ vector of error terms. We use that $\mathrm{E}[\boldsymbol{v}_t] = \mathbf{0}$ and $\mathrm{E}[\boldsymbol{v}_t' \boldsymbol{v}_t] = \boldsymbol{\Sigma}_t$. For the factors $\boldsymbol{f}_t$, we use that $\mathrm{E}[\boldsymbol{f}_t] = \mathbf{0}$, such that $\boldsymbol{\mu}_t$ captures the risk premia. The different approaches that we use to measure the integration in Sections 4.1.1 till 4.1.5 follow the structure of the factor model, but with different assumptions and structures on the parameters $\boldsymbol{\mu}_t, \boldsymbol{B}_t, \boldsymbol{f}_t$ and $\boldsymbol{v}_t$.

4.1.1 Cross Correlation

One of the most used measure for integration is the standard correlation between different sectors or countries. For this measure we structure our factor model of (4.1.1) in such way that there exist no $\boldsymbol{B}_t$ and $\boldsymbol{f}_t$. This means that the factor model is defined by

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{v}_t. \tag{4.1.2}$$

This integration measure is for example used by Quinn and Voth (2008) and Hilliard (1979). For the integration measure we take the average correlation of each pair. This can be done by constructing a lower triangular matrix of the correlation matrix and calculate the average of all the elements under the diagonal.

4.1.2 Forbes-Rigobon Correlation

An extension to the standard cross correlation is the integration measure of Forbes and Rigobon (2002). For this measure we use the same structure for $\boldsymbol{B}_t$ and $\boldsymbol{f}_t$ as for the cross correlation. This means that the factor model is equal to the model in (4.1.2). They use the following correlation to measure the integration

$$\rho_t^{\text{FR}} = \frac{\rho_t}{\sqrt{1 + \delta_t[1 - (\rho_t)^2]}}, \tag{4.1.3}$$

where ρ_t denotes the unadjusted correlation coefficient and δ_t the relative increase in variance compared to a period which has the minimum variance. This Forbes-Rigobon correlation corrects for hetereoskedasticity in the returns, because of the increase in the correlation by δ_t, the Forbes-Rigobon correlation will be higher in more volatile periods than in stable periods. We calculate δ_t as follows, for each rolling window of 60 months we calculate the average variance of the returns, which we denote by σ_h^2. For each rolling window of 60 months, we use a rolling window of 24 months and calculate the average variance. This gives us 37 average variances per rolling window of 60 months. We calculate the minimum of these 37 average variances and denote this minimum by σ_l^2. After this we can calculate the relative increase in variance δ_t for each rolling window of 60 months by

$$\delta_t = \frac{\sigma_h^2}{\sigma_l^2} - 1.$$

The unadjusted correlation coefficien ρ_t will be calculated in the same manner as the cross correlation in Section 4.1.1.

4.1.3 Principal Component

Another approach of Billio et al. (2017) to measure the financial integration is with the use of a Principal Component Analysis (PCA). With the factor model of (4.1.1) we can define factors that make a linear combination of the returns, such that $\boldsymbol{f}_t = \boldsymbol{B}'\boldsymbol{r}_t$. This means that the factor model will be adjusted to

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{B}\boldsymbol{f}_t + \boldsymbol{v}_t.$$

PCA finds linear combinations of $\boldsymbol{r}_t$ that are uncorrelated and have maximum variance. In order to solve this, we find that $\boldsymbol{B}$ contains the eigenvectors of the covariance matrix. Because of the properties of the eigenvectors we can write the returns as a linear combination of the factors, such that $\boldsymbol{r}_t = \boldsymbol{B}\boldsymbol{f}_t$. However, we apply PCA to the correlation matrix, such that we avoid that the eigenvectors tend more to returns with higher variance. Therefore, we can construct the factors by $\boldsymbol{f}_t = \boldsymbol{A}'\boldsymbol{S}^{-\frac{1}{2}}\boldsymbol{r}_t$, where $\boldsymbol{A}$ contains the eigenvectors of the correlation matrix and $\boldsymbol{S}$ is a diagonal matrix which contains the variances of the returns on the diagonal. We want to find K much smaller than N factors such that the variance explained by the first K factors is reasonably large. The fraction of variance explained by the first K factors is equal to $\frac{\lambda_1+\lambda_2+\cdots+\lambda_K}{\lambda_1+\lambda_2+\cdots+\lambda_N}$. Then we can make the multi factor regression

$$r_{i,t} = \beta_{i,0} + \beta_{i,1}f_{1,t} + \cdots + \beta_{i,K}f_{K,t} + v_{i,t} \qquad \text{for } i \in \{1, \cdots, N\}. \tag{4.1.4}$$

We will follow the method of Billio et al. (2017) and only use the first three factors to construct this regression. One method to measure the financial integration is to use the average of the $\bar{R}^2$ of the regression in (4.1.4). Another method to measure the integration is by the variance that is explained by the first principal component. This is equal to

$$\frac{\lambda_1 \boldsymbol{a}_1' \boldsymbol{S} \boldsymbol{a}_1}{\text{tr}(\boldsymbol{S})}, \tag{4.1.5}$$

where λ_i is the eigenvalue for the i^{th} principal component and $\boldsymbol{a}_i$ the corresponding eigenvector.

4.1.4 GARCH

Another method to measure the financial integration is by using multivariate GARCH models. In the factor model (4.1.1), the conditional variance of $\boldsymbol{r}_t|\boldsymbol{\mathcal{I}}_{t-1}$ is given by $\boldsymbol{H}_t = \boldsymbol{B}\boldsymbol{\Omega}_t\boldsymbol{B}' + \boldsymbol{\Psi}_t$, where $\boldsymbol{\Omega}_t$ denotes the conditional variance of $\boldsymbol{f}_t$ and $\boldsymbol{\Psi}_t$ the conditional variance of $\boldsymbol{v}_t$. Therefore the factor model that we use will be defined by

$$\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{B}\boldsymbol{f}_t + \boldsymbol{v}_t.$$

We can model the conditional variance $\boldsymbol{H}_t$ with the dynamic conditional correlation (DCC) model of Engle (2002). This model is an extension of the constant conditional correlation (CCC) model. The DCC model is given by

$$\boldsymbol{r}_t|\boldsymbol{\mathcal{I}}_{t-1} \sim N(\boldsymbol{\mu}_t, \boldsymbol{H}_t) \tag{4.1.6}$$

$$\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t, \tag{4.1.7}$$

where $\boldsymbol{D}_t$ is a diagonal matrix with the conditional standard deviations $\sqrt{h_{ii,t}}$ and $\boldsymbol{R}_t$ a matrix with the correlations $\rho_{ij,t}$. The DCC GARCH model ensures that the conditional covariance matrix $\boldsymbol{H}_t$ is positive definite, by splitting the covariance matrix into standard deviations and correlations.

In order to estimate this model we define $\boldsymbol{\varepsilon}_t = \boldsymbol{r}_t - \boldsymbol{\mu}_t$ and $\boldsymbol{z}_t = \boldsymbol{D}_t^{-1}\boldsymbol{\varepsilon}_t$. We use a two step estimation. First, we estimate univariate GARCH(1,1) models with volatility targeting for the conditional volatilities. This is defined as

$$h_{ii,t} = (1 - \alpha_{ii} - \beta_{ii})\hat{\sigma}_{ii} + \alpha_{ii}\varepsilon_{ii,t-1} + \beta_{ii}h_{ii,t-1}, \tag{4.1.8}$$

where $\hat{\sigma}_{ii} = \frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_{it}^2$, the sample variance of the returns. We can now construct the standardised residuals as $\hat{z}_{it} = \hat{\varepsilon}_{it}/\sqrt{\hat{h}_{ii,t}}$. Second, we estimate the parameters γ and δ for the conditional correlations where we use correlation targeting. This is defined as

$$\boldsymbol{Q}_t = (1 - \delta - \gamma)\hat{\bar{\boldsymbol{Q}}} + \gamma\hat{\boldsymbol{z}}_{t-1}\hat{\boldsymbol{z}}_{t-1}' + \delta\boldsymbol{Q}_{t-1}, \tag{4.1.9}$$

where we use that $\hat{\bar{\boldsymbol{Q}}} = \frac{1}{T}\sum_{t=1}^{T}\hat{\boldsymbol{z}}_t\hat{\boldsymbol{z}}_t'$. After that, we can construct the correlations for the matrix $\boldsymbol{R}_t$ as

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}.$$

4.1.5 Asset Pricing Model

One of the most popular factor model is the CAPM model. For this model we assume that the factor in (4.1.1) is the market return and for the expectation and variance of the error terms $\boldsymbol{v}_t$ we assume that $\mathrm{E}[\boldsymbol{v}_t] = \boldsymbol{0}$ and $\mathrm{E}[\boldsymbol{v}_t'\boldsymbol{v}_t] = \boldsymbol{\Sigma}$. This results in the following model for the CAPM

$$\boldsymbol{r}_t = \boldsymbol{\mu} + \boldsymbol{\beta}_t\boldsymbol{r}_t^m + \boldsymbol{v}_t.$$

We follow the conditional one factor model of Choudhry and Jayasekera (2015) and Jayasinghe et al. (2014) for the time varying beta, which is defined as

$$\mathrm{E}_{t-1}[r_{i,t}] = \frac{\mathrm{cov}_{t-1}(r_{i,t}, r_{m,t})}{\mathrm{var}_{t-1}(r_{m,t})}\mathrm{E}_{t-1}[r_{m,t}], \tag{4.1.10}$$

where $r_{i,t}$ and $r_{m,t}$ are the excess returns of asset i and the market respectively. We model the conditional variance of the CAPM model with the use of GARCH models. Therefore we use the DCC-GARCH model which is explained in Section 4.1.4. We use the DCC-GARCH model for each combination of asset excess return and excess market return, and construct for each asset the conditional covariance matrix $\boldsymbol{H}_t$ as in (4.1.7). This means that the covariance matrix $\boldsymbol{H}_t$ is a 2×2 matrix for each pair. We can estimate the time varying beta, which denotes a measure for the integration, by

$$\hat{\beta}_t = \frac{\hat{\boldsymbol{H}}_{t,(1,2)}}{\hat{\boldsymbol{H}}_{t,(2,2)}},$$

where $\hat{\boldsymbol{H}}_{t,(1,2)}$ is an estimation for the conditional covariance between an asset and the market, $\hat{\boldsymbol{H}}_{t,(2,2)}$ denotes as an estimation for the conditional variance of the market. We take the average of the time varying betas as a measure for the integration. We will use the different sectors of all the countries in Europe as a proxy for the market.

4.2 Regime switching

We will also consider the regime switching model of Bekaert and Harvey (1995). This model is a combination of a completely integrated market and completely segmented market, which is defined as

$$\mathrm{E}_{t-1}[r_{i,t}] = \xi_{i,t-1}\lambda_{t-1}\operatorname{cov}_{t-1}(r_{i,t}, r_{w,t}) + (1-\xi_{i,t-1})\lambda_{i,t-1}\operatorname{var}_{t-1}(r_{i,t}), \tag{4.2.1}$$

where $\xi_{i,t-1}$ will be the measure of integration. For the regime switching model in (4.2.1) we can use that $\xi_{i,t-1}$ is the conditional probability of being in regime 1. After that we let s_t denotes the unobserved state which is generated by a first order Markov process such that $\Pr[s_t|s_{t-1}, s_{t-2}, \cdots, s_1, y_{t-1}, y_{t-2}, \cdots, y_1, \boldsymbol{\theta}] = \Pr[s_t|s_{t-1}; \boldsymbol{\theta}]$.

4.2.1 Filter

We denote the true unobserved state as

$$\boldsymbol{\xi}_t = \begin{pmatrix} I(s_t = 1) \\ \vdots \\ I(s_t = M) \end{pmatrix}$$

where $I(s_t = i)$ is equal to one if the true unobserved state is i and zero otherwise. The true state s_t is unobserved but we can make an inference on s_t. For this inference we will use the Hamilton filter Hamilton (1989) and the Kim smoother Kim (1994). The Hamilton filter is defined as follows First we have the prediction step: $\hat{\boldsymbol{\xi}}_{t+1|t} = \boldsymbol{P}\hat{\boldsymbol{\xi}}_{t|t}$ and the update step as

$$\hat{\boldsymbol{\xi}}_{t|t} = \begin{bmatrix} \Pr(s_t = 1|\mathcal{I}_t) \\ \vdots \\ \Pr(s_t = M|\mathcal{I}_t) \end{bmatrix} = \begin{bmatrix} \Pr(s_t = 1|\mathcal{I}_{t-1}, \boldsymbol{y}_t) \\ \vdots \\ \Pr(s_t = M|\mathcal{I}_{t-1}, \boldsymbol{y}_t) \end{bmatrix} = \frac{1}{f(\boldsymbol{y}_t|\mathcal{I}_{t-1})} \begin{bmatrix} f(s_t = 1, \boldsymbol{y}_t|\mathcal{I}_{t-1}) \\ \vdots \\ f(s_t = M, \boldsymbol{y}_t|\mathcal{I}_{t-1}) \end{bmatrix}$$

$$= \frac{1}{f(\boldsymbol{y}_t|\mathcal{I}_{t-1})}\begin{bmatrix} f(\boldsymbol{y}_t|s_t=1,\mathcal{I}_{t-1})\Pr(s_t=1|\mathcal{I}_{t-1}) \\ \vdots \\ f(\boldsymbol{y}_t|s_t=M,\mathcal{I}_{t-1})\Pr(s_t=M|\mathcal{I}_{t-1}) \end{bmatrix} = \frac{1}{f(\boldsymbol{y}_t|\mathcal{I}_{t-1})}\begin{bmatrix} f(\boldsymbol{y}_t|s_t=1) \\ \vdots \\ f(\boldsymbol{y}_t|s_t=M) \end{bmatrix} \odot \hat{\boldsymbol{\xi}}_{t|t-1}.$$

We denote $\boldsymbol{f}_t$ as the vector of probability densities given the regime, such that

$$\boldsymbol{f}_t = \begin{pmatrix} f(\boldsymbol{y}_t|s_t=1) \\ \vdots \\ f(\boldsymbol{y}_t|s_t=M) \end{pmatrix}.$$

In this way we can write the updating step as as

$$\hat{\boldsymbol{\xi}}_{t|t} = \frac{\boldsymbol{f}_t \odot \hat{\boldsymbol{\xi}}_{t|t-1}}{\boldsymbol{1}'_M\left[\boldsymbol{f}_t \odot \hat{\boldsymbol{\xi}}_{t|t-1}\right]} \tag{4.2.2}$$

where $\odot$ denotes point wise multiplication and $\boldsymbol{1}_M$ denotes a vector of length M containing ones. For the smoother we will use that by definition $\hat{\boldsymbol{\xi}}_{t|T} = \mathrm{E}[\boldsymbol{\xi}_t|\boldsymbol{\mathcal{I}}_T]$. We use the law of iterated expectations to calculate $\hat{\boldsymbol{\xi}}_{t|T}$, which is defined by

$$\hat{\boldsymbol{\xi}}_{t|T} = \mathrm{E}[\boldsymbol{\xi}_t|\boldsymbol{\mathcal{I}}_T] = \mathrm{E}[\mathrm{E}(\boldsymbol{\xi}_t|\boldsymbol{\xi}_{t+1},\boldsymbol{\mathcal{I}}_T)|\boldsymbol{\mathcal{I}}_T].$$

We can define the inner expectation $\mathrm{E}(\boldsymbol{\xi}_t|\boldsymbol{\xi}_{t+1},\boldsymbol{\mathcal{I}}_T)$ as follows,

$$\begin{aligned}
\mathrm{E}(\boldsymbol{\xi}_t|\boldsymbol{\xi}_{t+1},\boldsymbol{\mathcal{I}}_T) &= \begin{pmatrix} \Pr(s_t=1|s_{t+1}=k,\boldsymbol{\mathcal{I}}_T) \\ \vdots \\ \Pr(s_t=M|s_{t+1}=k,\boldsymbol{\mathcal{I}}_T) \end{pmatrix} \\
&= \begin{pmatrix} \Pr(s_t=1,s_{t+1}=k|\boldsymbol{\mathcal{I}}_T) \\ \vdots \\ \Pr(s_t=M,s_{t+1}=k|\boldsymbol{\mathcal{I}}_T) \end{pmatrix} /\Pr(s_{t+1}=k|\boldsymbol{\mathcal{I}}_T) \\
&= \begin{pmatrix} \Pr(s_t=1|\boldsymbol{\mathcal{I}}_T) \\ \vdots \\ \Pr(s_t=M|\boldsymbol{\mathcal{I}}_T) \end{pmatrix} \odot \begin{pmatrix} \Pr(s_{t+1}=k|s_t=1) \\ \vdots \\ \Pr(s_{t+1}=k|s_t=M) \end{pmatrix} /\Pr(s_{t+1}=k|\boldsymbol{\mathcal{I}}_T) \\
&= \hat{\boldsymbol{\xi}}_{t|t} \odot \boldsymbol{P}'\left(\boldsymbol{e}_k \oslash \hat{\boldsymbol{\xi}}_{t+1|t}\right) \\
&= \hat{\boldsymbol{\xi}}_{t|t} \odot \boldsymbol{P}'\left(\boldsymbol{\xi}_{t+1} \oslash \hat{\boldsymbol{\xi}}_{t+1|t}\right).
\end{aligned}$$

The Kim smoother is defined as

$$\hat{\boldsymbol{\xi}}_{t|T} = \mathrm{E}\left[\hat{\boldsymbol{\xi}}_{t|t} \odot \boldsymbol{P}'\left(\boldsymbol{\xi}_{t+1} \oslash \hat{\boldsymbol{\xi}}_{t+1|t}\right)|\boldsymbol{\mathcal{I}}_T\right] = \hat{\boldsymbol{\xi}}_{t|t} \odot \boldsymbol{P}'\left(\hat{\boldsymbol{\xi}}_{t+1|T} \oslash \hat{\boldsymbol{\xi}}_{t+1|t}\right),$$

where $\oslash$ is defined as element by element deviation. We can estimate the parameters in our regime switching model by maximum likelihood. The likelihood function is defined as

$$\mathcal{L}(\boldsymbol{y}_T,\cdots,\boldsymbol{y}_1;\boldsymbol{\theta}) = \prod_{t=1}^{T}\Pr[\boldsymbol{Y}_t=\boldsymbol{y}_t|\boldsymbol{y}_{T-1},\cdots,\boldsymbol{y}_1] = \prod_{t=1}^{T}\hat{\boldsymbol{\xi}}'_{t|t-1}\boldsymbol{f}_t.$$

For the maximum likelihood we need to maximise the log likelihood, which is given by

$$l(\boldsymbol{y}_T, \cdots, \boldsymbol{y}_1; \boldsymbol{\theta}) = \sum_{t=1}^{T} \log(\hat{\boldsymbol{\xi}}'_{t|t-1} \boldsymbol{f}_t)$$

4.2.2 EM algorithm

However, we cannot observe the state s_t the world is in, so we use the Expectation Maximisation Algorithm (EM algorithm) to estimate the parameters. The EM algorithm contains two steps. Firstly, we have the E-step where we take the expectation of the log complete data likelihood function with respect to $s_T|\mathcal{I}_T$ given θ. Secondly, we have the M-step where we maximise the expected log likelihood function with respect to θ. We consider the observations $s_{1:T}$ as a path and we need to sum over all the possible paths in the likelihood function. We define the Kronecker delta $\delta_{ij}(t)$ which is one if $s_t = i$ and $s_{t-1} = j$. And we define $\delta_j(t) = 1$ if $s_t = j$. Then the joint likelihood of $\boldsymbol{y}_{1:T}$ and $s_{0:T}$ is

$$f(\boldsymbol{y}_{1:T}, s_{1:T}|\boldsymbol{\theta}, \mathbf{P}, \boldsymbol{\rho}) = \prod_{t=1}^{T} \left[\prod_{i,j=1}^{M} \Big(f_i(\boldsymbol{y}_t) p_{i,j} \Big)^{\delta_{i,j}(t)} \right] \left(\prod_{j=1}^{M} p_j^{\delta_j(0)} \right),$$

in this way the log likelihood will be defined as

$$\log f(\boldsymbol{y}_{1:T}, s_{1:T}|\boldsymbol{\theta}, \mathbf{P}, \boldsymbol{\rho}) = \sum_{t=1}^{T} \left[\sum_{i,j=1}^{M} \Big(\log\, [f_i(\boldsymbol{y}_t) p_{i,j}] \Big) \delta_{i,j}(t) \right] + \left(\sum_{j=1}^{M} \log\, [p_j] \delta_j(0) \right). \quad (4.2.3)$$

For the EM algorithm we need to maximise the expectation of (4.2.3).

4.2.3 Estimation

In order to estimate the model of Bekaert and Harvey (1995), we will use the econometric model

$$\boldsymbol{r}_t = \xi_{t-1} \lambda^I \operatorname{cov}_{t-1}(\boldsymbol{r}_t, r_{w,t}) + (1 - \xi_{t-1}) \boldsymbol{\lambda}^S \operatorname{var}(\boldsymbol{r}_t) + \boldsymbol{e}_t \quad (4.2.4)$$

$$r_{w,t} = \lambda_{t-1} \operatorname{var}(r_{m,t}) + e_{w,t}. \quad (4.2.5)$$

We define the error term under integration as $e^I_{i,t} = r_{i,t} - \lambda^I \operatorname{cov}_{t-1}(r_{i,t}, r_{m,t})^I$ and under segmentation as $e^S_{i,t} = r_{i,t} - \lambda^S_i \operatorname{var}_{t-1}(r_{i,t})^S$. The disturbance vector of the market is equal to $e^I_{w,t} = r_{w,t} - \lambda^I \operatorname{var}_{t-1}(r_{w,t})^I$ under integration and $e^S_{w,t} = r_{w,t} - \lambda^S_w \operatorname{var}_{t-1}(r_{w,t})^S$ under segmentation. Let $\boldsymbol{e}^I_t = [e^I_{i,t}, e^I_{w,t}]'$ and $\boldsymbol{e}^S_t = [e^S_{i,t}, e^S_{w,t}]'$, then we can construct the variances matrices of the disturbances vectors $\boldsymbol{\Sigma}^I$ and $\boldsymbol{\Sigma}^S$ under integration and segmentation respectively. This means that the log likelihood, which we want to maximise is defined as

$$L = \sum_{t=1}^{T} \log\left(\xi_{t|T} f_{1,t} + (1-\xi_{t|T}) f_{2,t}\right) \tag{4.2.6}$$

$$f_{1,t} = (2\pi)^{-1} |\boldsymbol{\Sigma}^I|^{-1/2} \exp\{-\frac{1}{2}(\boldsymbol{e}_t^{I\prime}(\boldsymbol{\Sigma}^I)^{-1}\boldsymbol{e}_t^I)\} \tag{4.2.7}$$

$$f_{2,t} = (2\pi)^{-1} |\boldsymbol{\Sigma}^S|^{-1/2} \exp\{-\frac{1}{2}(\boldsymbol{e}_t^{S\prime}(\boldsymbol{\Sigma}^S)^{-1}\boldsymbol{e}_t^S)\}. \tag{4.2.8}$$

For the EM algorithm, we use the Hamilton filter and Kim smoother in the E-step to obtain $\boldsymbol{\xi}_{t|T}$ and $\boldsymbol{P}^*$. In the M-step we get the analytical results for the parameters under segmentation.

$$\hat{e}_{i,t} = r_{i,t} - \hat{\mu}_i^S \tag{4.2.9}$$

$$\sigma_{i,S}^2 = \sum_{t=1}^{T} \hat{e}_{i,t}^2 \xi_{t|T} / \sum_{t=1}^{T} \xi_{t|T} \tag{4.2.10}$$

$$\hat{\lambda}_i = \sum_{t=1}^{T} \xi_{t|T} r_{i,t} / \left(\sum_{t=1}^{T} \xi_{t|T} \sigma_{i,S}^2\right). \tag{4.2.11}$$

For the parameters under integration, we will use a numerical optimisation of the log likelihood function L over λ and $\boldsymbol{C}$, where $\boldsymbol{C}$ is the Cholesky decomposition of $\boldsymbol{\Sigma}^I$. This means that $\boldsymbol{C}\boldsymbol{C}' = \boldsymbol{\Sigma}^I$.

4.3 Diagnostic Tools

We will use different diagnostic tools, which will help us to understand the effects of the integration between different industries or countries. First, we will consider diversification benefits, which could be helpful for investors. Second, we will use bootstrapping techniques to determine whether the integration is constant over time.

4.3.1 Diversification Benefits

We want to investigate whether the integration between industries will benefit investors. Therefore we consider the benefits of diversification, which we will calculate by the reduce in portfolio variance. In order to calculate this, we consider a portfolio of N assets, the variance of such a portfolio is given by

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \mathrm{cov}(r_i, r_j),$$

where w_i and w_j are the weights for asset i and j respectively. We will assume an equally weighted portfolio, such that the weight of each asset is equal to $1/N$. The $1/N$ portfolio is a portfolio which is known as hard to beat in the literature. Therefore, the variance of this portfolio is equal to

$$\sigma_p^{2*} = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\sigma_i\sigma_j\rho_{ij},$$

where the ith asset has variance σ_i^2, and ρ_{ij} denotes the correlation between asset i and j. For example, for a portfolio with 2 assets with variance σ_1^2 and σ_2^2 and correlation ρ_{12}, the variance is equal to

$$\sigma_p^{2*} = \frac{1}{4}\left(\sigma_1^2 + \sigma_2^2 + 2\sigma_1\sigma_2\rho_{12}\right)$$

When there are no diversification benefits than $\rho_{12} = 1$, this means that $\sigma_p^{2,NB} = \frac{1}{4}(\sigma_1 + \sigma_2)^2$. In general for N assets, the variance of the portfolio with no diversification benefits is equal to $\sigma_p^{2,NB} = \frac{1}{N^2}(\sigma_1 + \sigma_2 + \cdots + \sigma_N)^2$. The reduction in variance denotes a measure of diversification benefits. We calculate the benefits by

$$\frac{\sigma_p^{2*} - \sigma_p^{2,NB}}{\sigma_p^{2,NB}}. \tag{4.3.1}$$

4.3.2 Constant integration over time

After we have calculated the integration over time, with a rolling window of 60 months. It can happen that we suspect that the integration does not have much fluctuations over time. Therefore, we will test whether the integration stays constant over time i.e. $\rho_t = \rho$ for every t. In order to do this we will estimate the integration over the whole sample period. By using bootstrapping methods we simulate the time series 1000 times and use these series to create a 95% confidence interval around the integration. With this confidence interval we can calculate the number of times the integration which is calculated with the rolling windows lies outside this confidence interval. If this number is reasonable small we can conclude that the integration calculated is constant over time. In order to calculate the bounds of the confidence intervals, we will order the 1000 bootstrapped calculations for the integration. After that, we use the 2.5% highest and lowest calculation of the integration as an upper and lower bound for the integration.

5 Results

In this section, we will discuss the results of our investigation. First of all, we will discuss the results for the integration between the European countries for each industry. In order to do this, we will split the integration measures between the correlation measures and the other measures. One of the reasons for this split is that we can compare the measures based on correlation with each other. Another reason is that the integration measures within both groups show similar patterns for the integration. After the integration between the European countries, we will discuss the integration between European and non-European countries. We will use the same split between the integration measures as for the integration between the European countries. After these results, we will discuss the results for the integration between industries for each country in the same manner as the integration between European countries. Finally, we will give an overview of all the results.

5.1 Integration between EU countries

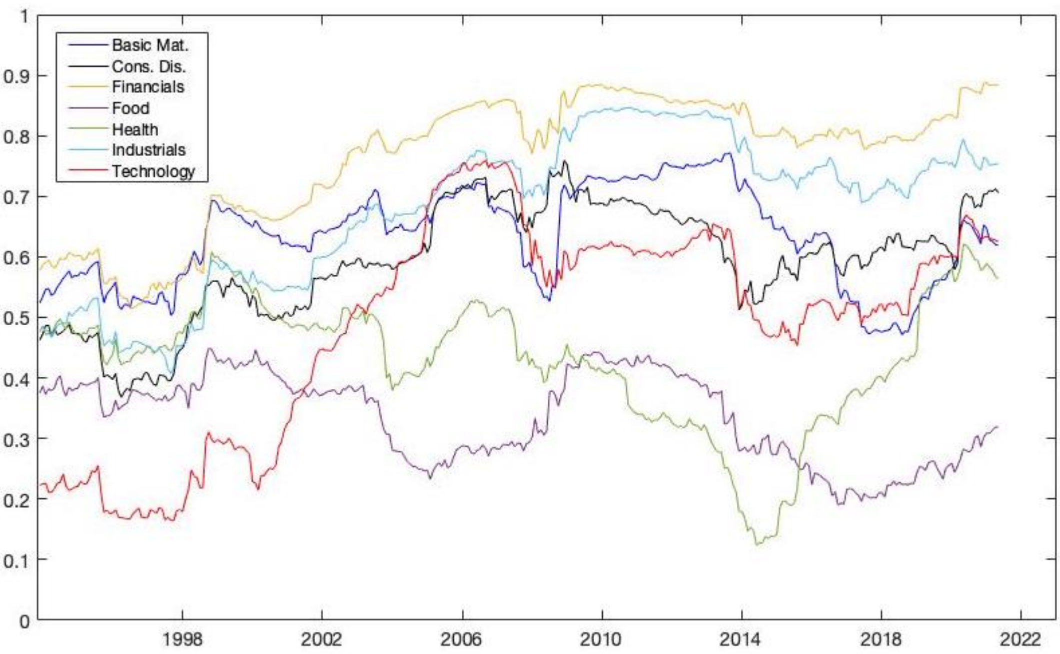


Figure 4: The integration between different European countries for specific industries, which is denoted as the cross correlation

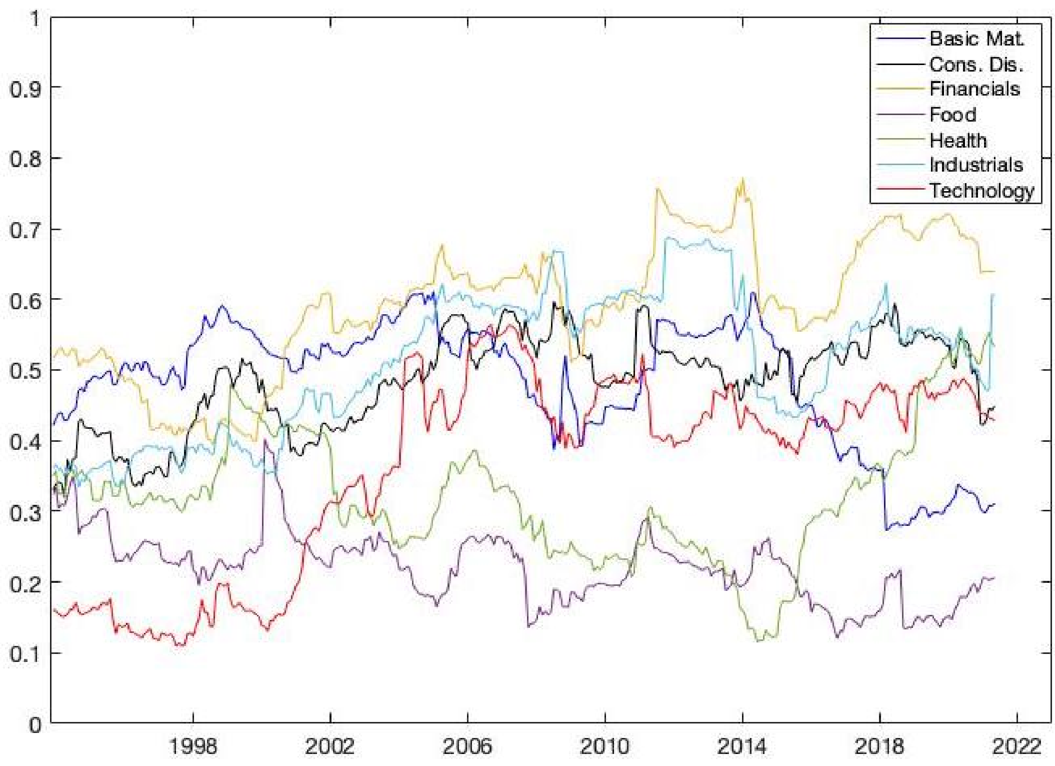


Figure 5: The integration between different European countries for specific industries, which is denoted as the Forbes-Rigobon correlation

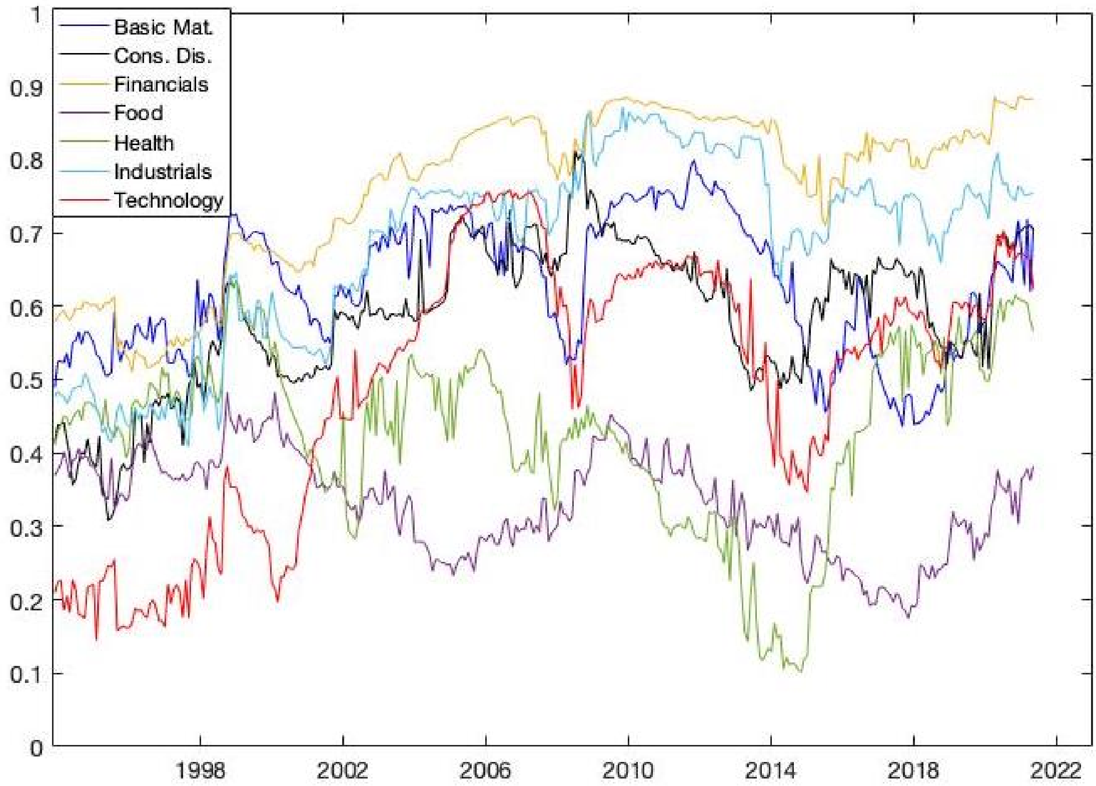


Figure 6: The integration between the EU countries for specific industries which is calculated by the DCC GARCH model

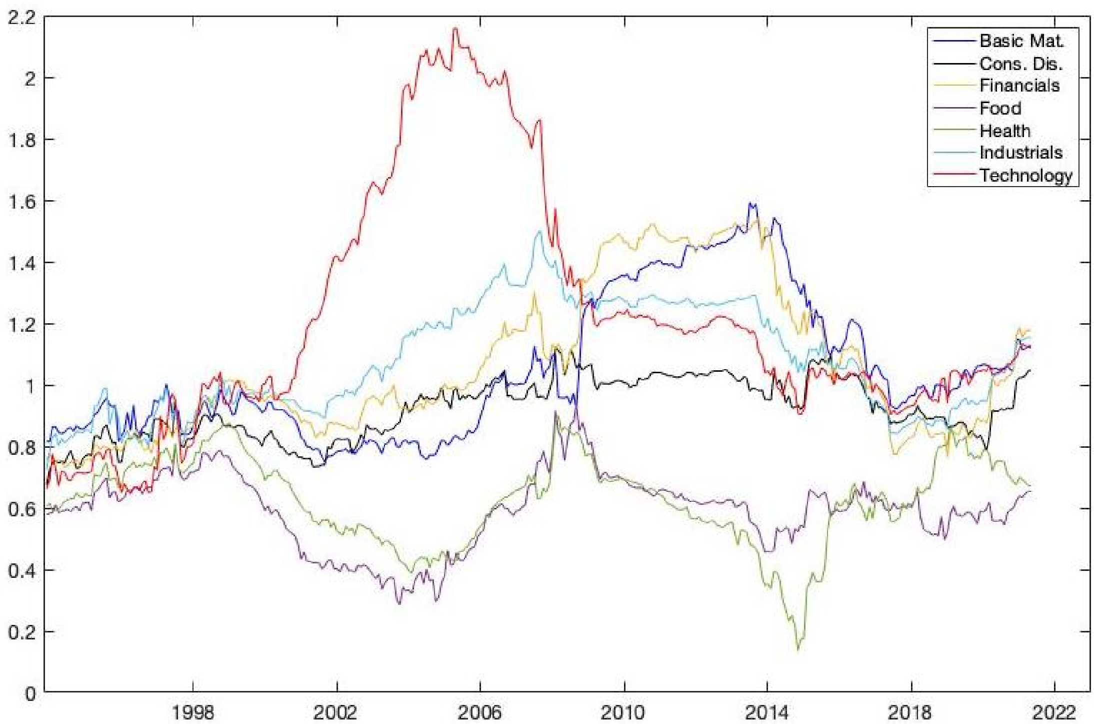


Figure 7: The integration between the EU countries for specific industries, which is denoted as the time varying betas of the CAPM model

5.1.1 Correlation measures

First, we discuss the results for the integration measures based on correlations. These are the cross correlation, Forbes-Rigobon correlation, DCC GARCH and the CAPM and are depicted in Figures 4 till 7 respectively. These integration measures show the following similarities. The integration has a positive trend over time for almost all the industries, except for the European countries in the food industry. Billio et al. (2017) also finds an increasing pattern for the integration between countries for these measures between 1990 and 2014. The integration decreases around 2000, 2008 and 2021. These periods are the Dot Com bubble, the credit crisis and the COVID-19 pandemic respectively. Although, the integration decreases in these periods, the crises do not cause a turning point in the integration trend. Pardal et al. (2020) and Borgioli et al. (2020) both study the integration between European countries around the COVID-19 pandemic and also find that the integration is high but there is a decrease in integration around these period.

In general, the integration is around 0.7 for most of the integration measures and industries. This is quite high and indicates that the European countries are more integrated with each other than segmented. The integration is the highest for the financial sector. This seems reasonable, because financial products are not bounded by national borders, which results in a higher correlation between other countries. This also applies to the integration between European countries in the industrial sector. However, the integration between the European countries in the food industry is the lowest, which is around 0.3. This indicates that the countries in this industry are more segmented with each other. An explanation for this is that companies in the food industry are mostly local and thus less correlated with companies in other countries. This also applies to the integration between countries for the health care sector.

There are also some differences between the integration measures. The integration measured by the cross correlation is higher than the integration measured by Forbes-Rigobon correlation, while the two have the same pattern. This can be an indication of a volatility effect. This volatility effect is also present in the DCC GARCH model, where there are more fluctuations in the integration over time relative to the cross correlation method. The integration measured by the CAPM model has less fluctuations over time than the DCC GARCH and the Forbes-Rigobon correlation measures and almost the same pattern as the cross correlation method. However, the CAPM model has a higher integration than the other methods and sometimes the integration exceeds one. However, this is not an upper bound for the CAPM model and we can compare the integration with the other measures by the ordering of the industries and the trend over time. There is a large increase in integration for the technology sector in the CAPM model, this is caused by the Dot Com bubble around 2000 where the technology stocks first strongly increased and later crashed. This increase and decrease in integration for the technology sector has a longer period, because of the rolling window that we use to calculate the integration.

Investors can use the integration to diversify their portfolios and reduce their risk. We calculate the reduction in variance with the cross correlation measure and this reduction is equal to $1-\rho_t$, where ρ_t is the integration on time t. This means that an integration of 0.7 is equal to a reduction of variance of 30%. Therefore, a higher integration between the European countries leads to lower diversification benefits. Figure 4 shows that the integration for the food industry is around 0.3 over time, this means that there is around 70% reduction in variance for this industry over time. The lowest reduction in variance is for the European countries in the financials sector, which is around 20% over time. The portfolio variances for the European countries for each industry are depicted in Figure 35 in Appendix A.1.

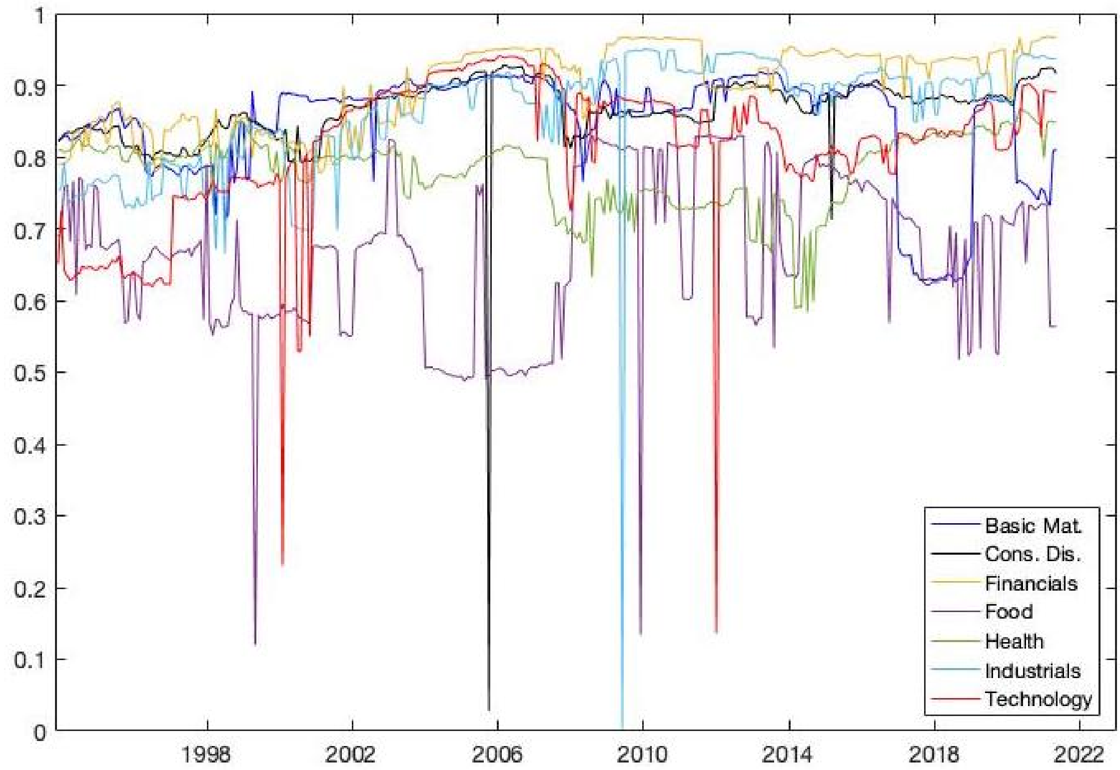


Figure 8: The integration between different European countries for specific industries, which is calculated by the R^2 method

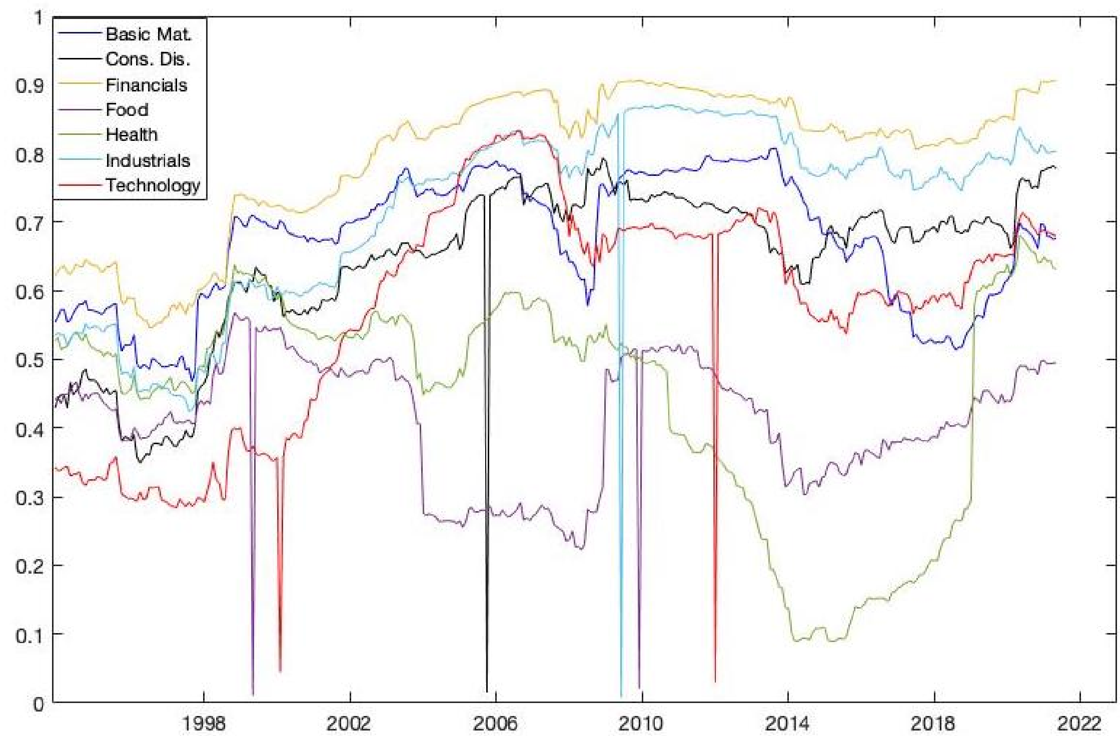


Figure 9: The integration between different European countries for specific industries which is calculated by the first principal component

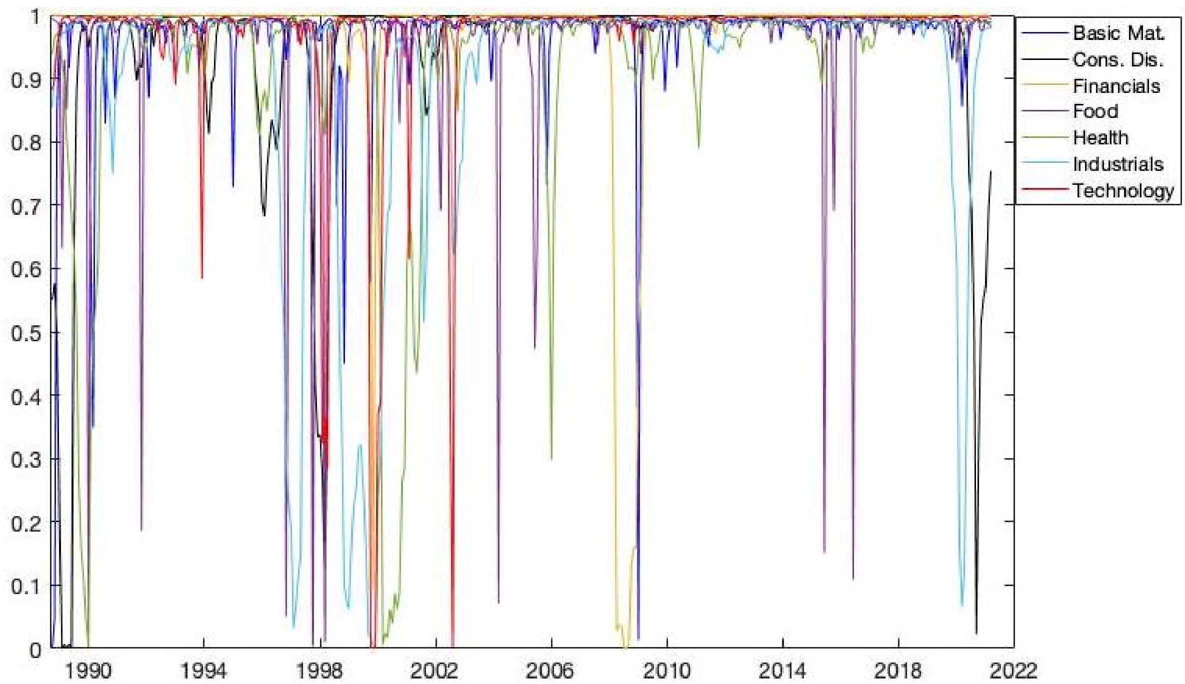


Figure 10: The smoothed inferences, which are used as a measure for integration between the European countries for an industry.

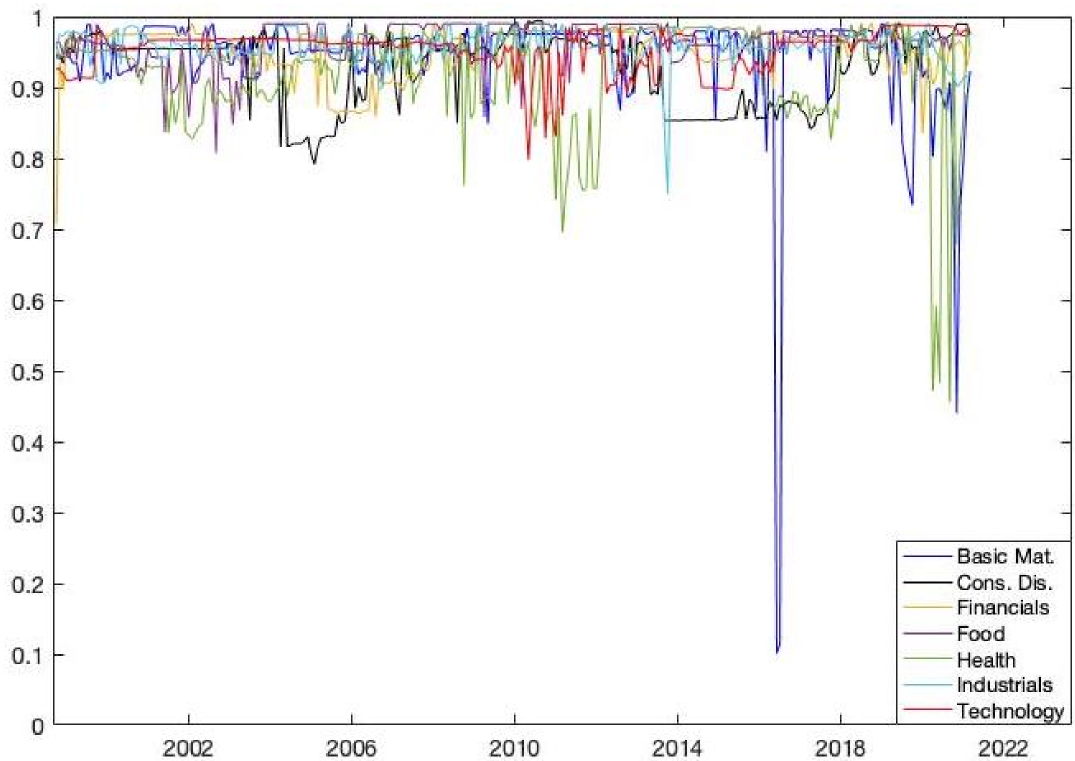


Figure 11: The smoothed inferences, which are used as a measure for integration between the European countries for an industry. The integration is calculated with a moving window of 120 months.

5.1.2 Other measures

Second, we discuss the results for the other integration measures, namely the R^2 method, the first principal component and the regime switching model. Figures 8 till 11 show the integration over time for these measures respectively. In general, the integration is very high and there are some troughs. A reason for these troughs in the integration is that the variance is higher around these periods, which makes it harder to explain by the methods. This pattern is most visible in the regime switching models and somewhat in the R^2 method. The first principal component method has more a trend pattern as for the correlation measures. The integration measured by the R^2 method and the first principal component is the highest for the financials sector and the lowest for the food industry. This is also the case for the correlation measures.

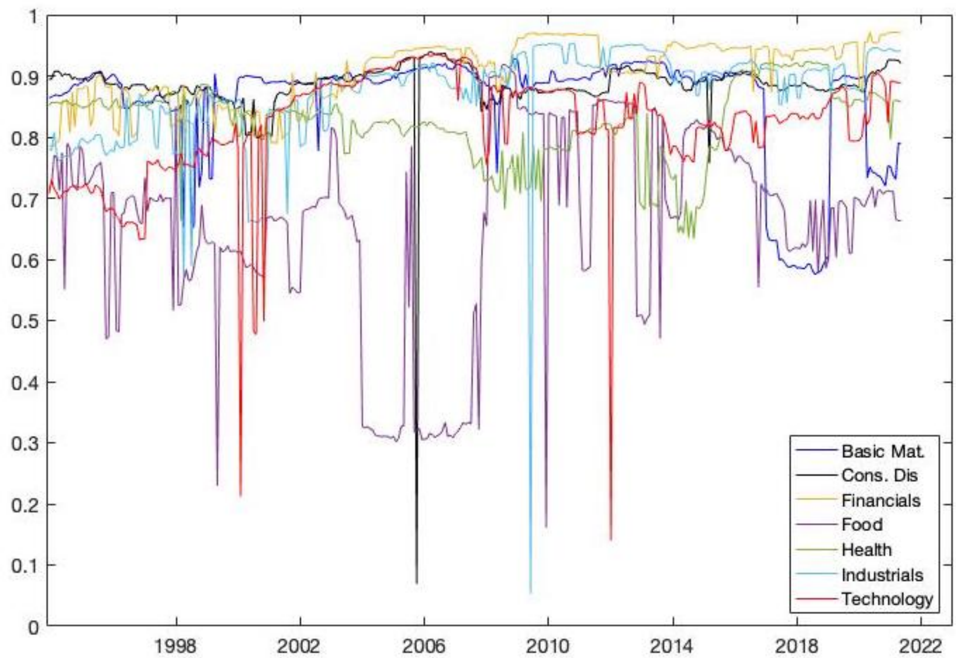


Figure 12: The amount of variance which is explained by the first 3 factors for the different European countries for specific industries

Figure 12 denotes the variance which is explained by the first three principal components. These three factors are used for the R^2 method. The three factors explain around 75% of the variance for all the industries. This variance is higher than when we only use one factor which can be found in Figure 9. The difference between the R^2 method and the first principal component is that we use a regression of the first three factors to get the R^2 and there is no regression for the first principal component. Further, using only the first principal component ensures that possible outliers get less weight.

Table 3: percent of the number of time which are outside the 95% confidence interval for the integration between countries

	Outside C.I. (%) EU
Basic Mat.	56
Cons. Dis.	52
Financials	67
Food	38
Health Care	58
Industrials	68
Technology	54

We test whether the integration measured with the R^2 method stays constant over time. Table 3 denotes the percent of integration outside the 95% intervals, which are calculated with the bootstrap measure. The lowest percentage is 38% for the food industry, this is quite higher than the 5% which we expected when the integration is constant over time. Therefore, we consider that the integration between the European countries measured with the R^2 method is not constant over time. The figures with the bootstrapped 95% lines for the different industries can be found in Figures 38 and 39 in Appendix A.3.

We calculate the integration between the European countries with the regime switching model in two ways. First, we use the whole sample to calculate the model. The transition probabilities for this model are in Table 6 in Appendix A.2. For the different industries, the transition probability p_{11} is between 0.961 and 0.994 and p_{22} is between 0.082 and 0.814, where state 1 denotes integration and state 2 denotes segmentation. The time that the world is integrated is between 0.900 and 0.969 and the time that the world is segmented is between 0.031 and 0.100. The time that the world is segmented is relative low for all the industries. This indicates that the crisis periods do not cause a turning point from an integrated market to a segmented market, but these periods influence the integration for a short period of time. The second method to calculate the integration with the regime switching model is by using a rolling window of 120 months. We use this method to get different variances and transition probabilities over time.

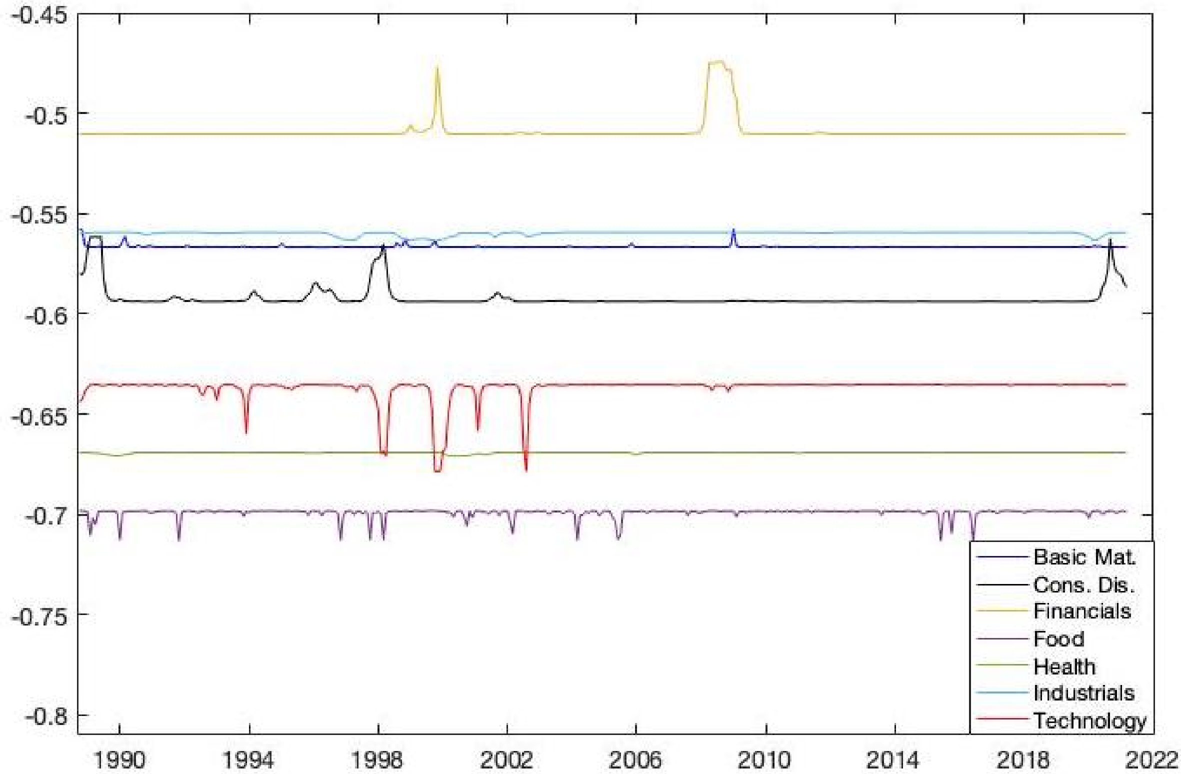


Figure 13: The reduction in variance for investing in the different EU countries based on the regime switching model over the whole sample.

Figure 13 denotes the reduction in variance for investing in the different European countries for each industry. The largest reduction in variance is by investing in the European countries in the food industry, which lead to a reduction of 70% in variance. The smallest benefits are by investing in the financial industry, this has a reduction of around 50% in variance. The cross correlation measure also finds that the highest benefits are by investing in the food industry and the lowest benefits by investing in the financial industry. The smoothed average variances and correlations over time can be found in Figure 44 and 45 in Appendix A.4.

5.1.3 Overview

The integration between the European countries for specific industries is quite high and has an increasing trend over time for most of the correlation measures. The integration is the highest for the financial sector and the lowest for the food industry. An explanation for this can be that companies in the food industry are mostly operating local and financial products are not necessarily restricted by national borders. However, there is decrease in integration around the period of the Dot Com bubble, the credit crisis and the COVID-19 pandemic. In the crisis periods there are some changes from an integrated market towards a segmented market in the regime switching model. These changes are for a short period and did not result into a turning point from an integrated market towards a segmented market. Investors can reduce the variance by investing into different European countries. The food industry has the largest reduction of variance and the lowest reduction is in the financial industry.

5.2 Integration between EU and non-EU countries

We investigate the effect of the three non-European countries on the integration measures. The three countries that we use are Canada, Japan and the United States. These three countries have a large influence on the stock market and we will investigate the influence of these countries on the integration measures. This shows us whether the European countries are more correlated with each other or that the non-European countries have more influence on this correlation. By comparing this integration with the integration between the European countries, we investigate whether it is beneficial for investors to invest in European countries or non-European countries.

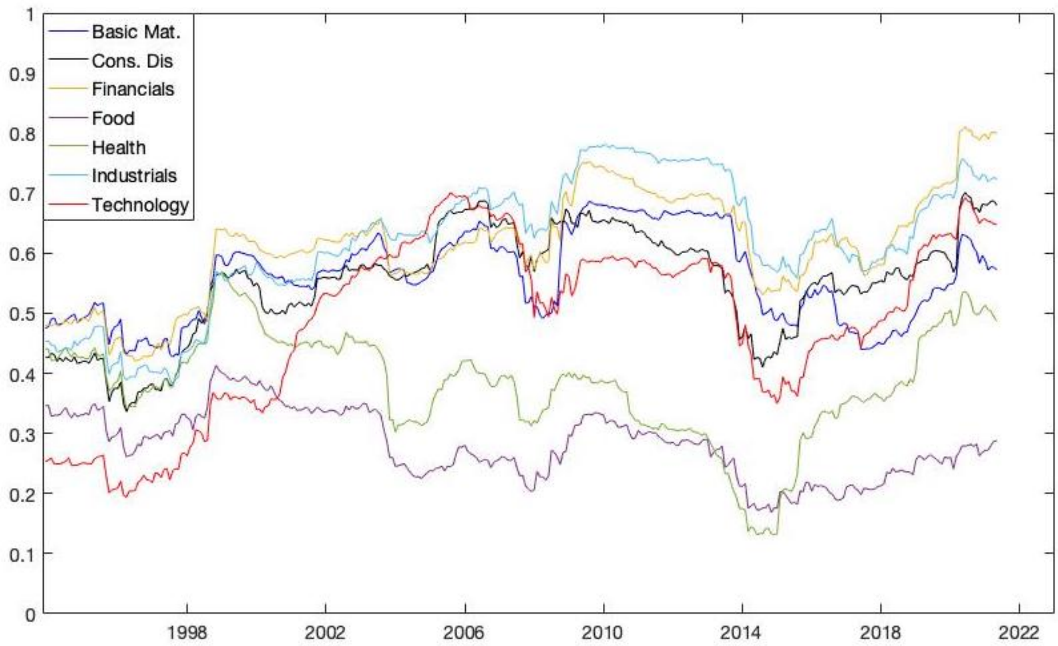


Figure 14: The integration between the European and non-European countries for specific industries, where we use the cross correlation as measure for the integration

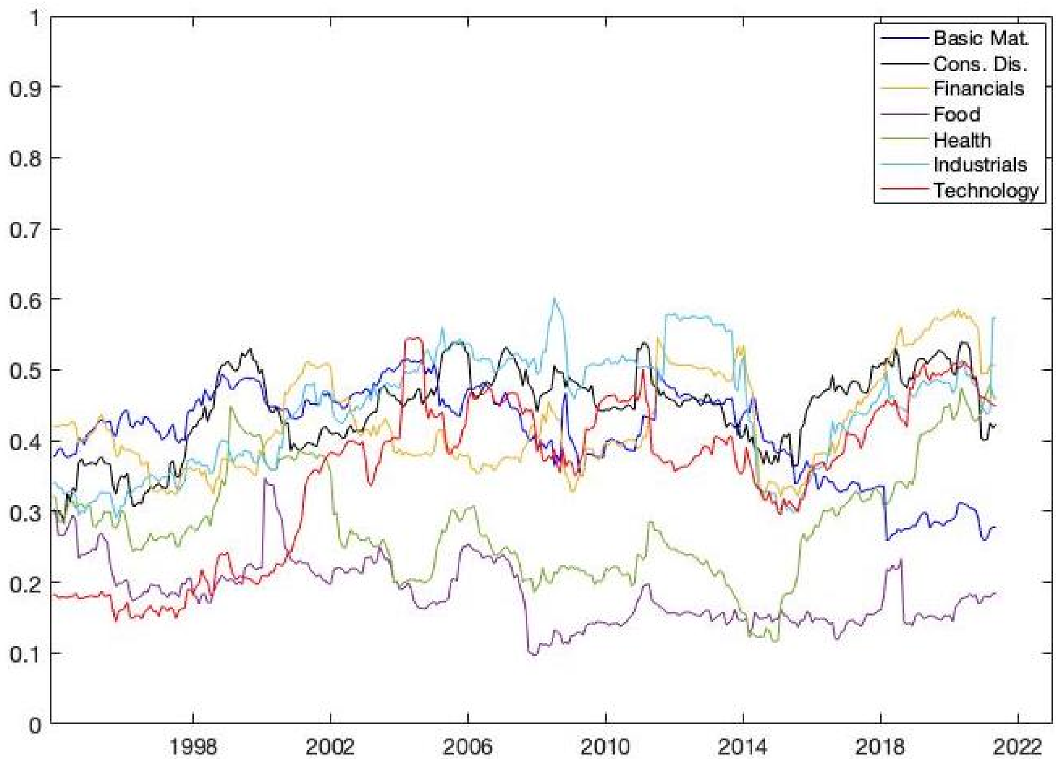


Figure 15: The integration between the European and non-European countries for specific industries, which is denoted as the Forbes-Rigobon correlation

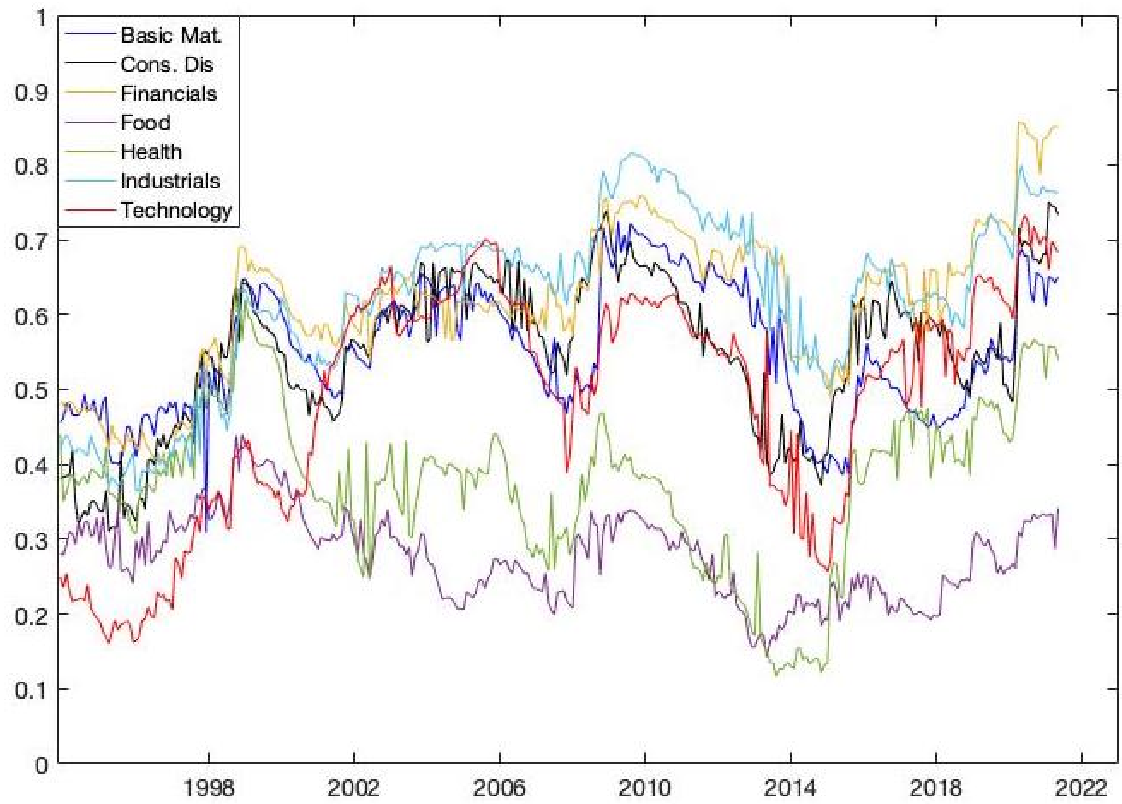


Figure 16: The integration between the European and non-European countries for specific industries, which is calculated by the DCC GARCH model

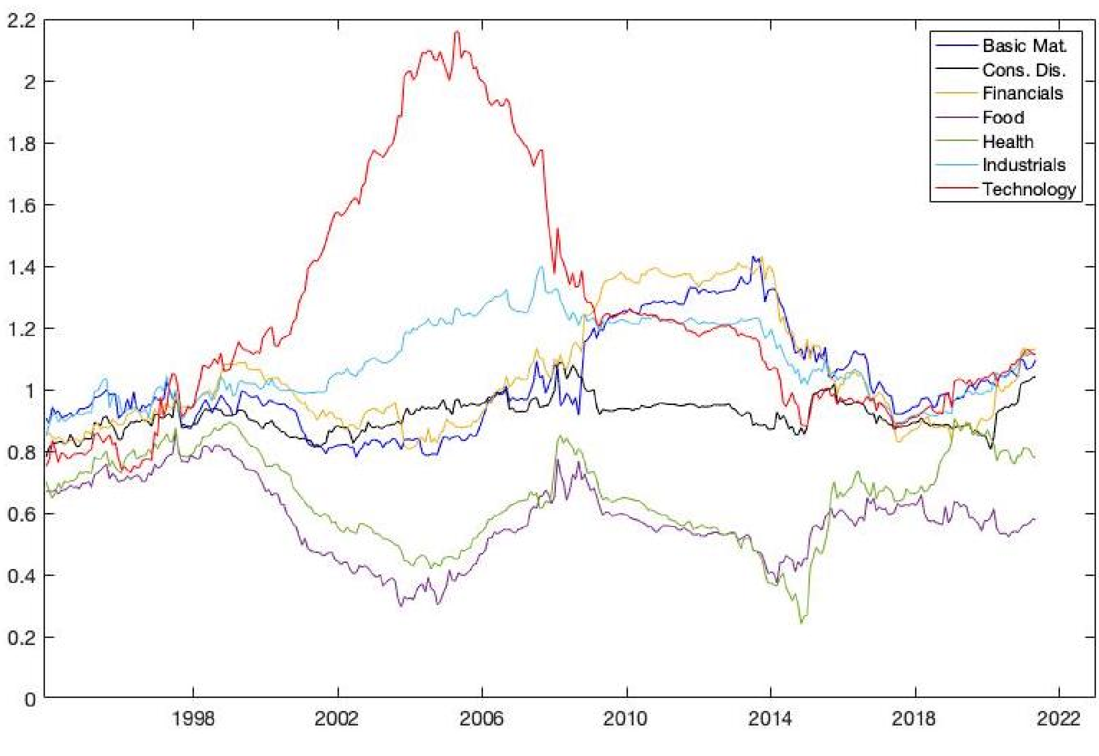


Figure 17: The integration between the European and non-European countries for specific industries which is denoted as the time varying betas of the CAPM model

5.2.1 Correlation measures

We discuss the effect of the three non-European countries, namely Canada, Japan and the United States, on the integration measures. We start with the correlation measures, which are the cross correlation, the Forbes-Rigobon correlation, the DCC GARCH model and the CAPM model. Figures 14 till 17 show the integration between the countries for these measures respectively. We observe the following similarities between the correlation measures, namely the integration has a positive trend over time for most of the industries, except for the food industry. This increasing trend is mostly visible in the cross correlation and DCC GARCH measure and less in the CAPM measure. The integration between all the countries has the same trend as the integration between the European countries only. The food industry has the lowest integration of all the industries for all the integration measures, this is also the case by the European countries. Another similarity with the European countries is that the integration of the CAPM model exceed one and there is a huge increase in integration for the technology sector which is caused by the Dot Com bubble.

There are some differences with the integration between the European countries. The integration in the industrial sector is the highest of the industries when we consider all the countries, but when we only consider the European countries the financial industry has the highest integration. Another difference is that the integration for all the countries is a little lower for most of the industries than for only the European countries. An explanation for this is that there are more countries used such that the correlation for some pair of returns can be lower. Another reason for this is that the European countries are stronger correlated with each other, because of the geographical location which makes it easier to trade. Furthermore, the European Union has a free open-border trade among its members. Almost all the European countries that we use are a member of the European Union. However, the United Kingdom left the European Union in February 2020.

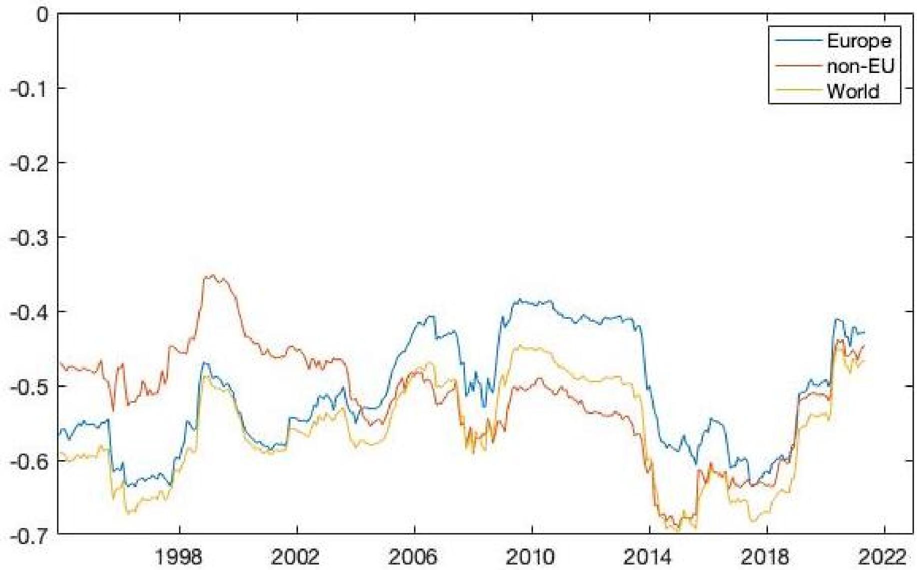


Figure 18: The reduction in variance by constructing a portfolio with the seven industries for the European countries and with the three non-European countries included, based on the cross correlation measure.

The lower integration between all the countries results in a larger reduction in variance in comparison with the integration between the European countries. The integration between all the countries have the same pattern as the integration between the European countries. This indicates that the reduction in variance for all the countries has the same pattern as the European countries. The portfolio variances for the countries are depicted in Figure 36 in Appendix A.1. In order to lower the risk for investors, we investigate the reduce in variance of the following three portfolios. One of the portfolios is a portfolio which contains all the European industries and countries (Europe), another is a portfolio with only the non-European assets (non-EU) and the last portfolio contains all the assets (World). Figure 18 denotes the reduction in variance for the three different portfolios. Most of the time, the portfolio which contain all the assets has the largest reduction in variance, but between 2008 and 2014 the portfolio with non-European assets has a bigger reduction. After 2004, there is a bigger reduction in variance by investing in the non-European assets than in the European assets.

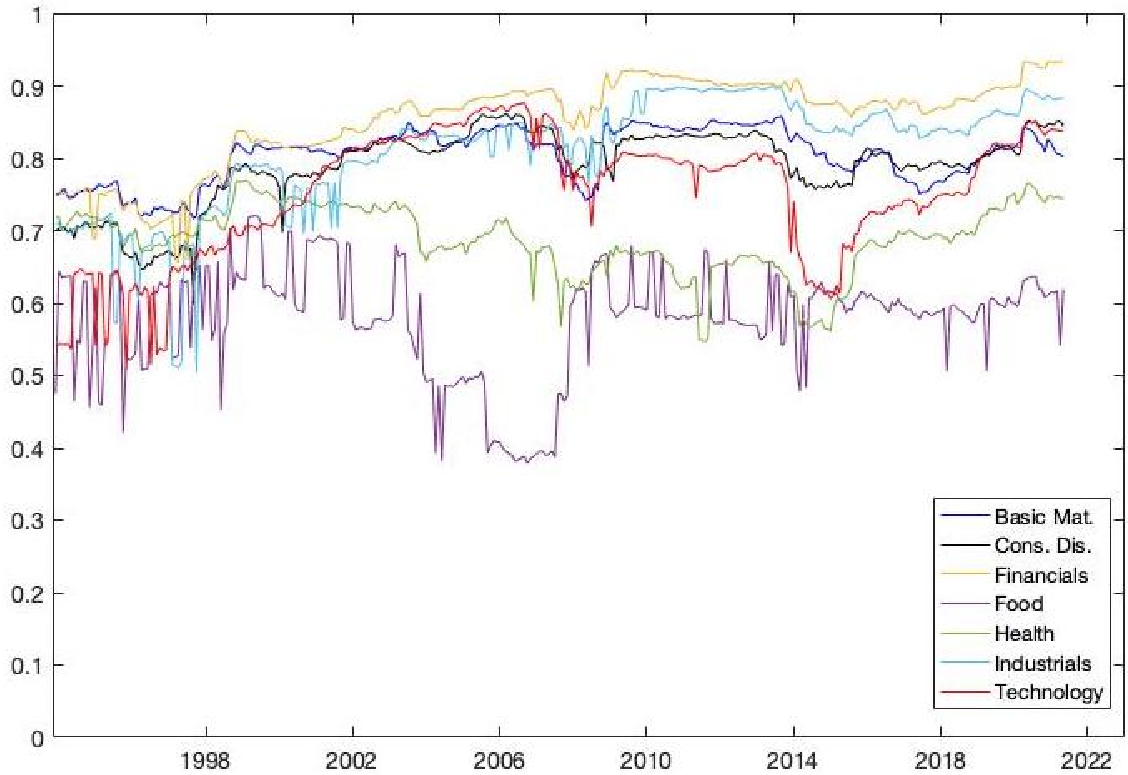


Figure 19: The integration between the European and non-European countries for specific industries, which is calculated by the R^2 method

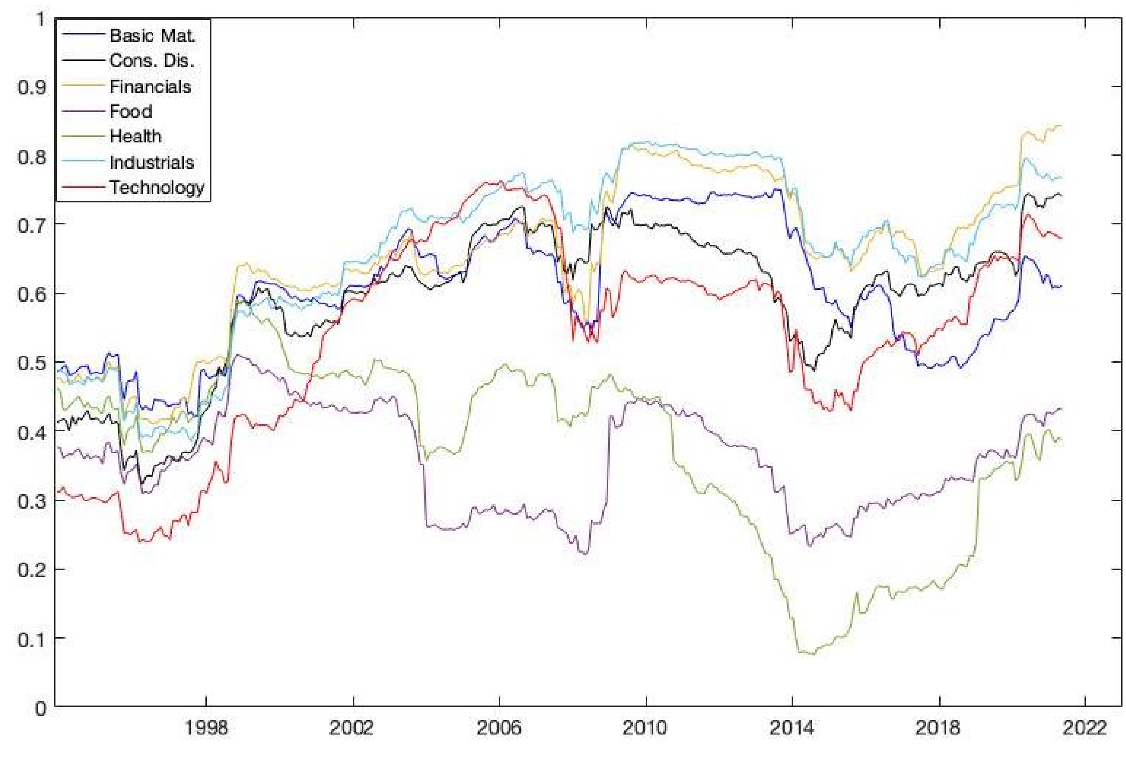


Figure 20: The integration between the European and non-European countries for specific industries calculated by the first principal component

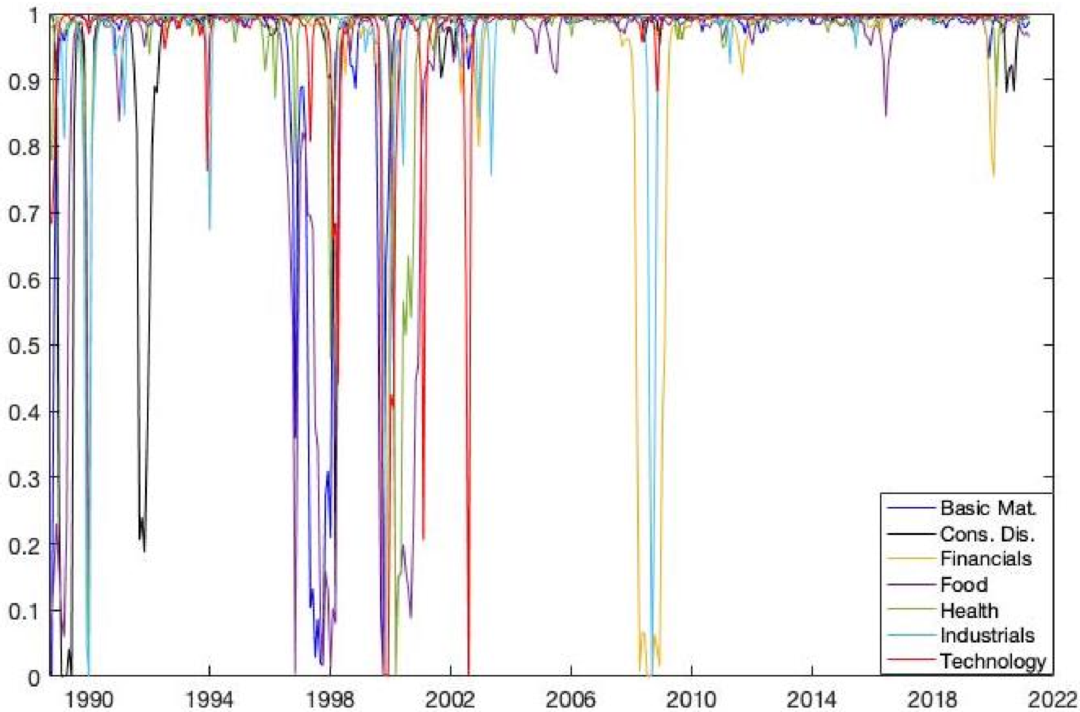


Figure 21: The smoothed inferences, which are used as a measure for integration between the European and non-European countries for an industry.

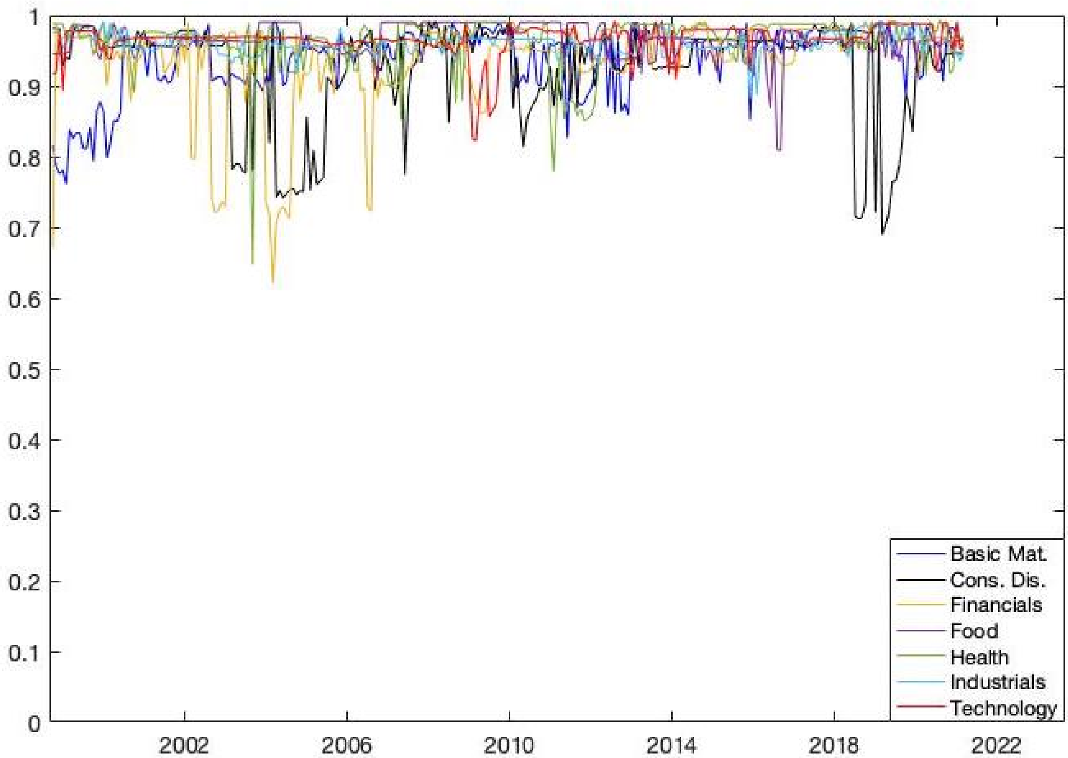


Figure 22: The smoothed inferences, which are used as a measure for integration between the European and non-European countries for an industry. The integration is calculated with a moving window of 120 months.

5.2.2 Other measures

The other integration measures that measure the integration between all the countries are the R^2, the first principal component and the regime switching measures. The integration measured by these methods can be found in Figures 19 till 22 respectively. There are some similarities with the integration measures for the European countries only. In general, the integration measures have the same pattern over time as the integration measures for the European countries. The integration measured by the R^2 method is the lowest for the food industry and the highest for the financials industry, which is the same for the European countries. Another similarity is that the lowest integration for the first principal component is for the countries in the food industry. There are also some similarities for the regime switching model, namely for both groups of integration there is a through in the financial sector around the credit crisis in 2008. Almost all industries are segmented for a short period around the Dot Com bubble in 2000, this is especially true for the technology sector.

However, there are also some differences with the integration between the European countries only. The integration measured with the R^2 method, the first principal component method and the regime switching model with a rolling window has less troughs when we include the non-European countries. Furthermore, the integration is lower than for the European countries, when we use the R^2 and first principal component measures. There are more differences for the first principal component measure. For instance, the highest integration between all the countries is for the industrial sector, while the integration between the European countries is the highest for the financial sector. This difference is also noticed before for the correlation measures. Another difference is that the integration for the health sector remains lower than the food sector after 2010. The integration measured with the regime switching model over the whole sample seems to be less influenced to the COVID-19 pandemic than the integration for the European countries. As a final point, the integration for the financial sector measured with the rolling window regime switching model is more segmented in the period 2002 till 2008.

The transition probabilities for the regime switching model can be found in Table 7 in Appendix A.2. In our regime switching model is state 1 denoted as integrated and state 2 as segmented. The transition probability p_{11} is quite high, namely between 0.979 and 0.988. On the other hand the transition probability p_{22} is between 0.506 and 0.753. The time that the model spend in the integrated state is also quite high for the different industries, namely between 0.920 and 0.969. Therefore, the time that the model spend in the segmented state is between 0.031 and 0.08. This is smaller than the time that the European markets are segmented. Even though the integration between all the countries is lower than the integration between the European countries, there might be some crisis periods that are only effected by the European countries.

Table 4: percent of the number of time which are outside the 95% confidence interval for the integration between countries

	Outside C.I. (%)
Basic Mat.	60
Cons. Dis.	69
Financials	64
Food	22
Health Care	57
Industrials	80
Technology	75

The R^2 measure seems to have a constant integration over time. Therefore, we use a bootstrap technique to determine whether the integration stays constant over time. Table 4 denotes the percentage of time where the integration is outside the 95% bootstrapped intervals. The lowest percentage is for the food industry, which is 22%. This is higher than the expected 5% for a constant integration over time. For this reason, we consider that the integration is not constant over time. The bootstrapped intervals together with the integration can be found in Figures 40 and 41 in Appendix A.3.

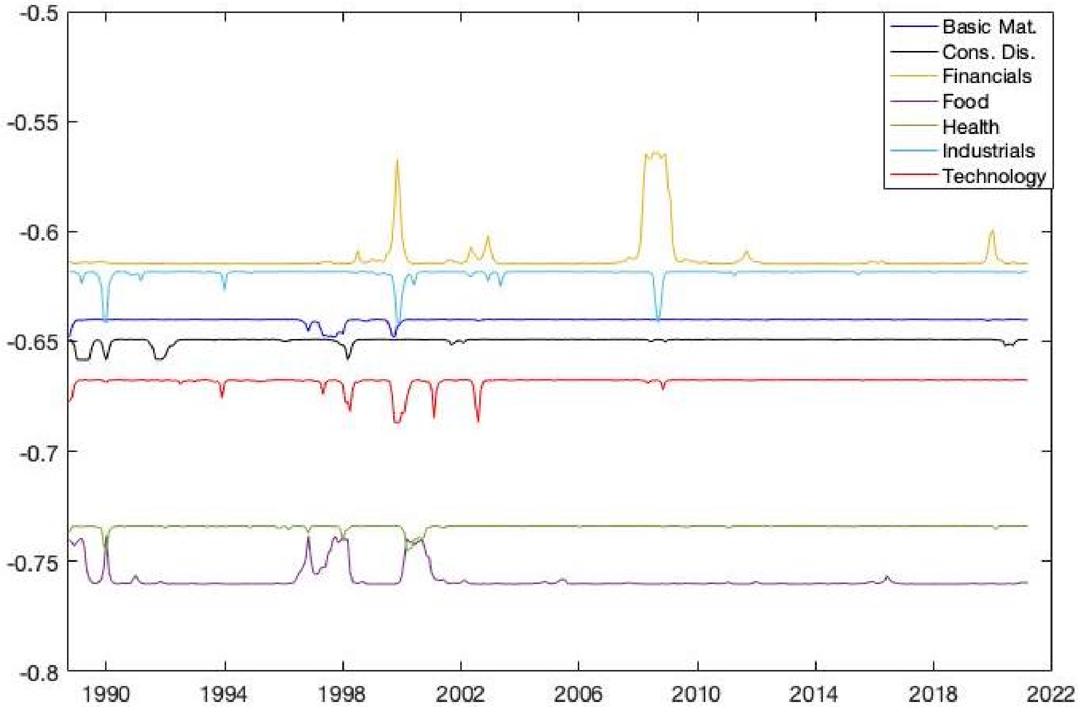


Figure 23: The reduction in variance for investing in the different countries, based on the regime switching model without a rolling window.

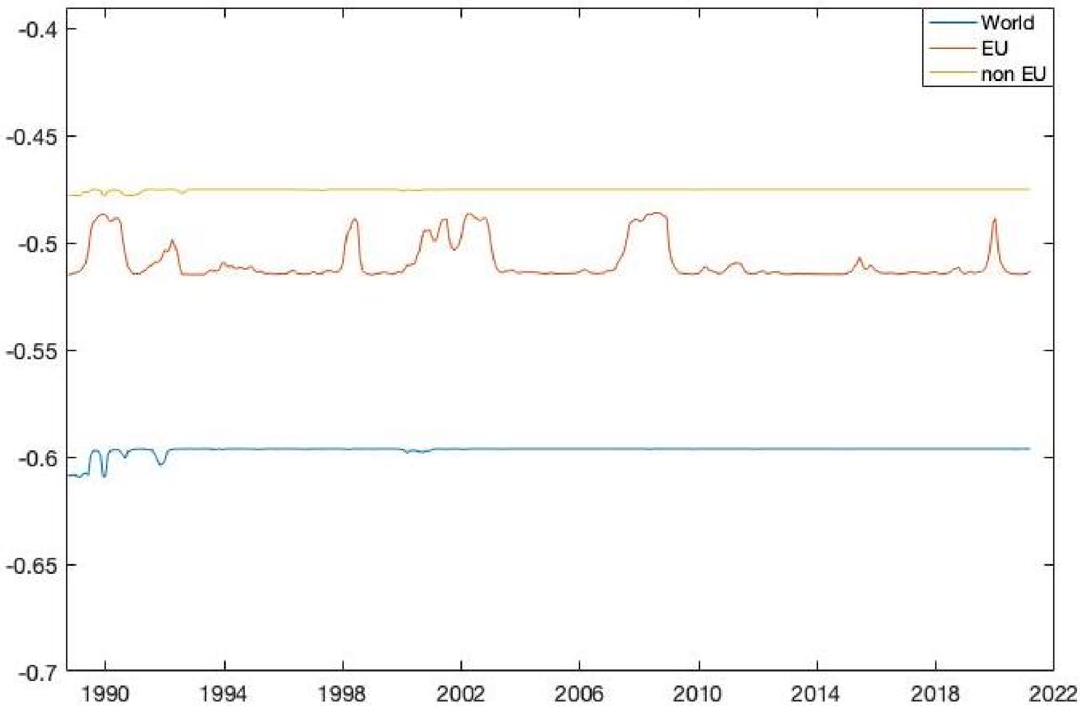


Figure 24: The reduction in variance for investing in the different countries, ased on the regime switching model without a rolling window.

Figure 23 denotes the reduce in variance by investing in the different industries. The largest reduction in variance is by investing in the food industry, which is around 75%. The smallest benefits are by investing in the financials sector, which is around 62% and around 57% during the crisis periods. The variances and correlations can be found in Figures 46 and 47 in Appendix A.4. We also investigate the diversification benefits by three different portfolios, which are a portfolio which contains only the European assets (EU), a portfolio which only contains the non-European assets (non-EU) and a portfolio which contains all the assets (World). Figure 24 denotes the reduction in variance of these portfolios. The largest reduction in variance is for the portfolio which contains all the assets and is around 60%. The smoothed average variances for these portfolios can be found in Figure 50 in Appendix A.4.

5.2.3 Overview

The integration between European and non-European countries have the same increasing pattern as the integration between the European countries for the correlation measures. The integration is still the lowest in the food industry. However, the integration between all the countries is lower for most of the industries. Another difference is that the correlation measures find that the industrial sector has the highest integration instead of the financial sector. The integration decreases around the crisis periods, but this decrease does not cause a turning point from integrated to segmented markets. The integration measured with the regime switching model has the same pattern as the integration between the European countries. However, the integration between all the countries measured with this model has less periods where the integration changed from integrated markets towards segmented markets. Investors can reduce their risk by investing in portfolios which contain all the countries and industries. Both the cross correlation measure and the regime switching model find that the reduction in variance is the highest by investing in a portfolio which contains all the assets.

5.3 Integration between industries

We also investigate the integration between different industries for specific countries. This shows us how the different industries in a country are correlated with each other over time. We investigate whether there are different patterns for the integration between industries in comparison with the integration between countries over time. This investigation shows us whether it is beneficial for investors to invest into different industries of a specific country or into different countries for a specific industry.

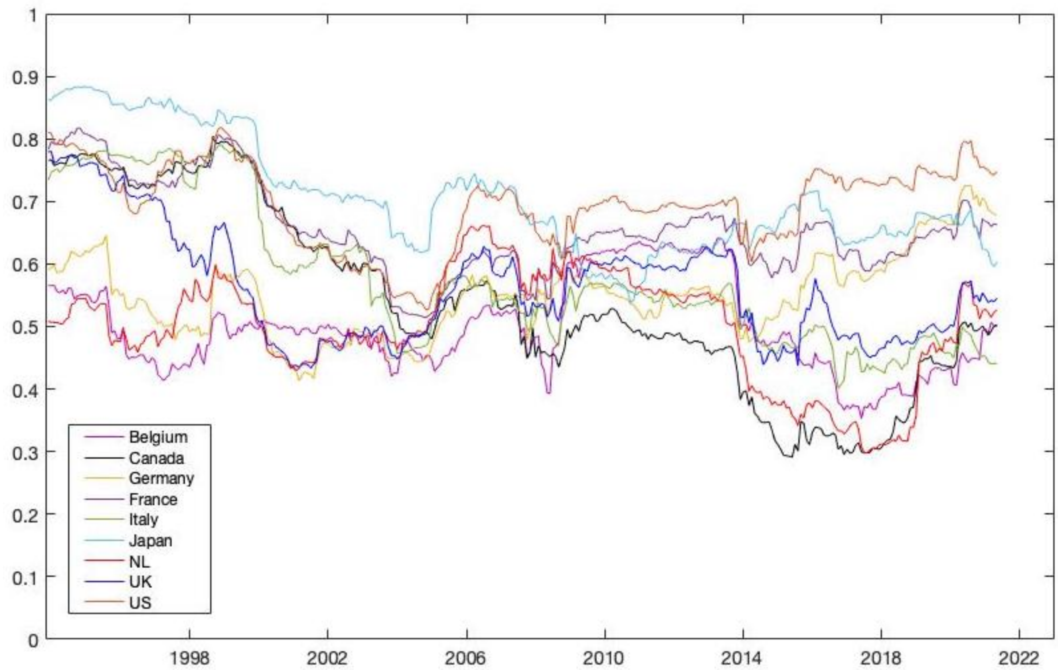


Figure 25: The integration between different industries for specific countries with the cross correlation method

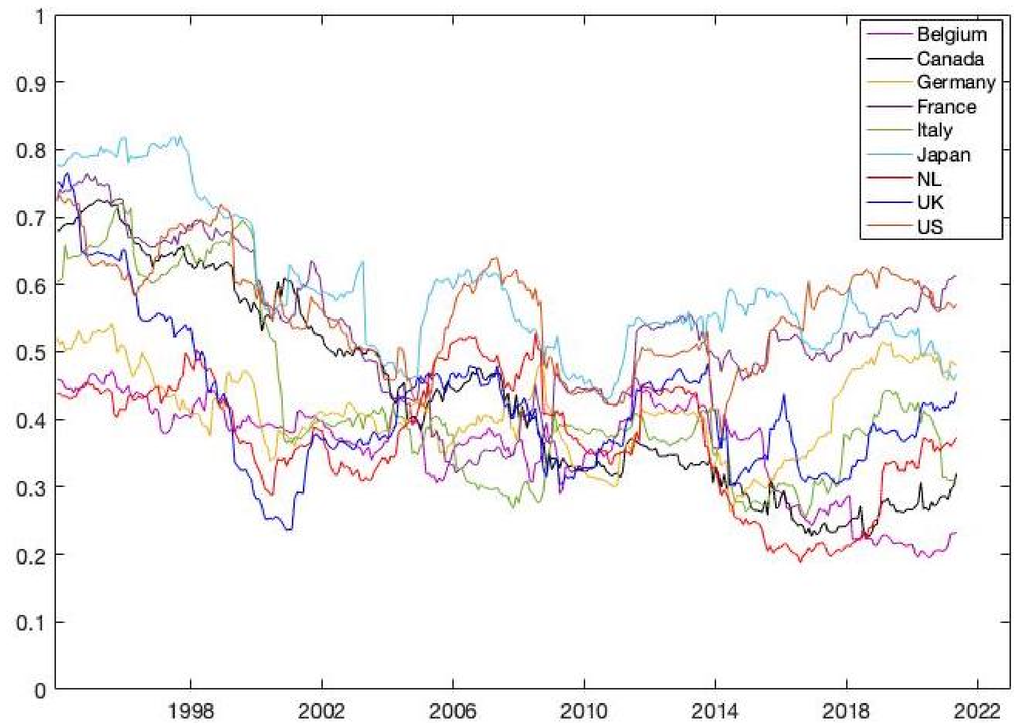


Figure 26: The integration between different industries for specific countries with the Forbes-Rigobon correlation

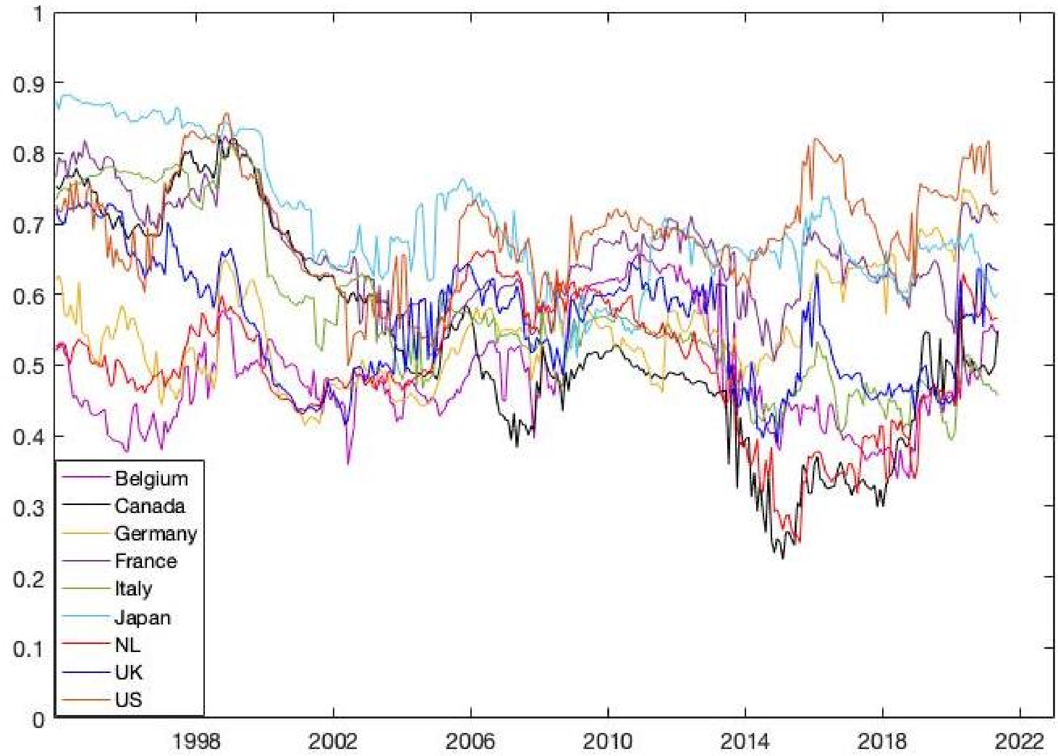


Figure 27: The integration between different industries where we use the DCC GARCH model

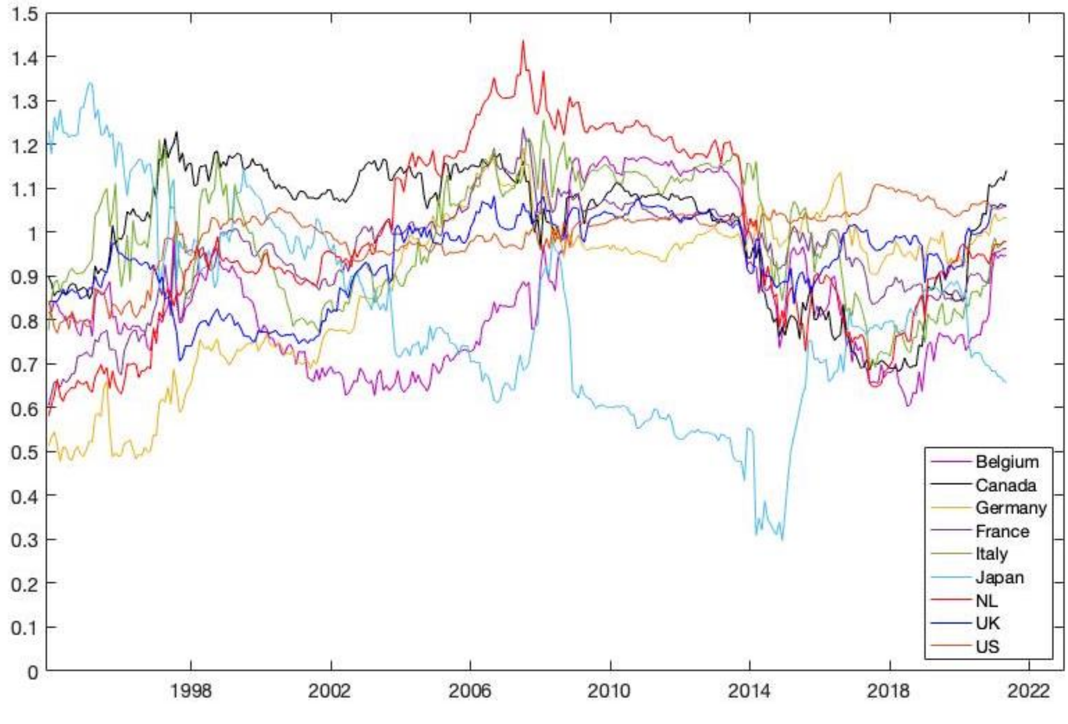


Figure 28: The integration between different industries, which are the time varying betas of the CAPM model.

5.3.1 Correlation measures

We also investigate the integration between different industries for specific countries. As before, we first look at the four correlation-based measures. Figures 25 till 28 denotes the integration for these measures respectively. First of all, we discuss the similarities between the different integration measures. The cross correlation, Forbes-Rigobon correlation and the DCC GARCH model show a same pattern for the integration. The integration decreases till 2006, but after 2006 there is an increase untill the credit crisis in 2008. This credit crisis causes a decrease in integration for a short period and after the crisis the integration turns back to the level before the crisis. There is another decrease in integration from 2014 till 2016 and after this period the integration increases till the COVID-19 pandemic in 2021, which cause a small decrease for a short period. All the integration measures show a decrease in integration for a short period due the credit crisis in 2008 and the COVID-19 pandemic in 2021, this is especially seen in the Forbes-Rigobon correlation and the DCC GARCH model. These two measures correct the integration for volatile periods. Another similarity between the cross correlation, Forbes-Rigobon correlation and the DCC GARCH model is that the integration between Belgian industries is the lowest till 2006, after 2006 the integration between Canadian and Dutch industries become the lowest. These measures show that the highest integration is between the Japanese and American industries.

However, there are also some differences between the integration measures. For instance, the integration measured with the Forbes-Rigobon is lower than the correlation measured with the cross correlation, this is because of the volatility correction by the Forbes-Rigobon correlation. The volatility also influences the DCC GARCH measure, because there are more fluctuations in this measure in comparison with the other measures. The CAPM model has a different pattern for the integration than the other three measures. The integration increases till 2014 and after 2014 the integration decreases till 2016, after 2016 the integration increases. This pattern is observable for almost all the countries, except for Japan. The integration between the Japanese industries decreases till 2016, and increases after 2016. This decrease ensures that the integration between the Japanese industries become the lowest of all the countries after 2006. Another difference is that the integration for the CAPM model exceeds one.

The integration between industries differs with the integration between the European countries. There is not an increasing trend over time for the integration between the industries, but there are periods of increasing and decreasing integration. In general, the level of integration between the industries is lower than the integration between the countries. The lower integration between the industries can be explained by the local demand of different products. For example, when the economy is growing, the purchasing power will be high and there is more demand for luxury products, like for example products in the technology sector while the demand for products in the food or health care industry remain the same. This difference will lower the integration between the industries, but not the integration between the countries for a industry. However, the differences between the industries for the integration between the countries is larger than the differences between the countries for the integration between the industries. The lowest integration between the countries, which is for the food industry, is lower than the lowest integration between the industries, which is for the Netherlands. The similarities between these two groups is that the crisis periods cause short periods of decrease in integration and not a turning point towards segmentation.

There are possibilities for investors to lower their risk by using diversification. The integration measured with the cross correlation method shows that a higher integration results in less reduction of variance. Therefore, the diversification benefits are the lowest for investing in the Japanese and American industries. The reduction in variance is the highest for the Belgian industries till 2008, after 2008 there are more benefits by investing in the Canadian and Dutch industries. The portfolio variances are depicted in Figure 37 in Appendix A.1.

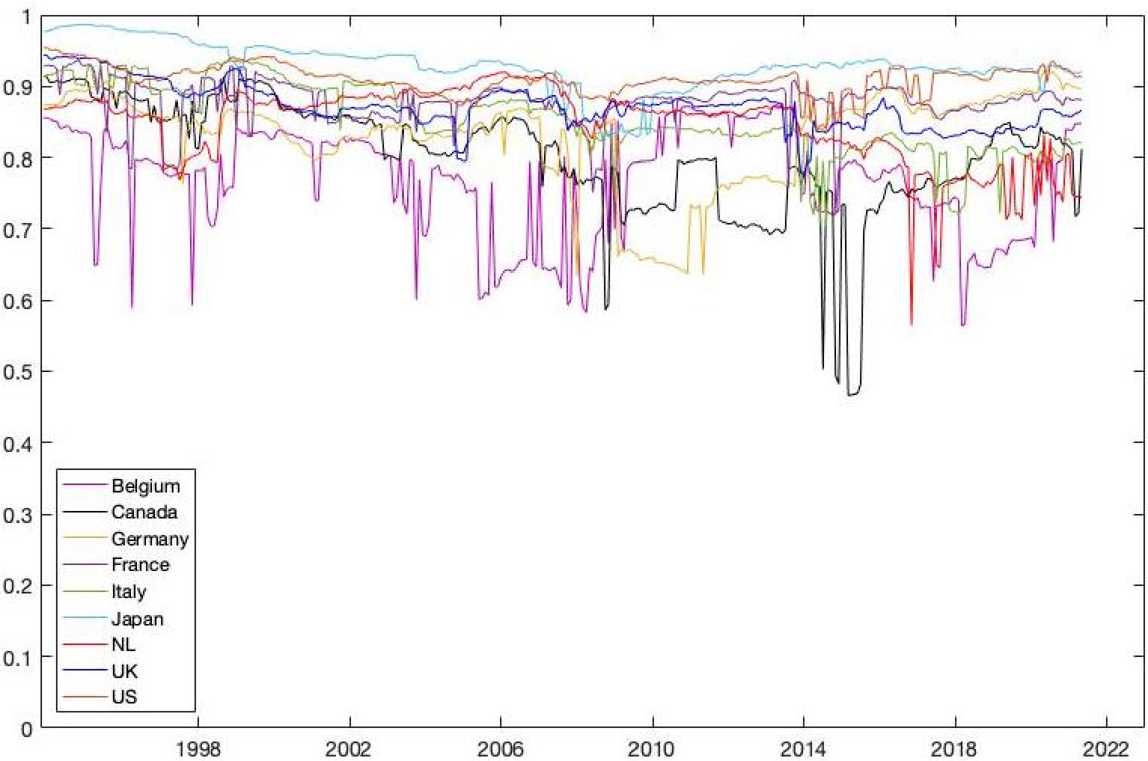


Figure 29: The integration between different industries for specific countries with the R^2 method

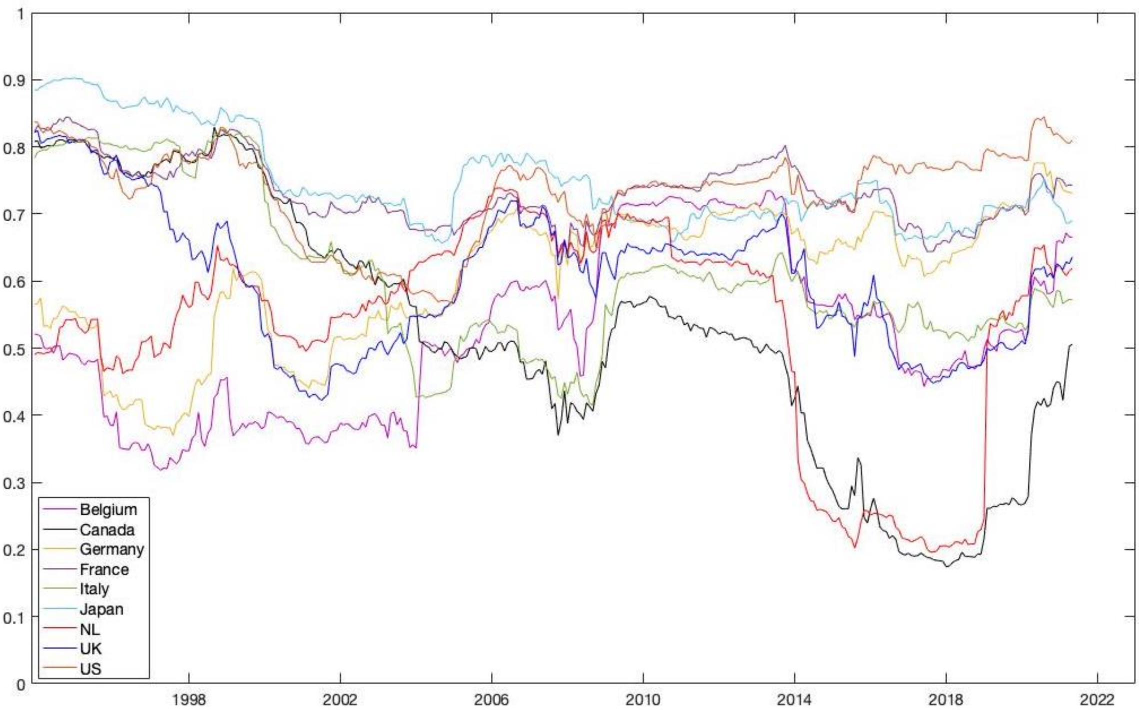


Figure 30: The integration between different industries for specific countries calculated with the first principal component

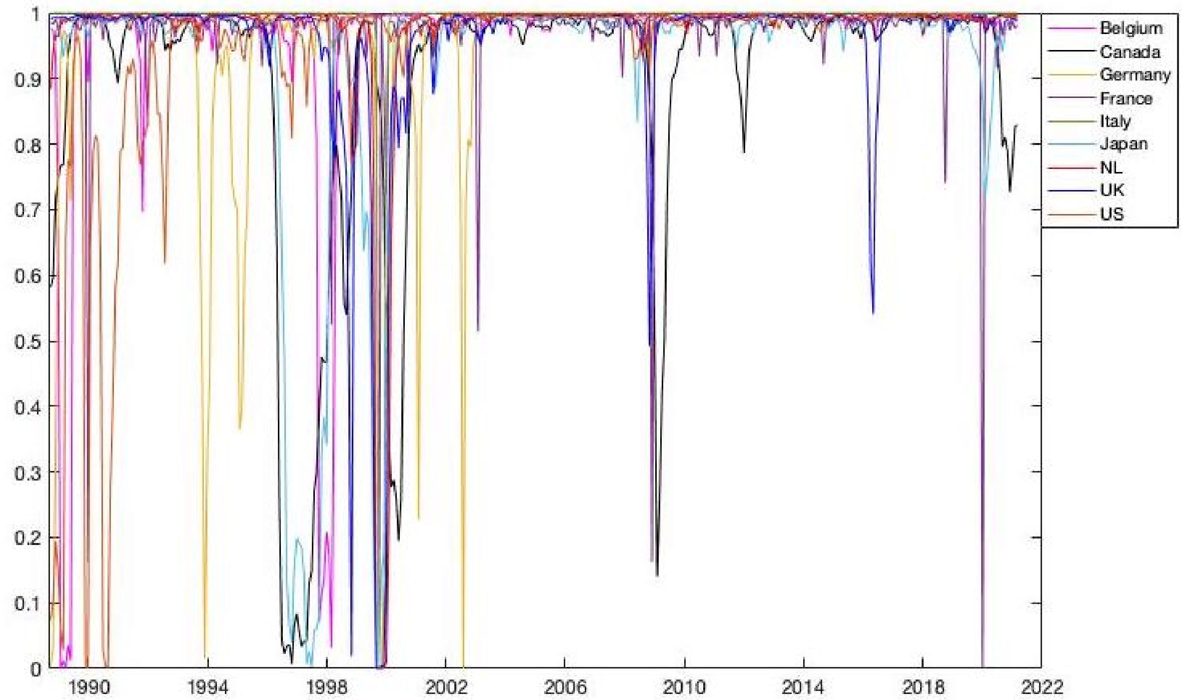


Figure 31: The smoothed inferences, which are used as a measure for integration between the industries of a country.

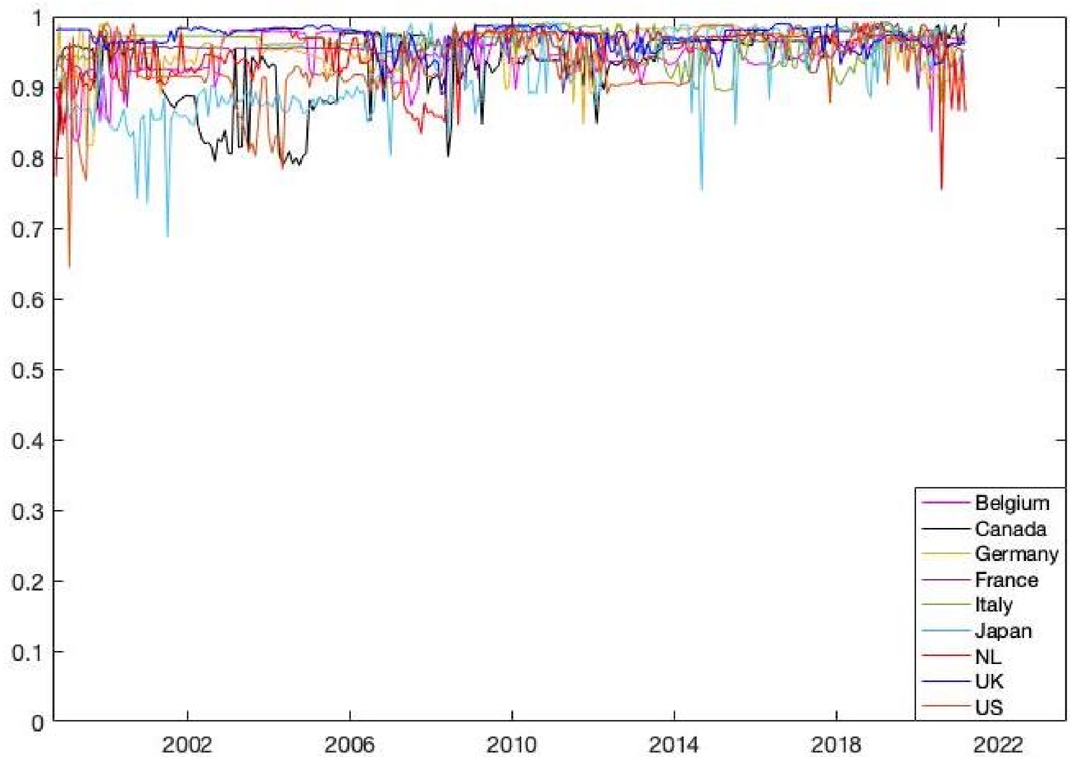


Figure 32: The smoothed inferences, which are used as a measure for integration between the industries of a country. The integration is calculated with a moving window of 120 months.

5.3.2 Other measures

The other measures that measure the integration between the industries are the R^2 method, the first principal component and the regime switching model. Figures 29 till 32 denotes the integration for these measures respectively. The integration for the R^2 method and the regime switching measures is quite high for all the countries, but there are some troughs. This is especially the case for the regime switching model without a rolling window, there are some changes from integrated markets towards segmented markets. The R^2 method and the first principal component measure show that the integration between the Japanese and American industries are the highest. The lowest integration is between the Belgian industries till 2004 for the first principal component measure, after 2004 the integration between the Dutch and Canadian industries become the lowest. This pattern is also observable for the R^2 method but the integration between the Belgian industries is the lowest till 2008 for this measure.

There are some differences between the measures. The integration measured with the first principal component measure has another pattern than the other measures. The integration is more similar to the correlation measures. However, the correlation measures show that there are less differences in integration between the countries and the first principal component measure shows that there are more differences between the countries. The integration measured by the R^2 and regime switching models is higher than the first principal component measure.

When we compare the integration between the industries with the integration between the European countries, we observe some differences. For instance, the integration between the industries measured with the R^2 method is higher and has less troughs. This integration seems to be more constant over time instead of the increasing pattern for the integration between European countries. The first principal component measure has no troughs for the integration between the industries. However, we observe a decrease in integration between 2014 and 2018 in both groups. For the integration between the European countries is this decrease measured in the health industry and for the integration between the industries is this decrease observable for the Dutch and Canadian industries. The regime switching models have similarities for the integration between European countries and between industries. The integration measured with the regime switching model without a rolling window has decreases around 1990, the Dot Com bubble in 2000, the credit crisis in 2008 and the COVID-19 pandemic in 2020 for both groups. These decreases are for a short period and did not cause a turning point from integration towards segmentation. The integration measured with a rolling window is in both groups high, but the integration between European countries has more troughs.

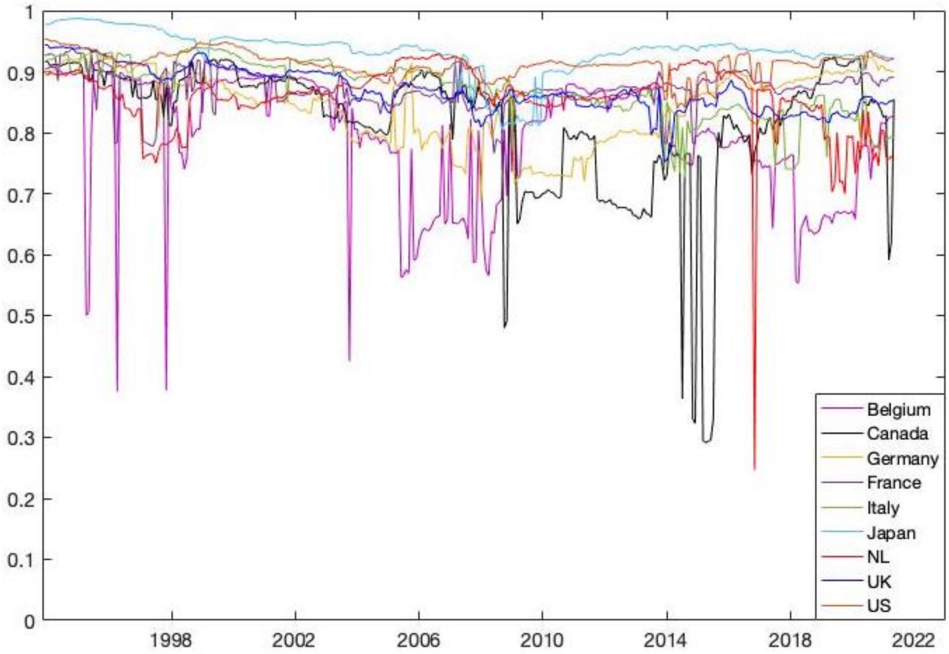


Figure 33: The amount of variance which is explained by the first 3 factors for the different industries for specific countries

The first three factors are used for the R^2 measure. Figure 33 denotes the explained variance for these three factors. The explained variance is quite high around 85% over time, but there are some periods where it dropped to 40%. The high amount of explained variance can also be seen in the integration between the European countries. However, the explained variance has less troughs in Figure 33 and these troughs still explain more variance, in comparison with the integration between the European countries.

The integration measured with the regime switching models is quite high, especially for the regime switching model with the rolling window of 120 months. There are some changes from integration towards segmentation mainly for the model without the rolling window. These changes are around the crisis periods in 2000, 2008 and 2021. We observe these troughs also around these periods for the integration between the European countries. The transition probabilities for the integration between industries can be found in Table 8 in Appendix A.2. The probability for staying in the integrated state varies from 0.971 to 0.997 and the probability for staying in the segmented state is between 0.000 and 0.846. The time that the world is in the integrated state is between 0.897 and 0.992. This confirms the high integration in Figure 31. The time that the world is in the segmented state varies between 0.008 and 0.103.

Table 5: percent of the number of time which are outside the 95% confidence interval

	Outside C.I. (%)
Belgium	47
Canada	46
Germany	50
France	67
Italy	49
Japan	53
NL	76
UK	69
US	43

The integration measured by the R^2 method in Figure 29 seems to be constant over time. Therefore, we use a bootstrap method to create 95% bootstrapped intervals. Table 5 denotes the percentage of time where the integration is outside this interval. The smallest number is 43% for the integration between the industries of the United States. This is much higher than the expected 5% for a constant integration. For this reason do we consider that the integration measured by the R^2 method is not constant over time. The integration combined with the bootstrapped intervals for each country can be found in Figures 42 and 43 in Appendix A.3.

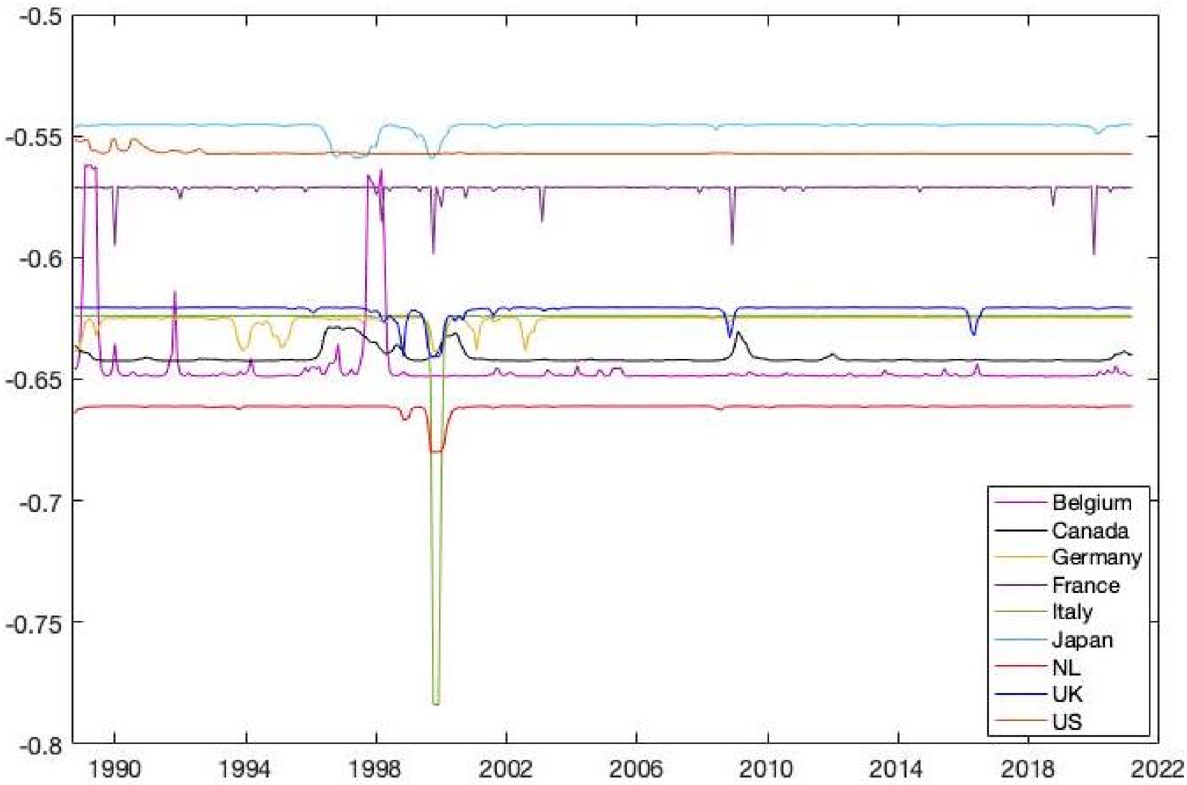


Figure 34: The reduction in variance for investing in the different industries, based on the regime switching model over the whole sample.

Figure 34 shows the reduction in variance for investing in the different industries of a specific country. The reduction in variance is the highest for investing in the Dutch industries, which is around 66%. The smallest benefits are for investing in the Japanese industries, which is a reduction of around 54% of variance. These industries have also the smallest and highest benefits for the cross correlation measure. The smoothed average variances and correlation for the regime switching model can be found in Figure 48 and 49 in Appendix A.4.

5.3.3 Overview

The integration between the different industries is around 0.6 for most of the countries for the correlation measures. This indicates that the markets are closer to be integrated than segmented over time. The integration between the industries has a different pattern for the correlation measures than the integration between the different countries. Instead of an increasing trend over time, the integration between industries has alternating periods of increases and decreases. The crisis periods cause a decrease in integration, but these decreases are for a short period and do not cause a turning point towards segmented markets. The integration measured with the regime switching model is often totally integrated. However, there are some troughs around the crisis periods, which are for a short period of time. Investors can reduce their risk by diversifying their portfolios. Both the cross correlation measure and the regime switching model indicates that the largest reduction in variance is by investing in the Belgian and Dutch industries and the smallest reduction in variance is by investing in the Japanese and American industries.

5.4 Overview of all the results

We give an overview about the results discussed in the sections before. For the integration between the European countries for specific industries, we observe an increasing pattern over time in integration for most of the correlation measures. However, there is decrease in integration around the period of the Dot Com bubble, the credit crisis and the COVID-19 pandemic. In the crisis periods there are some changes from an integrated market towards a segmented market in the regime switching model. These changes are for a short period and did not result into a turning point from an integrated market towards a segmented market.

When we also consider the integration between non-European countries, most of the integration measures have the same pattern as for the integration between only the European countries. However, the integration between all the countries is often lower. There are also less periods where the markets change from integrated towards segmented in the regime switching model. In this model there are less industries where the integration changed from integrated towards segmented in the period around the credit crisis in comparison with the integration between only the European countries.

Focusing on the integration between different industries for specific countries, most of the time the markets are more integrated with each other than segmented. The integration between the industries in the different countries are very close to each other around the crisis periods and often move up and down simultaneously. The integration measured with the regime switching model is most of the time fully integrated, however there are some troughs in the integration around the crisis periods.

Another feature of the integration that we investigate is the reduction in variance by involving the integration by creating portfolios. We find that there is a reduction in variance of at least 40%, when we construct a portfolio of all the assets with the cross correlation method as integration measure. The highest reduction in variance is by investing into the different countries in the food industry or by investing in the Dutch and Canadian industries. This measure shows that the lowest reduction in variance is by investing in the countries in the financial and industrial sector or by investing in the Japanese and American industries. The reduction of variance is around the 60% for the portfolio of all the assets, when we use the regime switching model as a measure for the integration. This measure shows us that the highest reduction in variance is by investing in the different countries in the food industry or by investing in the Dutch industries. The lowest reduction in variance is by investing in the countries in the financial industry or in the Japanese industries. This means that investors can lower their risk by using diversification.

6 Conclusion

In the last 30 years the world has changed. There have been several economic crises, like the Dot com bubble, the global credit crisis and the COVID-19 pandemic. Our research is focusing on the financial integration between different countries and between different industries for the period 1989 till 2021.

In our research, the integration measures that we use can be split in two groups. We have the correlation measures, which are the cross correlation, the Forbes-Rigobon correlation, the DCC GARCH model and the CAPM model. The integration between the European countries has a positive trend over time for almost all the industries. The integration measured with the correlation measures is the highest for the financial sector and the lowest for the food industry. The other measures that we use are the R^2 method, the first principal component and the regime switching models. The integration between European countries for these measures are almost constant over time, but the integration is quite high and there are some troughs towards segmentation. The three non-European countries which are Canada, Japan and the United States have influence on the integration between the countries. Although, the integration between all the countries follows the same patterns as the integration between the European countries, there are some differences. The integration between all the countries is lower and the highest integration is for the countries in the industrial sector. The lowest integration is still in the food industry. We also investigate the integration between the industries for specific countries. This integration has a different pattern for the correlation measures than the integration between the European countries. Instead of an increasing integration over time there are alternating periods of decreasing and increasing integration over time. The integration for the other measures has the same pattern, namely an almost fully integrated market with short periods of decreasing integration towards segmentation. The highest integration is for the Japanese and American industries and the lowest for the industries of Belgium and the Netherlands. A similarity between the integration between the European countries and the integration between industries is that the integration decreases around the crisis periods. These periods are for instance, the Dot Com bubble around 2000, the credit crisis around 2008 and the COVID-19 pandemic around 2021. These decreases are for a short period of time and do not cause a turning point from integrated towards segmented markets. The differences in the level of integration can be used for constructing portfolios that reduce the risk for investors. One of the methods that we use to calculate these diversification benefits is the cross correlation integration measure. This method indicates that a lower integration leads to a higher reduce in variance, such that the highest reduction in variance is by investing in countries in the food industry or into different Belgian and Dutch industries. There is a reduction in variance of at least 40% for a portfolio which contain all the assets. These diversification benefits are also measured by the regime switching model, where we find a reduction in variance around 60% over time for investing in all the assets. This measure shows that the reduction in variance is the highest by investing in Dutch industries or by investing in different countries in the food industry. This means that investors can lower their risk by diversifying their portfolios.

There are more methods to measure the integration. For example, Ahelegbey et al. (2020) use Bayesian methods to detect turning points in financial markets. They make use of a network VAR model to model the interconnectedness between financial markets. This model could be an extension to our research.

References

Ahelegbey, D. F., Billio, M., Casarin, R., et al. (2020). *Modeling Turning Points In Global Equity Market*. Università di Pavia, Department of Economics and Management.

Barr, D. G. and Priestley, R. (2004). Expected returns, risk and the integration of international bond markets. *Journal of International money and finance*, 23(1):71–97.

Bekaert, G. and Harvey, C. R. (1995). Time-varying world market integration. *the Journal of Finance*, 50(2):403–444.

Billio, M., Donadelli, M., Paradiso, A., and Riedel, M. (2017). Which market integration measure? *Journal of Banking & Finance*, 76:150–174.

Borgioli, S., Horn, C.-W., Kochanska, U., Molitor, P., Mongelli, F. P., et al. (2020). European financial integration during the covid-19 crisis. *Economic Bulletin Articles*, 7.

Carrieri, F., Errunza, V., and Sarkissian, S. (2004). Industry risk and market integration. *Management science*, 50(2):207–221.

Chambet, A. and Gibson, R. (2008). Financial integration, economic instability and trade structure in emerging markets. *Journal of International Money and Finance*, 27(4):654–675.

Chen, B. and Woo, Y. P. (2010). Measuring economic integration in the asia-pacific region: A principal components approach. *Asian Economic Papers*, 9(2):121–143.

Choudhry, T. and Jayasekera, R. (2015). Level of efficiency in the uk equity market: empirical study of the effects of the global financial crisis. *Review of Quantitative Finance and Accounting*, 44(2):213–242.

De Santis, G. and Gerard, B. (1998). How big is the premium for currency risk? *Journal of financial economics*, 49(3):375–412.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350.

Forbes, K. J. and Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The journal of Finance*, 57(5):2223–2261.

Fratzscher, M. (2002). Financial market integration in europe: on the effects of emu on stock markets. *International Journal of Finance & Economics*, 7(3):165–193.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the econometric society*, pages 357–384.

Hilliard, J. E. (1979). The relationship between equity indices on world exchanges. *The Journal of Finance*, 34(1):103–114.

Jayasinghe, P., Tsui, A. K., and Zhang, Z. (2014). New estimates of time-varying currency betas: A trivariate bekk approach. *Economic Modelling*, 42:128–139.

Johnson, R. and Soenen, L. (2003). Economic integration and stock market comovement in the americas. *Journal of Multinational Financial Management*, 13(1):85–100.

Kim, C.-J. (1994). Dynamic linear models with markov-switching. *Journal of Econometrics*, 60(1-2):1–22.

Pardal, P., Dias, R., Šuleř, P., Teixeira, N., and Krulickỳ, T. (2020). Integration in central european capital markets in the context of the global covid-19 pandemic. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 15(4):627–650.

Quinn, D. P. and Voth, H.-J. (2008). A century of global equity market correlations. *American Economic Review*, 98(2):535–40.

Rouwenhorst, K. G. (1998). International momentum strategies. *The journal of finance*, 53(1):267–284.

A Appendix

A.1 Variances Cross correlation

Figure 35 denotes the portfolio variances for the diversification benefits with the integration between the European countries. Figure 36 denotes the portfolio variances for the European and non European countries for each industry and Figure 37 denotes the portfolio variances for the industries for each country.

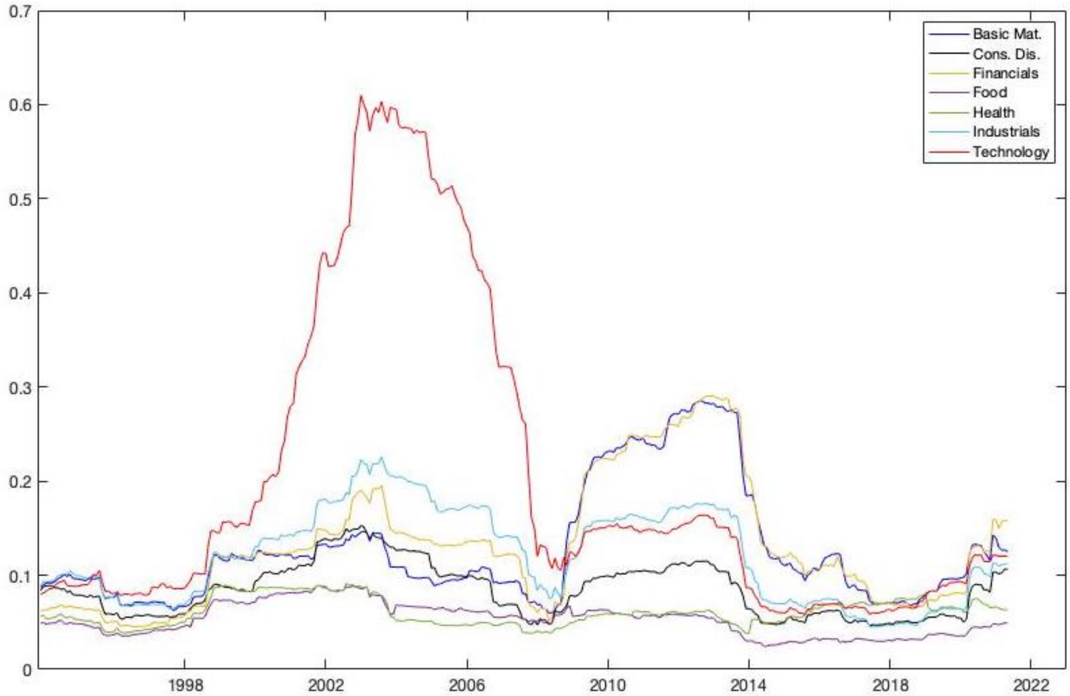


Figure 35: The variances for the different European countries of each industry with the cross correlation method.

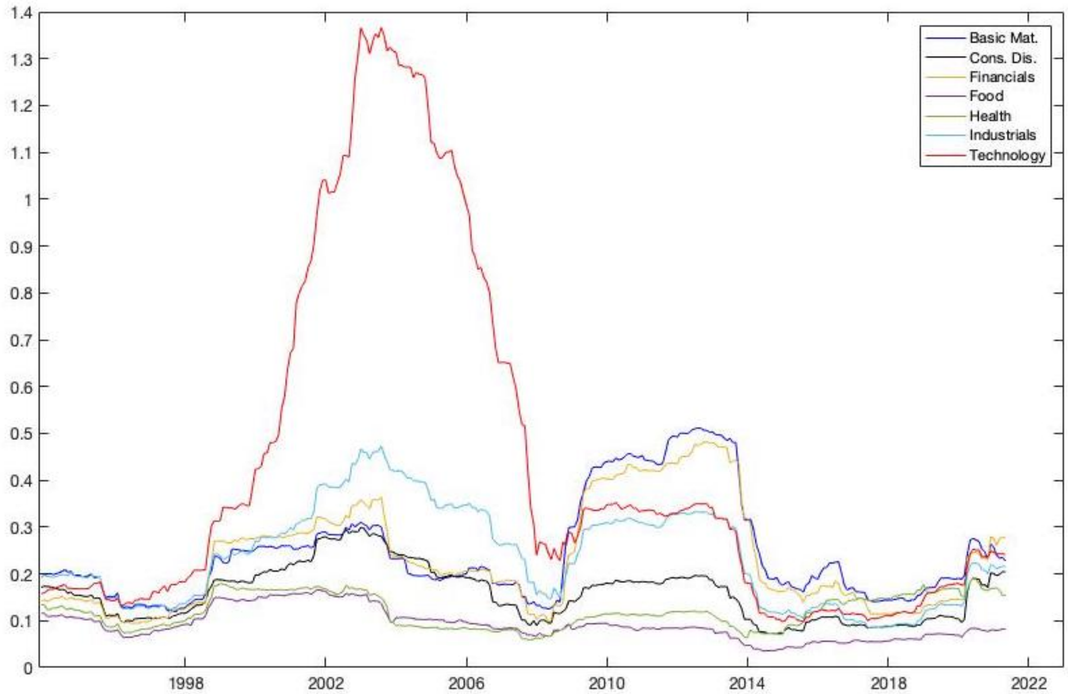


Figure 36: The variances for the different European and non European countries of each industry with the cross correlation method.

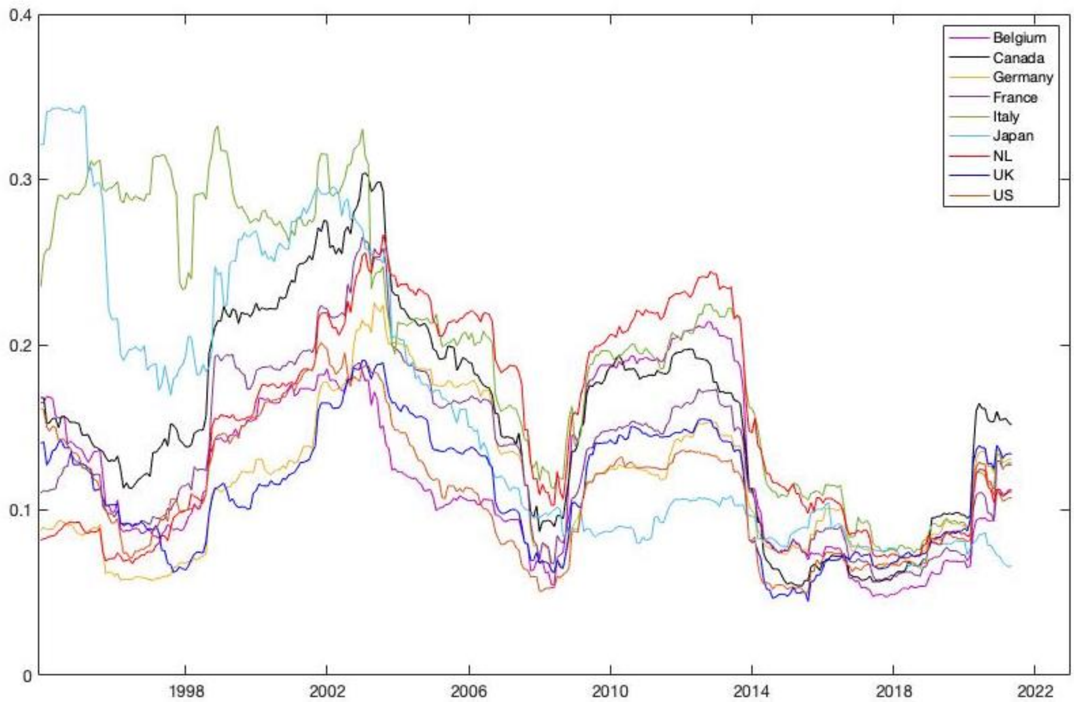


Figure 37: The variances for the different industries of each country with the cross correlation method.

A.2 Transition probabilities

Table 6: The transition probabilities for the regime switching model, which we use to calculate the integration between the European countries.

Industry	p11	p22	Time in state 1	Time in state 2
Basic Materials	0.978	0.299	0.969	0.031
Consumer Discretionary	0.987	0.791	0.941	0.059
Financials	0.994	0.814	0.967	0.033
Food	0.961	0.082	0.960	0.040
Health Care	0.980	0.780	0.915	0.085
Industrials	0.982	0.832	0.900	0.100
Technology	0.985	0.568	0.967	0.033

Note: p11 indicates $\Pr[S_t = 1|S_{t-1} = 1]$ and p22 indicates $\Pr[S_t = 2|S_{t-1} = 2]$, where state 1 denotes the state of integration and state 2 denotes the state of segmentation.

Table 7: The transition probabilities for the regime switching model, which we use to calculate the integration between all the countries.

Industry	p11	p22	Time in state 1	Time in state 2
Basic Materials	0.986	0.677	0.959	0.041
Consumer Discretionary	0.986	0.675	0.959	0.041
Financials	0.988	0.753	0.953	0.047
Food	0.979	0.762	0.920	0.080
Health Care	0.984	0.506	0.968	0.032
Industrials	0.984	0.522	0.967	0.033
Technology	0.985	0.513	0.969	0.031

Note: p11 indicates $\Pr[S_t = 1|S_{t-1} = 1]$ and p22 indicates $\Pr[S_t = 2|S_{t-1} = 2]$, where state 1 denotes the state of integration and state 2 denotes the state of segmentation.

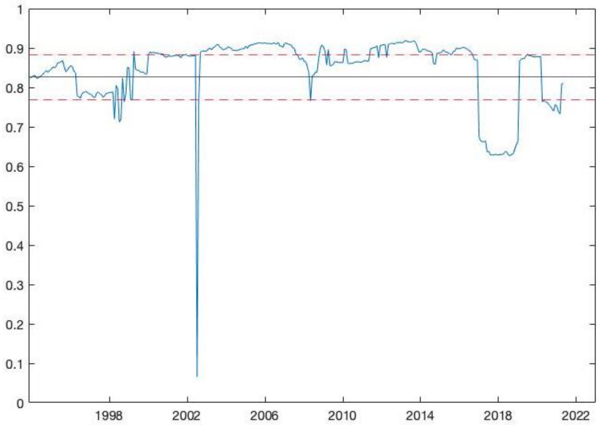
Table 8: The transition probabilities for the regime switching model, which we use to calculate the integration between the industries.

Country	**p11**	**p22**	**Time in state 1**	**Time in state 2**
Belgium	0.989	0.706	0.962	0.038
Canada	0.982	0.846	0.897	0.103
Germany	0.981	0.631	0.950	0.050
France	0.971	0.000	0.972	0.028
Italy	0.997	0.676	0.992	0.008
Japan	0.985	0.824	0.920	0.080
NL	0.994	0.744	0.975	0.025
UK	0.986	0.688	0.957	0.043
US	0.985	0.723	0.948	0.052

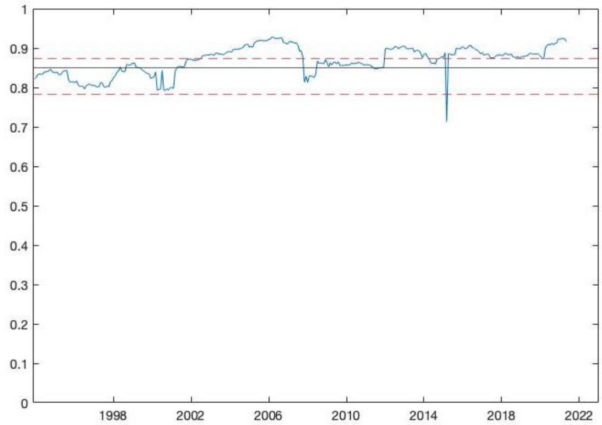
Note: p11 indicates $\Pr[S_t = 1|S_{t-1} = 1]$ and p22 indicates $\Pr[S_t = 2|S_{t-1} = 2]$, where state 1 denotes the state of integration and state 2 denotes the state of segmentation.

A.3 Constant R^2-test results

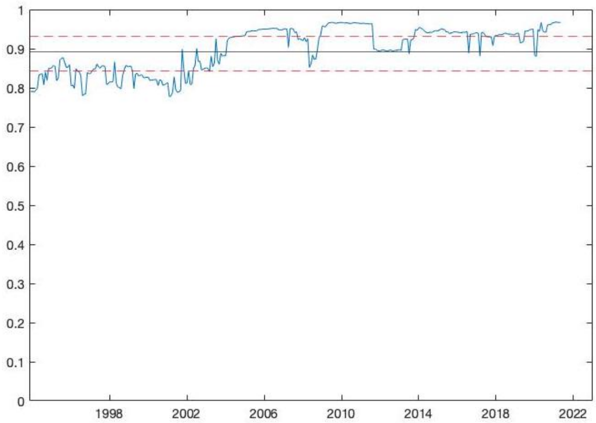
We denote the figures for testing whether the integration with the R^2 measure stays constant over time for the different European industries below.



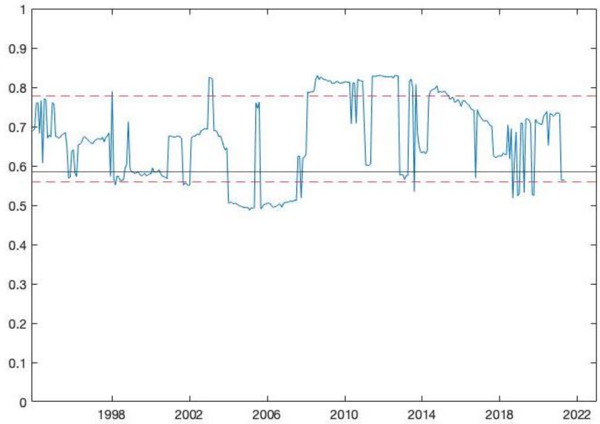
(a) Basic Materials



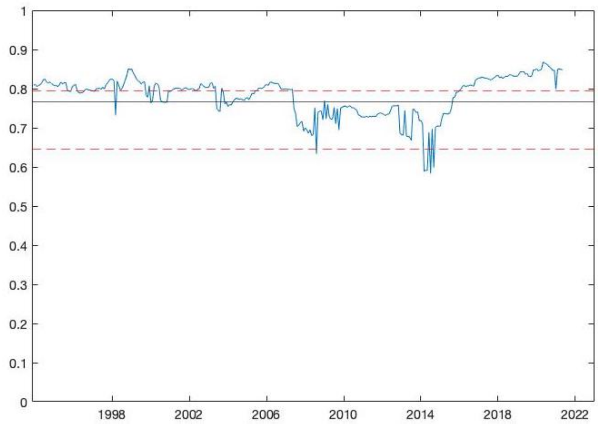
(b) Consumer Discretionary



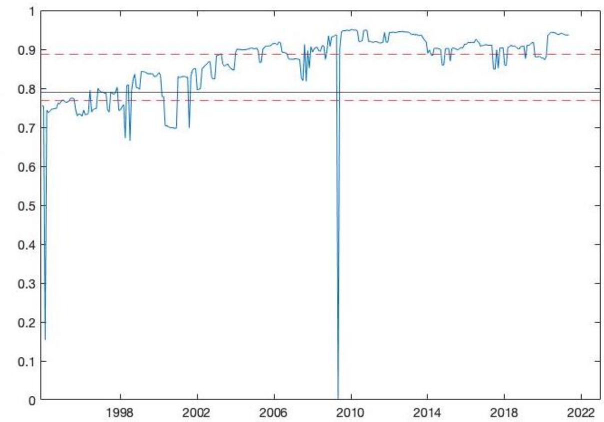
(c) Financials



(d) Food

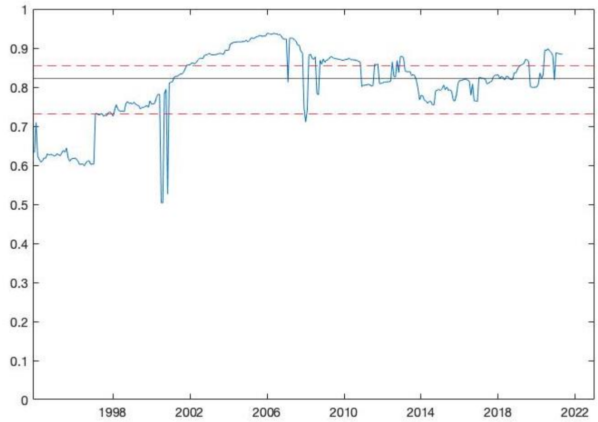


(e) Health Care



(f) Industrials

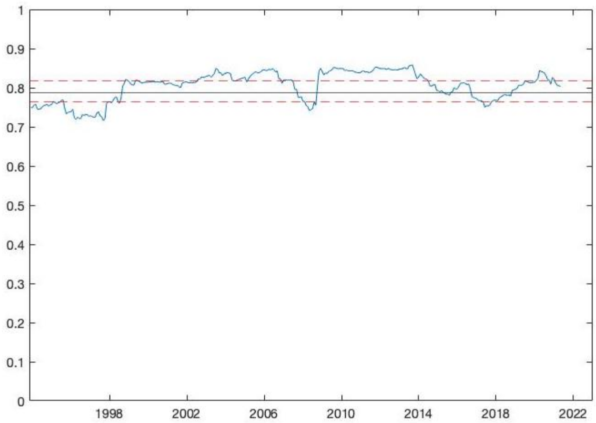
Figure 38: The R^2 tests for different European industries (a)-(f)



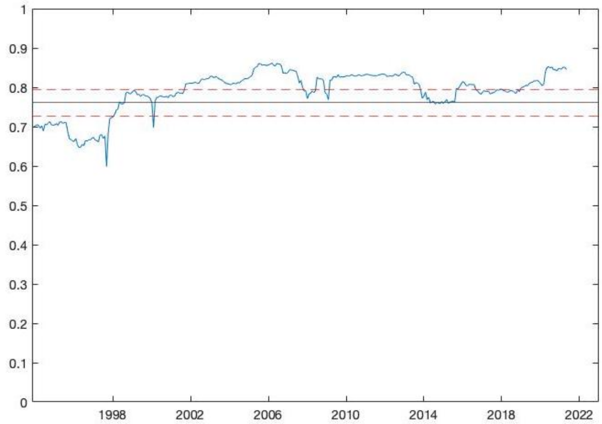
(a) Technology

Figure 39: The R^2 tests for different European industries

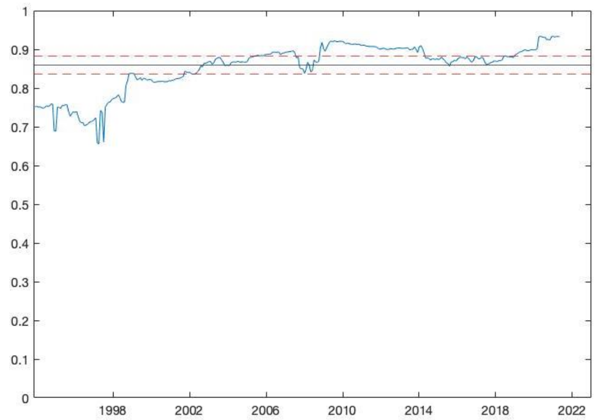
In Figure 40 and 41 we denote the test results of the constant R^2 test for the industries of all the countries.



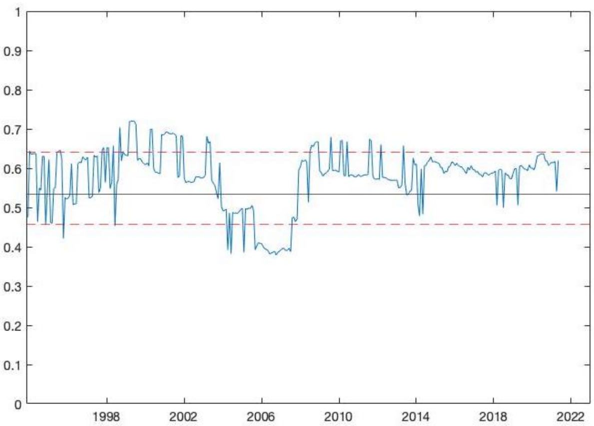
(a) Basic Materials



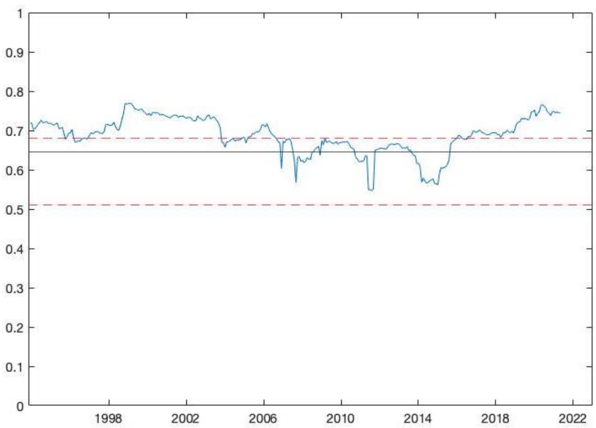
(b) Consumer Discretionary



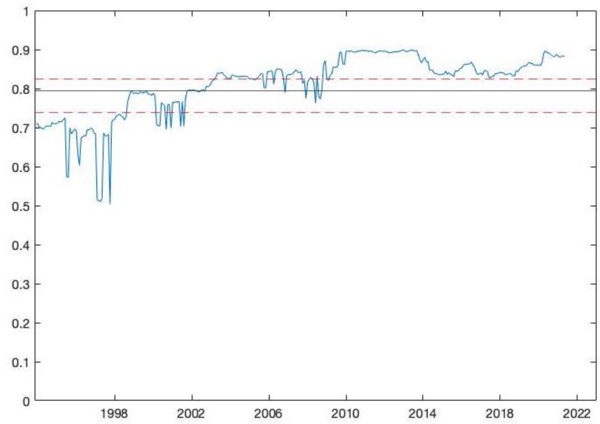
(c) Financials



(d) Food

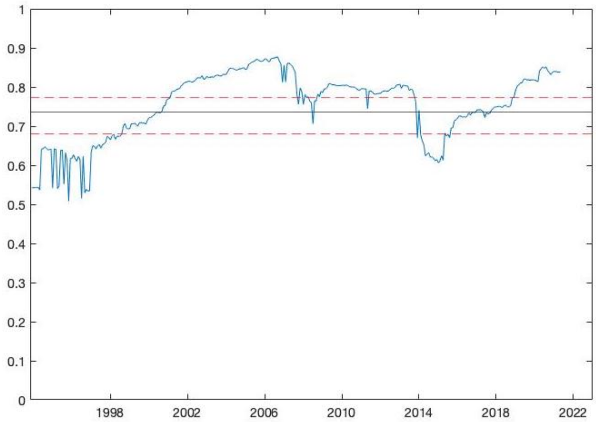


(e) Health Care



(f) Industrials

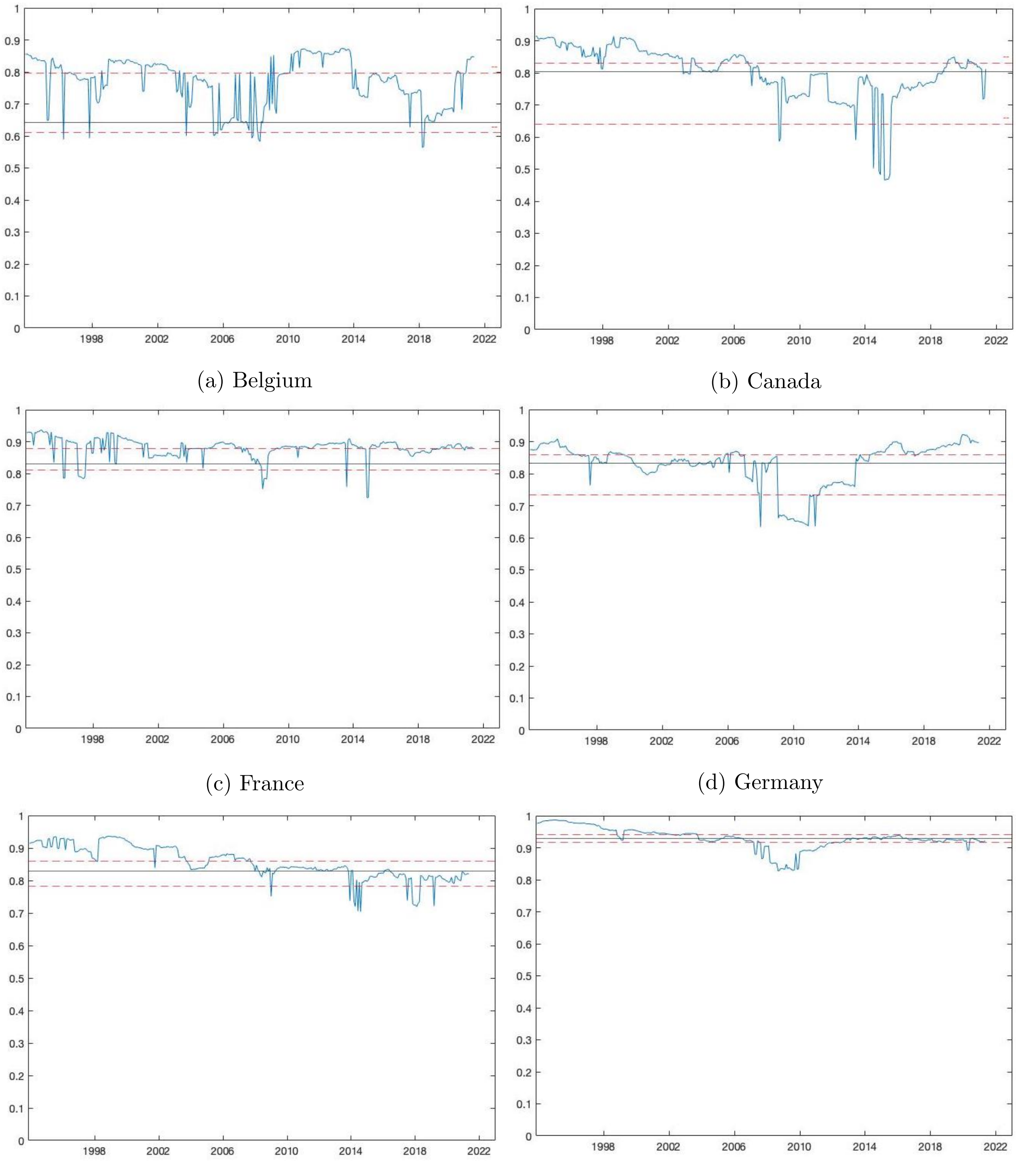
Figure 40: The R^2 tests for different industries (a)-(f)



(a) Technology

Figure 41: The R^2 tests for different industries

In Figure 42 and 43 we denote the test results of the constant R^2 test for the different countries.

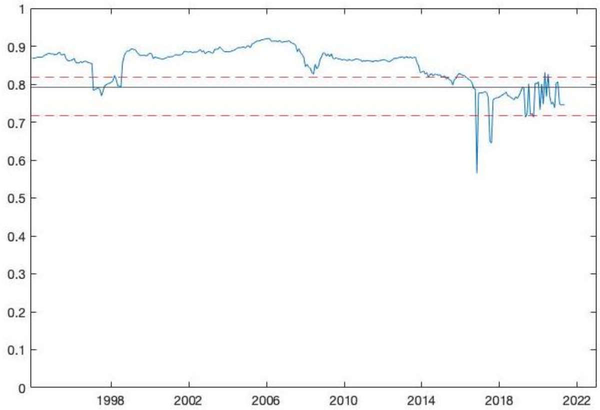


(a) Belgium (b) Canada

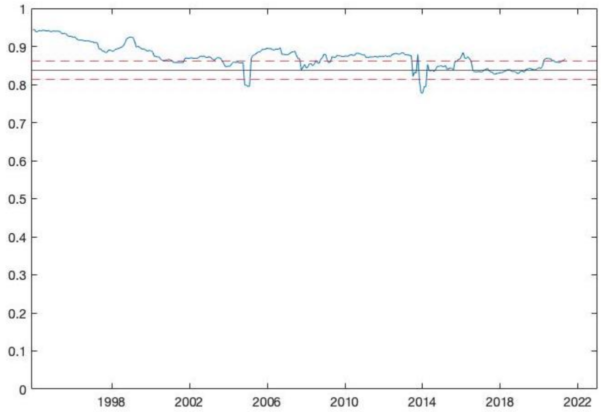
(c) France (d) Germany

(e) Italy (f) Japan

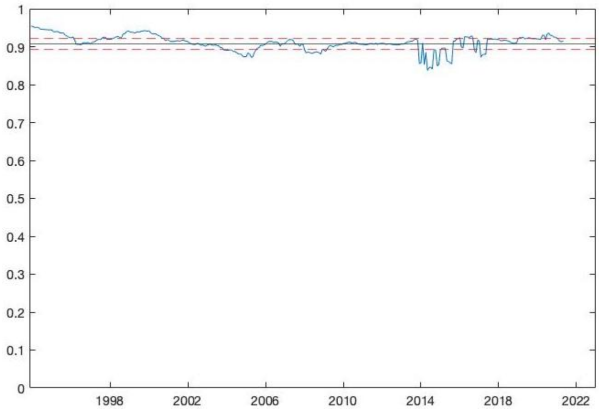
Figure 42: The R^2 tests for different countries (a)-(f)



(a) NL



(b) UK



(c) US

Figure 43: The R^2 tests for different countries (a)-(c)

A.4 Variances Regime Switching

Figure 44 denotes the smoothed average variances over time for the different European countries of each industry. In Figure 45, we denote the smoothed average correlations over time between the different European countries of each industry.

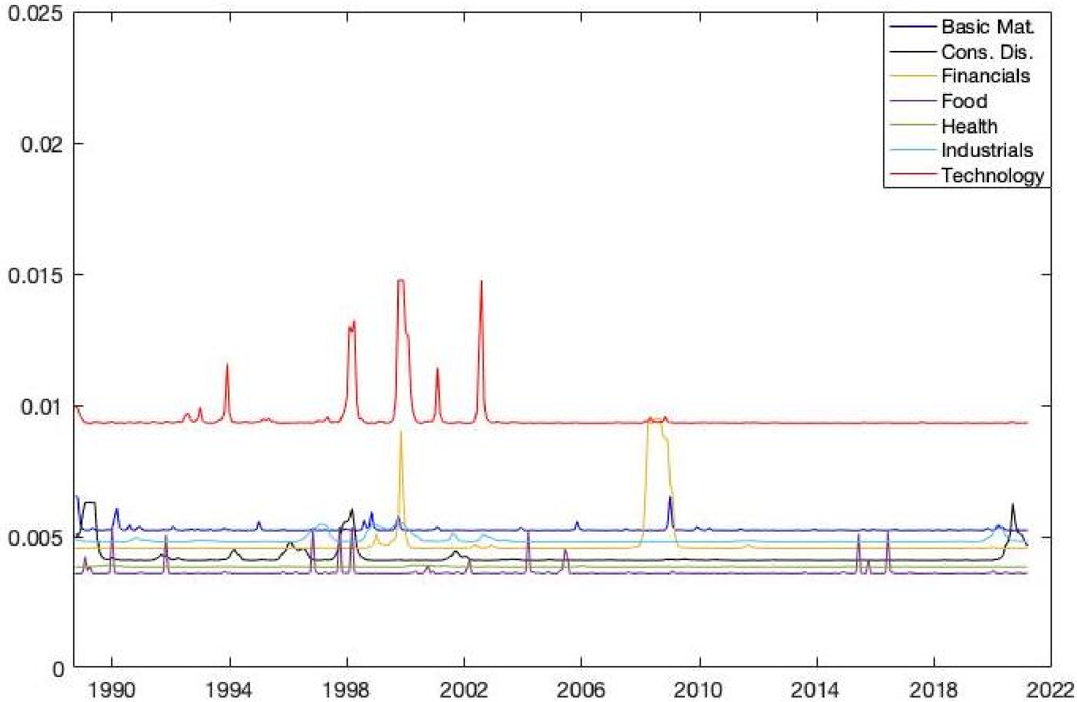


Figure 44: The smoothed average variances for the different EU countries of each industry.

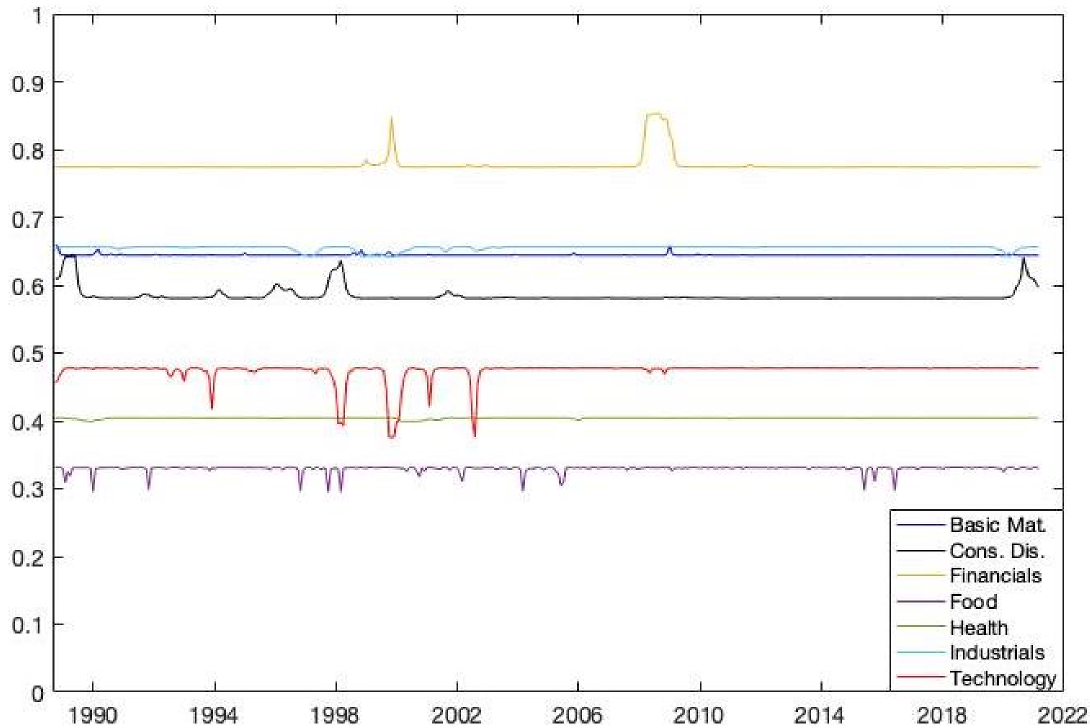


Figure 45: The smoothed average correlations for the different EU countries of each industry.

Figure 46 denotes the smoothed average variances over time for the different countries of each industry. In Figure 47, we denote the smoothed average correlations over time between the different countries of each industry.

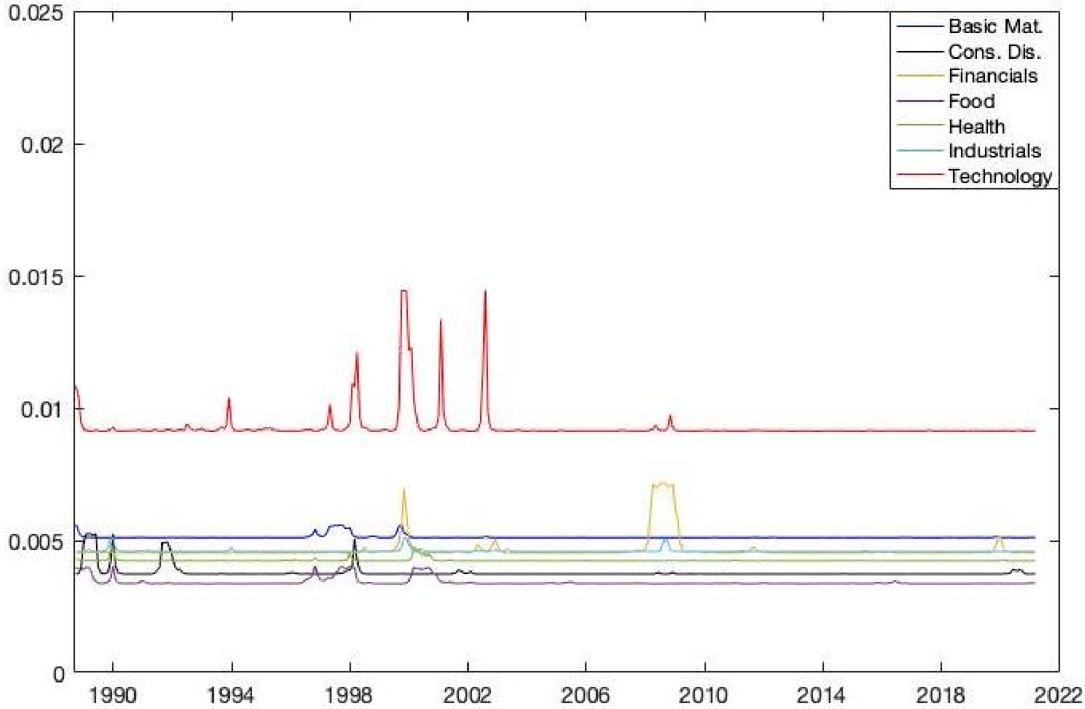


Figure 46: The smoothed average variances for the different countries of each industry.

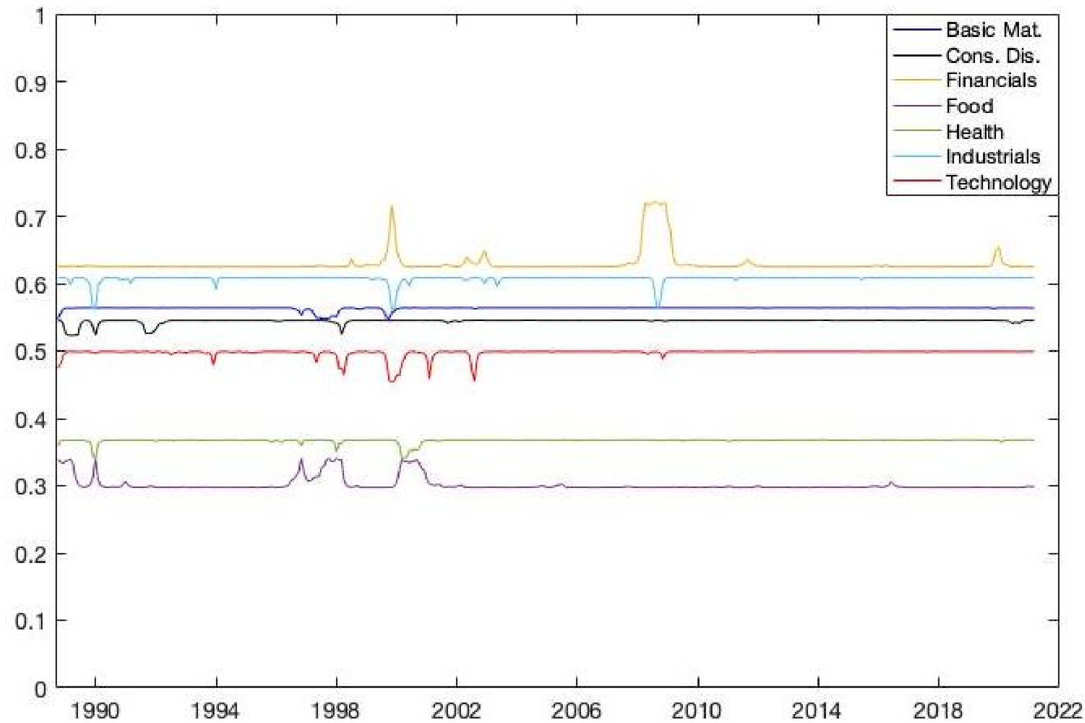


Figure 47: The smoothed average correlations for the different countries of each industry.

Figure 48 denotes the smoothed average variances over time for the different industries of each country. In Figure 49, we denote the smoothed average correlations over time between the different industries of each country.

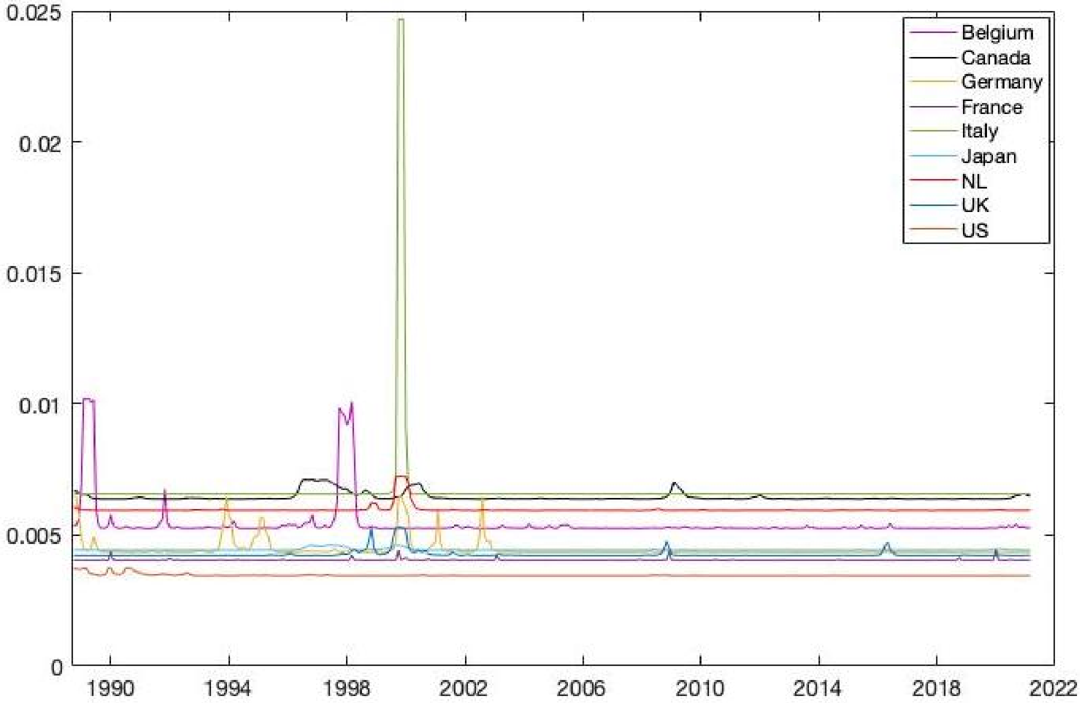


Figure 48: The smoothed average variance for the different industries of each country.

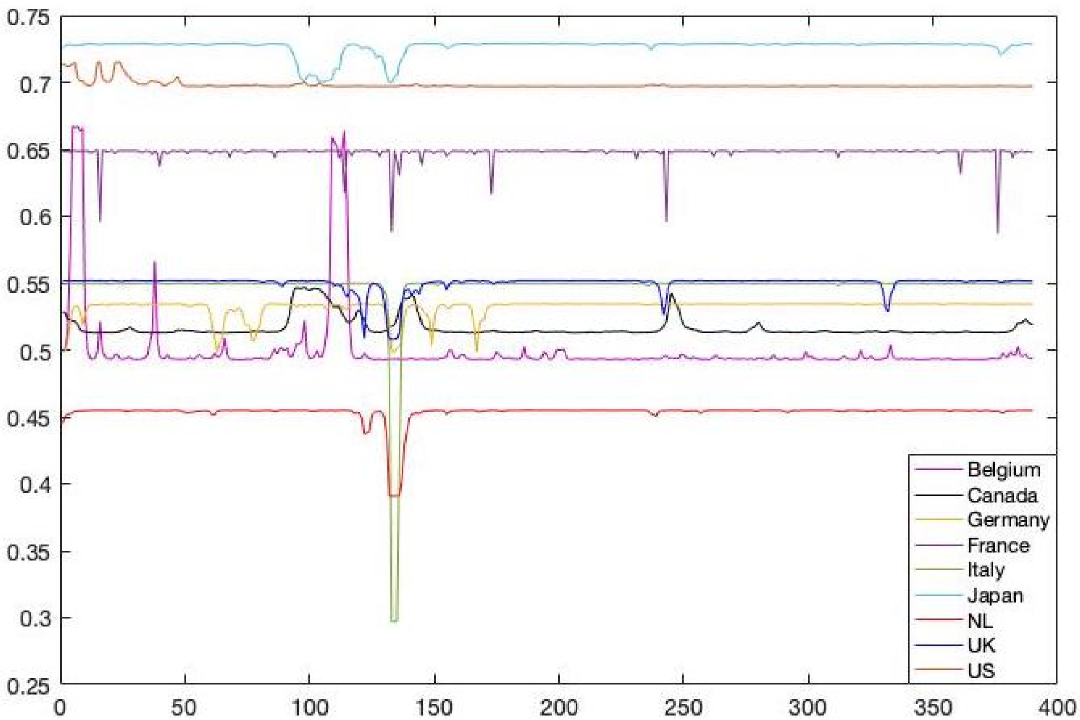


Figure 49: The smoothed average correlation between the different industries of each country.

Figure 50 denotes the smoothed average variances over time for the three portfolios, which contain all the assets of all the countries, all the assets of the European countries and all the assets of the non-European countries respectively.

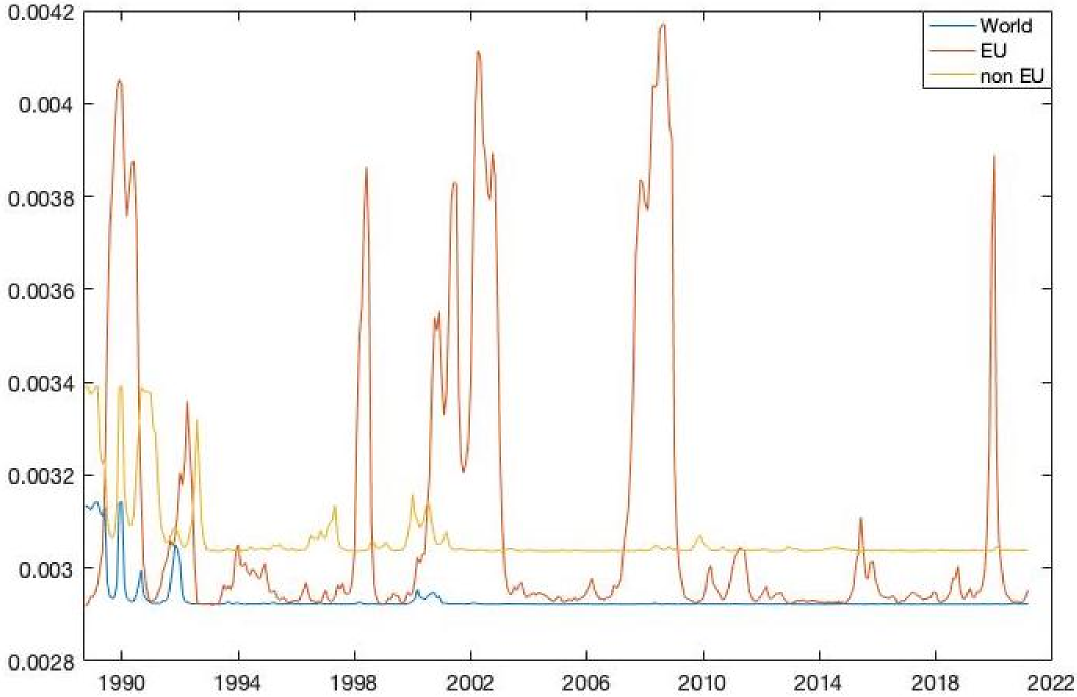


Figure 50: The smoothed average variances for the different countries.