The Idiosyncratic Volatility of European Stocks: Commonality and Effect on the Market Volatility

Ahmed KHALED FAROUK SOLIMAN¹ Erwan LE SAOUT^{1,2}

¹ University Paris 1 Panthéon-Sorbonne, PRISM Sorbonne

² Labex REFI

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Abstract

This paper studies the commonality in the idiosyncratic volatility of European stocks, and its effects on market portfolio volatility. We study publicly traded firms in 15 European countries and find that the idiosyncratic volatility is the main component of stock volatility. If we take a dynamic approach to estimating the correlations, we find evidence of substantial positive and negative correlations between each country's aggregate idiosyncratic volatility and its market portfolio volatility. We find also that the aggregate idiosyncratic volatility of countries at the European level has a common component. We use this component to improve the market portfolio volatility prediction.

¹ Correspondance: <u>Ahmed.Khaled-Farouk-Soliman@univ-paris1.fr</u>-

PRISM Sorbonne, 17 rue de la Sorbonne, 75231 Paris cedex, France

1. Introduction

The relation between risk and return is fundamental in the financial world. Modern portfolio theory (Markowitz, 1952; Sharpe, 1964; Lintner, 1965) shows that stock volatility has two components: first, systematic risk which is non-diversifiable and related to market volatility; and second, idiosyncratic risk which is specific to the firm. Modern portfolio theory assumes that the investor can decrease or eliminate idiosyncratic risk through diversification. However, studies show that idiosyncratic volatility is the main component of stock and portfolio return volatilities (Goyal and Santa-Clara, 2001; Cotter, O'Sullivan and Rossi, 2014; Nam, Khaksari and Kang, 2016). Further, there are many factors such as transaction costs (Constantinides, 1986; Uppal, 1993; Rowland, 1999), information costs (Merton, 1987; Brockman, Schutte and Yu, 2009), and investor characteristics (Barber and Odean, 1999, 2000, 2001; Liu, 2008; Malkiel and Xu, 2004) which might deter investors from holding a fully diversified portfolio. Recently, Herskovic, Kelly, Lustig and Van Nieuwerburgh (2016) proved the existence of a factor structure in the idiosyncratic volatility that is priced.

Thus, studying idiosyncratic risk is important because most investors, and especially private investors (Goetzmann and Kumar, 2008) are exposed to this kind of risk. The evolution of idiosyncratic volatility and its relation with returns will affect their investment strategies. In addition, according to the theory of efficient markets, many portfolio managers lose interest in active management of their portfolios. As a result, we have seen a shift towards passive portfolio management techniques, especially indexing. If the idiosyncratic volatility persists these portfolios will continue to be exposed to this risk although it will not be considered by portfolio managers.

The objective of this article is to present a new and comprehensive way to study aggregate (common) idiosyncratic volatility in the major European economies. We explore the aggregate idiosyncratic volatility and its behavior in a sample of different European countries. We examine the existence of a common factor in their aggregate idiosyncratic volatilities. Finally, we explain how a European common idiosyncratic volatility (ECIV) is affecting each country's stock market portfolio volatility and to what extent the ECIV improves each country's market portfolio volatility predictions over a period of months.

The article is organized as follows. Section 2 discusses the state of the art in the risk literature. It summarizes the main results and highlight three commonly used estimation methods.: portfolio volatility, average stock variance, and two measures of idiosyncratic volatility. Section 3 presents the empirical results for the evolution of aggregate idiosyncratic volatility, and some global risk measures. It provides evidence of European and regional common idiosyncratic volatility and its relation with each country's market portfolio volatilities.

2. Analysis of idiosyncratic risk

The literature on idiosyncratic risk is increasing. Our study of idiosyncratic volatility begins with a review of the literature, highlighting first the main results, and second the estimations used.

2.1. Main Findings

This section discusses the main findings related to idiosyncratic volatility. We focus on firm specific risk in relation to modern portfolio theory and the strand of work on the behavior of idiosyncratic volatility series. This subsection concludes with a discussion of the relationships identified between idiosyncratic volatility and expected stock returns.

Idiosyncratic risk in the Modern Portfolio Theory

The first works on modern portfolio theory (Markowitz, 1952; Sharpe, 1964.; Lintner, 1965), distinguish between market or systematic risk and firm specific or idiosyncratic risk. These authors consider that market risk which is non-diversifiable is the risk which should be priced and considered when estimating the required rate of return. It is represented by beta in the capital asset pricing model (CAPM). That is, an investor holding a market portfolio which by definition is the most diversifiable, will bear only the market risk which cannot be eliminated through diversification. Since it is assumed that the idiosyncratic risk is eliminated by diversification, this should not affect the required return or the asset pricing. By definition, the idiosyncratic risk (volatility) is the difference between the stock return volatility and the systematic volatility. In econometric terms, it is the standard deviation of the error term in the asset pricing model considered. However, the concept of idiosyncratic volatility differs among different theories and perspectives. For example, in a valuation theory context, the firm specific risk is affected by firm characteristics (Malagon et al., 2015). On the other hand, the costly arbitrage theory considers that the idiosyncratic volatility reflects only the investor's preferences. In this case, the idiosyncratic volatility is the stock specific risk and is not related to the firm's characteristics.

The study of idiosyncratic risk was triggered by three factors. First, the positive deterministic trend identified by Campbell, Lettau, Malkiel and Xu (2001) in the idiosyncratic volatility series in the United States stock market. Second, the fact that there are many reasons why investors are deterred from maintaining a well-diversified portfolio. Third, the idiosyncratic risk puzzle proposed by Ang, Hodrick, Xing and Zhang (2006; 2009) based on their observation of a negative relation between idiosyncratic risk and stock returns for the United States market and 23 other developed markets. In other words, idiosyncratic risk is negatively priced. Based on these three factors, we can identify four axes on which idiosyncratic volatility studies depend:

evolution of the idiosyncratic volatility series and its estimation methods, the factors affecting idiosyncratic risk, the relation between the idiosyncratic risk and the required return, and the reasons for the negative relation between idiosyncratic risk and stock return.

Idiosyncratic risk estimation and evolution

Initially, idiosyncratic risk was estimated as the standard deviation of the error term in the CAPM. However, the CAPM has several limitations. Many authors have tried to relax the model's assumptions such as the effect of taxes and dividends effect (Brenan, 1970), consideration of inflation and international assets (Stulz, 1981), or including an intertemporal dimension by relating the factors affecting consumption to the return on assets (Merton, 1973; Lucas, 1978; Breeden, 1979; Cox, Ingersoll and Ross; 1985). Malkiel and Xu (2002) tried to relax the perfectly diversified portfolio hypothesis. Campbell et al. (2001) developed a method to calculate firm idiosyncratic volatility without the need to estimate every firm's beta. Many studies employ the three-factor and five-factor models developed by Fama and French (1992, 2015) which are considered the most relevant asset pricing models. In the three-factor model, in addition to the market return, a high book to market ratio suggests that the firm is a persistent poor earner relative to a low book to market ratio. In addition, small firms experience longer periods of poor earnings than do big firms. In the latest version of their multifactorial model, Fama and French they propose that firm size and the book to market ratio represent the cross section of average returns. Their five-factor model includes operating profitability and investment.

Debate on the behavior of idiosyncratic volatility started with Campbell et al. (2001) who provided evidence of a strong positive deterministic trend in idiosyncratic volatility in the United States stock market during the period of 1962-1997. They found also that firm level volatility accounted for the largest share of stock volatility and the largest share of the variation in stock volatility. Other authors such as Goyal and Santa Clara (2001), Malkiel and Xu (2004),

Dennis and Strickland (2004), Irvine and Pontiff (2005), Fu (2009) and Abdoh and Varela (2017) have observed positive trends for the United States market. Guo and Savickas estimated idiosyncratic risk using the CAPM and the Fama and French three factor model and found that and increase in both cases. Fu (2009) shows that the idiosyncratic risk does not follow a random walk but is persistent, and work on the behavior of the average stock variance shows that it tends to increase (Whitelaw, 1994; Goyal and Santa Clara, 2001; Guo and Savickas, 2003). Herskovic, Kelly, Lustig and Van Nieuwerburgh (2016) confirm the existence of a positive trend in the idiosyncratic volatility of American companies, and found also that idiosyncratic volatilities across different industries show a substantial common variation. They argue that the common factor in the idiosyncratic volatility is priced². While Herskovic and colleagues link common idiosyncratic volatility³(CIV) to the income risk faced by households, Nam, Khaksari and Kang (2016) explain aggregate idiosyncratic volatility (AIV) time series behavior as a change in the price interaction among stocks. Caglayan, Xue and Zhang (2020) show that stock market characteristics such as turnover, information disclosure, avoidance of investor uncertainty, and macroeconomic factors such as GDP growth, exchange rate stability, and foreign debt health, are determinants of the country level idiosyncratic volatility⁴.

Several studies try to explain this positive trend. Xu and Malkiel (2003) and Dennis and Strickland (2004) explain is as due to an increase in institutional ownership, and although Kitagawa and Okuda (2016) do not discuss the trend in idiosyncratic volatility, they find a similar positive relation between idiosyncratic volatility and the foreign institutional ownership in the case of Japan. Both, Irvine and Pontiff (2009) and Abdoh and Varela (2017) suggest that increased product market competition is behind the increase in idiosyncratic volatility while

² They document a negative relation between the exposure of the stock to common idiosyncratic volatility and the stock returns.

³ Here we describe this as aggregate idiosyncratic volatility.

⁴ They estimate country-level idiosyncratic volatility using the Morgan Stanley Capital International investable market indexes for each country as the dependent variable in the Fama and French three factor-model. The volatility of the model residuals are the country-level i volatility.

Fink, Fink, Grullon and Weston (2010) observe a relation with the new listings. In a study of the Chinese stock market however, Nartea, Wu and Liu (2013) identify episodic behavior characterized by an autoregressive process of regime switches coinciding with reforms but do not observe a deterministic trend in idiosyncratic volatility. Similarly, Bekaert, Hodrick and Zhang (2012) find no evidence of an upward trend for 23 developed stock markets. This information is important for investors with undiversified portfolios. Brandt, Brav, Graham and Kumar (2010) studied United States stock markets and found that in 2003 that idiosyncratic volatility had dropped to below pre-1990 levels contradicting any evidence of a time trend during the 1962-1997 period. They point out that idiosyncratic volatility increases during attention-grabbing events and retail investor trading behaviors such as splitting, and is associated with increases in retail trading density. The rise in the idiosyncratic risk was an episodic phenomenon rather than a time trend. Nam, Khaksari and Kang (2016) found a similar pattern, and suggested also that the price interaction which increases with the increase in the number of listed firms, has a positive relationship with the idiosyncratic volatility.

2.2. Construction of Risk Measures

In this section we describe the methods used to estimate each risk measure considered in this paper. First, we compute the all share index volatility and the average stock volatility to proxy for global market risk. We estimate idiosyncratic volatility using two methods. First, we apply Fama and French's (1992, 2016) five-factor model and Carhart's (1997) momentum factor. Second, we calculate idiosyncratic volatility using principal component analysis.

2.2.1. Global Volatility Measures

In this subsection, we compute the market portfolio volatility and average stock volatility as measures of the stock market global risk, and assess their co-movement with idiosyncratic volatility. First, we compute the market portfolio variance using daily data. The portfolio considered is the equally weighted index for all shares. We use daily data to calculate the market portfolio variance V_{pt} for each month, based on the firms publicly traded on the stock market. We compute the annualized monthly volatility of the portfolio as the square root of the portfolio variance multiplied by the square root of the number of trading days in a month:

$$V_{pt} = \sum_{d=1}^{D_t} r_{Pd}^2 + 2\sum_{d=2}^{D_t} r_{Pd}^2 r_{pd-1}$$

where D_t is the number of days in the month *t* and r_{pd} is the portfolio returns in day *d*. The second term on the right-hand side was proposed by French, Schwert and Stambaugh (1987) and adjusts for autocorrelation of daily returns. Second, we compute average stock variance as the arithmetic mean of the daily variance in the stock returns:

$$V_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \left[\sum_{d=1}^{D_t} r_{id}^2 + 2 \sum_{d=2}^{D_t} r_{id} r_{id-1} \right]$$

where r_{id} is the return on the stock *i* on day *d* and N_t is the number of stocks existing during the month *t*. It should be noted that this is not a strict variance measure because our expectations are not based on the de-meaned returns. In the case of stocks maintained over short periods, removing the mean is not important. The advantage of this approach is that it does not require calculation of the conditional mean for each stock; this is calculated for all the firms traded on the market. Finally, we calculate average stock volatility as the square root of the average stock variance multiplied by the square root of the number of trading days in the month.

2.2.2. Estimation of idiosyncratic volatility estimation

As already mentioned, the idiosyncratic volatility can be estimated using a six-factor model (Fama and French, 1992,2016; Carhart, 1997) or a three-factor model based on principal component analysis.

2.2.2.1. The Realized Idiosyncratic Volatility (RIV)

We can estimate the firm specific risk as the realized idiosyncratic volatility. We follow Ang et al. (2006, 2009) to estimate idiosyncratic volatility. For each month and each country, we regress the excess return on the stock for different daily Fama and French (1992, 2016) risk factors and Carhart's (1997) momentum factor. The model can be written as:

$$R_{i\omega t} - r_t = \alpha_{i\omega t} + \beta_{mi\omega} (R_{m\omega t} - r_t) + \beta_{SMBi\omega} SMB_{\omega t} + \beta_{HMLi\omega} HML_{\omega t}$$
$$+ \beta_{RMWi\omega} MOM_{\omega t} + \beta_{RMWi\omega} RMW_{\omega t} + \beta_{CMAi\omega} CMA_{\omega t} + \varepsilon_{i\omega t}$$

where $R_{i\omega t}$ is the return on the stock i in the country ω during the month t; r_t is the risk free rate; $\alpha_{i\omega t}$ is the intercept; $\beta_{mi\omega}$ is the market coefficient; $R_{m\omega t}$ is the value weighted market return; $\beta_{SMBi\omega}$ is the size factor coefficient; $SMB_{\omega t}$ is the portfolio return small minus big; $\beta_{HMLi\omega}$ is the book to market coefficient; $HML_{\omega t}$ is the difference between the portfolio return including the high book to market ratio firms and the low book to market ratio portfolio returns ; $MOM_{\omega t}$ is the average return from high momentum portfolios minus the average return of low momentum portfolios; $RMW_{\omega t}$ is the average return on robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios; $CMA_{\omega t}$ is an investment factor estimated as the difference between the average return on the conservative investment portfolio and the average return on the aggressive investment portfolio; $\varepsilon_{i\omega t}$ is the residual. The realized idiosyncratic volatility is considered as the standard deviation of this residual. Since we use daily data, the standard deviation of the estimated residuals is also daily and is converted into a monthly standard deviation by multiplying the daily standard deviation by the square root of the number of trading days in the corresponding month.

2.2.2.2. Principal Component-Idiosyncratic Volatility

Principal component-idiosyncratic volatility (PCIV) is estimated using a return factor model; this is a purely statistical method since its factor $F_{\omega t}$ estimations rely on the first three principal components⁵ of the cross section of returns within the same day. The model is described as:

$$R_{i\omega t} - r_t = \alpha_{i\omega t} + \beta_{Fi\omega}F_{\omega t} + v_{i\omega t}$$

where $R_{i\omega t}$ is the return of the stock i in the country ω during the month t; r_t is the risk free rate; $\alpha_{i\omega t}$ is the intercept; $\beta_{Fi\omega}$ is the component loadings; $F_{\omega t}$ are the first three principal components in the cross section of returns in each market; $v_{i\omega t}$ is the residual.

2.2.2.3. Common Idiosyncratic Volatilities

At the country level, we consider the cross-section average idiosyncratic volatility as the country's AIV. We then consider the first principal component of the cross-section of all countries' AIV as the ECIV. Based on the correlations⁶ between countries' AIVs, we identify three groups of countries and estimate the first principal component of the AIVs of the countries within each group.

3. Empirical Results

In this section, we describe the sample and the data used in the model. We discuss the main observations of the evolution of the different risk measures and their correlations.

⁵ Since the first principal component accounts for most of the variance, roughly 10%, we estimate a factor model using only this component. We report the cross-section average of idiosyncratic volatility based on this model (see figure 2).

⁶ These are discussed in section 3.3. Dynamic correlation structure.

Subsection 3.x.x discusses the capacity of the ECIV to predict the national stock market index volatilities, that is it show how the ECIV affects the market portfolio volatility.

3.1. Data

We extract from Bloomberg market data from January 1st 2004 to June 31st 2018. We collect daily stock prices, return indexes, market values, number of shares outstanding, trading volumes, dividends, and book-to-market ratios. All values are in euros. Fama and French factors are obtained from the Ken French website.

Our sample is composed of the firms listed on 15 European stock markets: Austria, Belgium, Finland, France, Germany, Greece, Italy, Latvia, Lithuania, Netherlands, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

Country	Firms Number	Return	SD	MAX	MIN
Austria	83	1.06%	12.30%	15.17%	-12.57%
Belgium	347	1.12%	16.96%	14.19%	-12.60%
Finland	151	0.79%	10.55%	17.36%	-14.68%
France	1 188	1.56%	8.72%	19.59%	-15.60%
Germany	611	1.30%	8.07%	18.85%	-18.18%
Greece	189	1.49%	13.30%	29.31	-25.39%
Italy	521	0.40%	8.43%	17.47%	-16.21%
Latvia	27	3.44%	7.30%	32.87%	-21%
Lithuania	34	1.54%	5.79%	24.24%	-17.20%
Netherlands	147	1.08%	14.13%	17.56%	-15.78
Portugal	59	1.85%	8.46%	18.80%	-17.28%
Spain	257	1.39%	7.58%	15.80%	-14.30%
Sweden	886	1.31%	19.94%	20%	-17.80%
Switzerland	orland 543		9.17%	13.44%	-10.91
UK	1 502	0.88%	14.17%	1.356	-1.44

Table 1 : Monthly Returns

Table 1 reports the average monthly firm returns. These firm returns are used to calculate the excess returns. Table 2 presents the summary statistics for our sample. It shows considerable variation among countries in terms of rates of return and market capitalization. In January 2019, the biggest stock market in Europe was the United Kingdom London Stock Exchange with 2.7 trillion euros of market capitalization. The smallest market is the Riga Stock Exchange with market capitalization of 1 billion euros. The weighted monthly returns value ranges from -1.6% for Italy to 19.4% for Lithuania.

National Index	Return	σ	Cap
ATX (Austria)	12.00%	0.299	135 717
Bel20(Belgium)	4.50%	0.223	394 408
HEX (Finland)	2.50%	0.237	142 961
CAC 40 (France)	2.90%	0.045	2 086 940
DAX (Germany)	7.20%	0.195	2 038 038
ASE (Greece)	7.20%	0.238	45590
FTSE MIB (Italy)	-1.60%	0.206	529110
RIGSE (Latvia)	16.20%	0.309	1004
VILSE (Lithuania)	19.40%	0.391	3571
AEX (Netherlands)	1.80%	0.216	991086
PSE 20 (Portugal)	-0.70%	0.238	68099
IBEX 35 (Spain)	9.00%	0.224	800754
OMXS 30 (Sweden)	5.50%	0.269	504978
SMI (Switzerland)	3.80%	0.168	1519367
FTSE (100) UK	1.10%	0.183	2720240

Table 2: Rates of return and the market capitalization summary statistics

3.2. Different measures of risk behavior

We focus on global risk, and the idiosyncratic volatility measures behavior and its correlations to explain the dynamics of this relationship. We predict market portfolio volatility using the ECIV.

3.2.1. Portfolio Volatility and Average Stock Volatility

First, we present the results for the all shares market index portfolio volatility and the average stock volatility. Table 3 panel A reports the summary statistics of the standard deviation of the all shares market index portfolio variance. Greece has the highest portfolio volatility with an average standard deviation over the period of 0.044; Germany has the lowest portfolio volatility with an average standard deviation of 0.011 over the period.

In terms of average stock volatility, over the whole period the United Kingdom is ranked highest and Latvia is ranked lowest.

In line with the theory, in the case of every country market portfolio volatility is less than average stock volatility. The graphs (figure 1 and 2) show that volatility measure movements are synchronized, especially during recessions and crisis. This suggests the existence of a common component driving idiosyncratic volatility and moving in harmony with market portfolio volatility.

In addition, in line with CLMX (2001) and Malkiel and Xu (2003), average idiosyncratic volatility is the main component of average stock volatility. This suggests that idiosyncratic volatility is the main driver of stock volatility.

3.2.2. Realized idiosyncratic volatility and principal component idiosyncratic volatility

Table 4 panels A and B respectively report the summary statistics for realized idiosyncratic volatility or RIV, and the principal component idiosyncratic volatility or PCIV.

First, we calculate the statistics for every firm series, and then average them at country level to obtain the average for each country. In general, each country's RIV is slightly higher than its PCIV. On average over the whole period, Austria has the lowest RIV (0.0454), and Greece has the highest RIV (0.1085). Greece also has the highest expected idiosyncratic volatility (PCIV 0.1088), and Latvia has the lowest expected idiosyncratic volatility (PCIV 0.0412). AIV values are higher than the market portfolio volatility values for all countries which demonstrates the benefits derived from diversification.

Figure 1 depicts the RIV behaviors and figure 2 presents the PCIV values⁷. We add market portfolio volatility (*Vol_ind* and *totvol*) to the idiosyncratic volatility measures to obtain the average stock volatility. We observe four peaks which occur for all the volatility measures we use. The first occurs in the early 2000s, and refers to the the dot com bubble period and the telecoms crash. Also, in 2001, European countries suffered inflation due to imbalances following introduction of the Euro in 1999. The second peak corresponds to the emergence in October 2008 of the global financial crisis which pushed the developed economies into recession. The third peak refers to the August 2010 sovereign debt crisis. Following this, nearly all the countries in the sample experienced volatility increases. The fourth peak occurred in 2016 following the results of the United Kingdom referendum and Brexit.

The graphs in figures 1 and 2 identify three stylized facts that apply to all our sample countries. First, idiosyncratic volatility whether RIV or PCIV accounting for around 90% of stock total volatility. Second, substantial co-movement between each market's AIV and their market portfolio volatility (Vol_ind). This points to the importance of assessing the correlation between AIV and market portfolio volatility in order to understand how idiosyncratic volatility affects market volatility at both the national and regional levels.

⁷ We present idiosyncratic volatility estimated using the first principal component, and then the first three principal components.

Panel A: Market Portfolio Volatility								
Pays	Mean	SD	MAX	MIN	Median			
Austria	0.016	0.006	0.041	0.006	0.014			
Belgium	0.015	0.007	0.051	0.004	0.013			
Finland	0.026	0.011	0.074	0.009	0.023			
France	0.017	0.008	0.05	0.005	0.015			
Germany	0.011	0.006	0.037	0.004	0.01			
Greece	0.044	0.023	0.094	0.016	0.039			
Italy	0.033	0.013	0.086	0.01	0.03			
Latvia	0.015	0.005	0.038	0.006	0.015			
Lithuania	0.019	0.009	0.063	0.005	0.016			
Netherlands	0.027	0.012	0.079	0.01	0.024			
Portugal	0.021	0.008	0.053	0.008	0.02			
Spain	0.025	0.01	0.062	0.008	0.024			
Sweden	0.029	0.013	0.083	0.009	0.026			
Switzerland	0.02	0.007	0.049	0.007	0.018			
UK	0.026	0.009	0.068	0.011	0.024			
]	Panel B: Av	erage Stoc	k Volatility	у				
Pays	Mean	SD	MAX	MIN	Median			
Austria	0.048	0.007	0.077	0.031	0.047			
Belgium	0.056	0.008	0.091	0.04	0.055			
Finland	0.078	0.011	0.119	0.055	0.076			
France	0.065	0.009	0.096	0.048	0.063			
Germany	0.061	0.019	0.109	0.029	0.062			
Greece	0.112	0.016	0.14	0.087	0.111			
Italy	0.075	0.013	0.119	0.051	0.074			
Latvia	0.047	0.011	0.075	0.022	0.047			
Lithuania	0.055	0.015	0.101	0.023	0.053			
Netherlands	0.074	0.013	0.126	0.049	0.071			
Portugal	0.06	0.009	0.091	0.039	0.061			
Spain	0.059	0.01	0.095	0.037	0.059			
Sweden	0.085	0.013	0.136	0.064	0.082			
Switzerland	0.061	0.009	0.097	0.047	0.059			
UK	0.068	0.009	0.107	0.053	0.066			

Table 3: Global risk measures summary statistics	

Third, the existence of a synchronous movement of average cross-sectional idiosyncratic volatility across European countries.

Although it is not based on asset price model risk factors, the remaining estimates are based on PCIV which we believe captures the main components accounting for the common variance among stocks.

Panel A: Realiz	ed Idiosy	ncratic V	olatility	Panel B: PCIV				
Country	Mean	SD	Median	Country	Mean	SD	Median	
Austria	0.0454	0.0454 0.006 0.0445		Austria	0.0413	0.0209	0.0448	
Belgium	0.053	0.0072	0.0518	Belgium	0.0496	0.0213	0.0500	
Finland	0.0728	0.0092	0.0716	Finland	0.0674	0.0219	0.0655	
France	0.0618	0.0313	0.0599	France	0.0588	0.0288	0.0592	
Germany	0.06	0.0528	0.061	Germany	0.0572	0.0500	0.0581	
Greece	0.1085	0.0167	0.1083	Greece	0.0936	0.0422	0.0913	
Italy	0.0687	0.0097	0.068	Italy	0.0630	0.0194	0.0621	
Latvia	0.0463	0.011	0.0456	Latvia	0.0412	0.0255	0.0423	
Lithuania	0.0541	0.0139	0.0523	Lithuania	0.0468	0.0214	0.0476	
Netherlands	0.0673	0.0104	0.0653	Netherlands	0.0621	0.0247	0.0590	
Portugal	0.057	0.007	0.058	Portugal	0.0514	0.0283	0.0529	
Spain	0.0536	0.0071	0.0531	Spain	0.0483	0.0262	0.0504	
Sweden	0.0805	0.01	0.0776	Sweden	0.0749	0.0290	0.0722	
Switzerland	0.0573	0.0222	0.0562	Switzerland	0.0528	0.0201	0.0522	
UK	0.0641	0.0259	0.0632	UK	0.0568	0.0253	0.0562	

Table 4: Idiosyncratic volatility measure summary statistics

3.3. Dynamic Correlation Structure

The observed co-movements of idiosyncratic volatility and market portfolio volatility allows computation of the correlation between these two measures to understand the interactions between these risk measures. First, we compute the correlation between idiosyncratic volatility and market portfolio volatility over the whole period analyzed. They are very weak and close to zero for all countries. However, we can see that the correlation between each country's idiosyncratic volatility and market volatility is not constant and is changing over time. We prefer to use a rolling correlation to investigate the relationship between idiosyncratic volatility and market volatility.

We choose a rolling correlation with a 12 month observation window. The dynamic correlations between idiosyncratic volatility and market volatility are not constant. Figure 3 provides the correlations for all the countries considered and shows that they are positive during recessions, and reach extremely high levels (over 85%). This is consistent with the results from prior studies. In periods of economic expansion (or at least periods of no economic distress), we expect the correlation between idiosyncratic volatility and market volatility to decrease to very low levels or even to disappear. We find that the correlations not only decrease to zero but also become significantly negative (-0.6). This explains why we observe a weak or no correlation between idiosyncratic volatility over the sample period.

The observed negative rolling correlations are due to the market portfolio trend turning positive prior to a recession and before idiosyncratic volatility turns positive. Since recession is a systematic rather than an idiosyncratic risk, it is reasonable to expect market portfolio volatility to rise faster before a recession compared to average cross-section idiosyncratic volatility. This holds for all the countries in our sample. Before the recessions, the correlations become negative; after the recession becomes established and recognized officially by all the agents, the correlations become highly positive.

We examine the distribution of the dynamic correlations to confirm the presence of a non-null correlation between idiosyncratic volatility and market volatility, whether negative or positive. To scrutinize those correlations, figure 4 reports the distribution of the correlations between individual idiosyncratic volatility and market portfolio volatility. We observe numerous

moderate correlations (positive and negative) over the whole period although the occurrence of a non-null correlation is more probable than a weak or no correlation.

To check the robustness of our results, we use an alternative measure of systematic risk, the volatility index or VIX, and compute the dynamic correlations between cross average idiosyncratic volatility. This results in stronger correlations than in the case of the stock market portfolio. However, similar to stock market volatility, the correlations between idiosyncratic volatility and the VIX have strong negative coefficients⁸. This confirms the existence of a substantial dynamic correlation between the aggregate idiosyncratic risk and systematic risk.

Correlations	Aust	Bel	Fin	Fra	Ger	Grc	Itl	Lat	Lit	Neth	Por	Sp	Swe	Swit	UK
Austria	1														
Belgium	0.337	1													
Finland	0.37	0.824	1												
France	0.176	0.876	0.74	1											
Germany	0.014	0.741	0.555	0.881	1										
Greece	0.371	0.122	0.078	-0.147	-0.177	1									
Italy	0.294	0.479	0.55	0.249	-0.047	0.432	1								
Latvia	0.341	0.008	-0.122	-0.111	-0.03	0.557	0.04	1							
Lithuania	0.526	0.272	0.144	0.143	0.192	0.474	0.058	0.689	1						
Netherlands	0.229	0.91	0.856	0.864	0.733	0.088	0.51	-0.053	0.165	1					
Portugal	0.244	0.388	0.496	0.221	-0.074	0.221	0.735	-0.148	-0.105	0.403	1				
Spain	0.489	0.584	0.624	0.373	0.118	0.305	0.697	-0.046	0.068	0.526	0.604	1			
Sweden	0.165	0.858	0.851	0.877	0.732	-0.096	0.417	-0.218	0.054	0.885	0.351	0.511	1		
Switzerland	0.32	0.894	0.795	0.859	0.712	0.103	0.494	0.077	0.344	0.891	0.356	0.496	0.863	1	
UK	0.626	0.616	0.625	0.414	0.145	0.385	0.664	0.24	0.446	0.559	0.517	0.659	0.48	0.633	1

Table 5: AIV correlations among European Countries

⁸ Results not reported here but available on request.

Another stylized fact that is confirmed is the synchronous movement of average cross-sectional idiosyncratic volatilities across European countries. The correlations between idiosyncratic volatilities across Europe are very high. This holds for both estimation methods - RIV and PCIV. We observe very persistent co-movements among some groups of countries. Out of the 15 countries in the sample, 7 have correlations above 60%. However, not all correlations between countries are strong. Table 5 reports the correlations between countries' AIVs estimated using the three-factor principal component model.

By clustering the correlations hierarchically, we can identify three groups of countries which show strong correlations. The first group includes France, Germany, Sweden, Switzerland, Belgium and the Netherlands which are among the biggest economies in the sample. The second group includes Italy, Portugal, Spain and the United Kingdom. It contains mainly countries of sovereign debt crisis. The third group includes Austria, Greece, Latvia and Lithuania. Figure 5 depicts this clustering.

3.4. Aggregate idiosyncratic volatilities have some common components

To investigate the existence of co-movements among countries' AIVs, we perform principal component analysis of the whole sample. We repeat the analysis to extract principal components for groups 1, 2 and 3 to identify the interactions between the first principal component in each group and possible spill-over effects. Table 6 reports the results of the principal component analysis. For all countries, we find that the first three principal components explain 80% of the variance While the first principal component of the first group explains 84% of the total variance among the countries in that group, the proportion of the variance is relatively smaller for the second and third groups (73% and 62% respectively).

3.5. Idiosyncratic volatility spillovers

Having confirmed the existence of significant synchronous movements between the European idiosyncratic volatilities, we explore possible idiosyncratic volatility spillovers among these groups. In other words, we are interested in possible interdependence among the principal components and the volatility of the three groups. We estimate a vector autoregression (VAR) model of the first principal component of each group. Table 7 presents the model results. Before fitting the model, we test series stationarity. All the three first components of the different groups are non-stationary. Therefore, we include the series of each group principal component of group 1, and the lagged values of the first component of group 2 has a significant effect at the 3rd, 6th and 9th lags. Note that the coefficient of the 6th lag of group 2 is negative. In the second model the dependent variable is the first principal component of the second group, and the 8th lag of the first group principal component is statistically significant and negative. To test for causality, we report the p values of the Granger causality test for each model. The results show a causality relation between the first principal component of the first group and the first principal component of the second group.

In model 3, the first component of the third group has negative significant coefficients at the 4th and the 5th lags. However, the Granger causality test shows the absence of causality. The first group's principal component has negative significant coefficients at the 1st, 4th and 8th lags. Since the Granger causality test p value is less than 1%, we can say that a causality relation exists. Therefore, we prove the existence of spillover effect. The first two groups have substantial interdependence. However, the effect of the second group of countries on the idiosyncratic volatility of the first group is more pronounced.

Table 6: PCA results for the AIV

	Panel A : The sample							
All Countries	PC1	PC2	PC3					
Standard Deviation	2.716	1.703	1.431					
Proportion of Variance	0.492	0.193	0.136					
Cumulative Proportion	0.492	0.685	0.822					
	Panel E	3 : Group 1						
Group1	PC1	PC2	PC3					
Standard Deviation	2.435	0.719	0.432					
Proportion of Variance	0.847	0.074	0.027					
Cumulative Proportion	0.847	0.921	0.947					
	Panel (C : Group 2						
Group2	PC1	PC2	PC3					
Standard Deviation	1.715	0.709	0.571					
Proportion of Variance	0.736	0.126	0.082					
Cumulative Proportion	0.736	0.861	0.943					
	Panel [) : Group 3						
Group3	PC1	PC2	PC3					
Standard Deviation	1.58	0.84	0.735					
Proportion of Variance	0.624	0.177	0.135					
Cumulative Proportion	0.624	0.8	0.935					

3.6. Predicting market portfolio volatility

Having provided evidence of a common component in countries' AIVs, we need to examine the capacity of the ECIV to predict each country's market portfolio volatility and the sample market portfolio volatility. We focus on the effect of the first principal component on countries' AIV on the market volatility of each country and test its influence on European market volatility.

Panel A - Model 1 : PC1 ~PC1 +PC2						
Independent Variable	estimate	std.error	statistic	p.value		
PC grp1 lag1	-0.706	0.134	-5.284	0		
PC grp 2 lag 3	0.27	0.16	1.687	0.093		
PC grp 1 lag 4	-0.334	0.159	-2.096	0.037		
PC grp 2 lag 6	-0.288	0.162	-1.777	0.077		
PC grp1 lag 8	-0.344	0.154	-2.238	0.026		
PC grp 2 lag 9	0.434	0.153	2.834	0.005		
PC grp2 lag 10	0.39	0.131	2.984	0.003		
Granger Causality pvalue				0.004304		

Table 7: VAR model results

Panel C - Model 3 : PC1 ~PC1 +PC3								
Independent Variable	dependent estimate std.error statistic Variable							
PC grp1 lag 1	-0.527	0.094	-5.596	0				
PC grp1 lag 2	-0.203	0.103	-1.978	0.049				
PC grp3 lag 4	-0.267	0.15	-1.782	0.076				
PC grp3 lag 5	-0.286	0.151	-1.902	0.059				
PC grp1 lag 8	-0.301	0.094	-3.219	0.002				
Granger Causality pvalue				0.361742				

	Panel B - Model 2: PC2 ~PC1 +PC2							
	Independent Variable	estimate	std.error	statistic	p.value			
	PC grp2 lag 1	-0.536	0.118	-4.529	0			
	PC grp2 lag 2	-0.316	0.138	-2.282	0.024			
	PC grp1 lag 8	-0.388	0.139	-2.795	0.006			
	PC grp2 lag 8	0.244	0.143	1.704	0.09			
	PC grp2 lag 9	0.334	0.138	2.414	0.017			
	PC grp2 lag 10	0.23	0.118	1.949	0.053			
Granger Causality pyalue					0.002279			

Panel D - Model 3 : PC3 ~PC1 +PC3									
Independent Variable Estimate std.error statistic p.value									
PC grp1 lag 1	-0.141	0.057	-2.456	0.015					
PC grp3 lag 1	-0.421	0.083	-5.06	0					
PC grp3 lag 2	-0.269	0.09	-3.006	0.003					
PC grp1 lag 4	-0.113	0.063	-1.775	0.077					
PC grp3 lag 4	-0.205	0.091	-2.246	0.026					
PC grp3 lag 5	-0.193	0.092	-2.108	0.036					
PC grp1 lag 8	-0.152	0.057	-2.668	0.008					
Granger Causality pvalue				0.005377					

The main tools are the VAR model and the Granger causality test. The results are reported in the annex. For most of our sample countries the principal component of the countries' AIV has a significant effect on national stock market volatility. National market volatility has a significant effect on predicting national AIV in the cases of Belgium, Finland, France, Germany, and Italy. We observe that the second and the third lags of the ECIV affect 12 out of the 15 stock market volatilities. These results confirm the effect of ECIV on market volatilities.

We can also forecast domestic market volatility using the fitted VAR model for each country, for the last four months in our time period. the green line in figure 6 presents real market portfolio volatility and the forecast values of market portfolio volatility using the convenient VAR setting for each country. The yellow and red lines are respectively the upper and lower bounds of the confidence interval. The graphs in figure 6 show that in the majority of cases, the model forecasts are close to the realized market volatility values.

4. Conclusion

We proposed a new approach to study the commonality in idiosyncratic volatilities across major European stock markets. We highlighted the importance and advantages of taking account of Idiosyncratic volatility when considering index management. First, we proved that on average idiosyncratic volatility accounts for 90% of stock volatility. Second, we showed that there is substantial correlation between idiosyncratic volatility and market portfolio volatility in a dynamic approach to 12 month rolling correlations. We observed that before each crisis period the correlation between AIV and market volatility turned significantly negative because market volatility reacts before a crisis more rapidly than idiosyncratic volatility. Third, we identified important commonality between countries' AIV and the volatility spillover effect among the three groups. We showed that the common component in the AIV of the second group which includes mainly countries with debt problems, has a strong effect on the first group

of countries. Finally, we showed that there is an unexpected significant effect of a ECIV on countries' stock market volatilities which allows us to predict quite accurate values for each market using a VAR model.

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Figure 2: The PCIV























0.5

Figure 4 : Dynamic correlation distribution per country



Figure 5 : Clustering AIVs correlations





Figure 6: Predicting the Market Volatility per country









Sweden









3

Volatility

1

Switzerland



Annexe: The Interactions between the ECIV and each market's portfolio Volatility

				Aus	stria				
Vol_Ind~PC1+Vol_Ind						PC1~PC	1+Vol_Inc	1	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
PC1_ts.l1	0.169	0.019	8.983	0.000	PC1_ts.l1	-0.595	0.070	-8.495	0.000
Vol_ind_ts.l1	0.383	0.070	5.455	0.000	PC1_ts.l2	-0.212	0.093	-2.271	0.024
PC1_ts.l2	0.107	0.025	4.245	0.000	Vol_ind_ts.l2	-0.699	0.280	-2.494	0.013
PC1_ts.l3	0.100	0.026	3.787	0.000	PC1_ts.l3	0.193	0.099	1.957	0.052
Vol_ind_ts.l3	0.158	0.074	2.130	0.034	Vol_ind_ts.l4	0.475	0.278	1.707	0.089
PC1_ts.l4	0.052	0.027	1.913	0.057	PC1_ts.l7	-0.176	0.093	-1.893	0.060
Vol_ind_ts.l4	0.126	0.075	1.684	0.094	PC1_ts.l8	-0.275	0.080	-3.414	0.001
Vol_ind_ts.l6	0.237	0.076	3.137	0.002	Granger Causality				0.377
PC1_ts.l7	-0.045	0.025	-1.816	0.071					
Granger Causality				0.045					

				Belg	gium				
	Vol_Ind~F	PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	ł	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
PC1_ts.l1	0.245	0.026	9.260	0.000	PC1_ts.l1	-0.557	0.074	-7.543	0.000
Vol_ind_ts.l1	0.410	0.071	5.799	0.000	PC1_ts.l2	-0.239	0.097	-2.476	0.014
PC1_ts.l2	0.160	0.035	4.619	0.000	Vol_ind_ts.l2	-0.773	0.208	-3.706	0.000
PC1_ts.l3	0.122	0.037	3.298	0.001	PC1_ts.l3	0.231	0.103	2.232	0.027
Vol_ind_ts.l3	0.216	0.077	2.801	0.006	PC1_ts.l8	-0.173	0.096	-1.815	0.071
PC1_ts.l5	0.067	0.038	1.739	0.084	PC1_ts.l9	0.151	0.086	1.762	0.080
Vol_ind_ts.I7	0.133	0.080	1.664	0.098	Granger Causality				0.021
PC1_ts.l8	-0.058	0.034	-1.677	0.095					
Vol_ind_ts.l9	0.152	0.072	2.113	0.036					
Granger Causality				0.056					

				Finl	and				
	Vol_Ind~I	PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	ł	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.41	0.08	5.12	0.00	PC1_ts.l1	-0.49	0.08	-6.16	0.00
PC1_ts.l2	0.11	0.06	1.71	0.09	PC1_ts.l2	-0.25	0.09	-2.77	0.01
PC1_ts.l3	0.22	0.06	3.41	0.00	Vol_ind_ts.l2	0.26	0.13	2.03	0.04
Granger Causality				0.03	PC1_ts.l3	0.16	0.09	1.76	0.08
					Vol_ind_ts.l3	-0.48	0.13	-3.82	0.00
					PC1_ts.l4	-0.21	0.10	-2.16	0.03
					PC1_ts.l8	-0.16	0.08	-2.01	0.05
					Granger				0 10
					Causality				5.10

				Fra	nce				
	Vol_Ind~F	PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	I	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.444	0.082	5.417	0.000	PC1_ts.l1	-0.594	0.079	-7.478	0.000
PC1_ts.l2	0.085	0.047	1.792	0.075	PC1_ts.l2	-0.228	0.093	-2.437	0.016
PC1_ts.l3	0.126	0.049	2.545	0.012	PC1_ts.l3	0.235	0.097	2.422	0.016
PC1_ts.l6	-0.084	0.047	-1.780	0.077	Vol_ind_ts.l3	-0.614	0.168	-3.651	0.000
Vol_ind_ts.l6	0.216	0.090	2.396	0.018	Vol_ind_ts.l6	0.330	0.178	1.858	0.065
PC1_ts.l7	-0.124	0.043	-2.900	0.004	PC1_ts.l8	-0.245	0.066	-3.690	0.000
Granger Causality				0.023	Granger Causality				0.075

				Gerr	nany				
	Vol_Ind~I	PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	ł	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.365	0.086	4.251	0.000	PC1_ts.l1	-0.516	0.086	-6.030	0.000
PC1_ts.l2	0.080	0.031	2.570	0.011	PC1_ts.l2	-0.197	0.096	-2.055	0.041
PC1_ts.l3	0.133	0.033	4.050	0.000	PC1_ts.l3	0.315	0.101	3.113	0.002
PC1_ts.l4	0.062	0.034	1.814	0.071	Vol_ind_ts.l3	-1.073	0.277	-3.877	0.000
Vol_ind_ts.l5	0.166	0.092	1.803	0.073	Vol_ind_ts.l6	0.521	0.284	1.834	0.068
Vol_ind_ts.l6	0.265	0.092	2.886	0.004	PC1_ts.l8	-0.279	0.088	-3.167	0.002
PC1_ts.l7	-0.060	0.032	-1.902	0.059	Granger Causality				0.011
PC1_ts.l8	-0.060	0.028	-2.108	0.036					
Granger Causality				0.008					

				Gre	ece				
	Vol_Ind~I	PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	1	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.442	0.083	5.360	0.000	PC1_ts.l1	-0.611	0.080	-7.655	0.000
Vol_ind_ts.l4	0.196	0.087	2.268	0.024	PC1_ts.l2	-0.236	0.092	-2.555	0.011
Vol_ind_ts.l6	0.197	0.086	2.280	0.024	PC1_ts.l3	0.159	0.095	1.678	0.095
PC1_ts.l7	-0.156	0.092	-1.709	0.089	Vol_ind_ts.l3	-0.157	0.081	-1.937	0.054
Granger Causality				0.175	PC1_ts.l4	-0.166	0.095	-1.747	0.082
					PC1_ts.l8	-0.268	0.068	-3.933	0.000
					Granger Causality				0.621

				lta	aly				
	Vol_Ind~F	PC1+Vol_I	nd			PC1~PC	1+Vol_Ind	1	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.333	0.082	4.039	0.000	PC1_ts.l1	-0.625	0.080	-7.820	0.000
PC1_ts.l2	0.197	0.079	2.508	0.013	PC1_ts.l2	-0.241	0.097	-2.488	0.014
PC1_ts.l3	0.257	0.083	3.097	0.002	PC1_ts.l3	0.226	0.103	2.198	0.029
PC1_ts.l4	0.178	0.084	2.114	0.036	Vol_ind_ts.l3	-0.393	0.103	-3.823	0.000
Vol_ind_ts.l6	0.167	0.087	1.926	0.055	PC1_ts.l8	-0.239	0.066	-3.629	0.000
PC1_ts.l7	-0.173	0.067	-2.592	0.010	Granger Causality				0.043
Vol_ind_ts.l7	0.206	0.086	2.380	0.018					
Granger Causality				0.043					

				Lat	via				
	Vol_Ind~F	PC1+Vol_I	nd			PC1~PC	1+Vol_Ind	ł	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
PC1_ts.l1	0.089	0.020	4.385	0.000	PC1_ts.l1	-0.594	0.072	-8.192	0.000
Vol_ind_ts.l1	0.236	0.071	3.313	0.001	PC1_ts.l2	-0.181	0.086	-2.098	0.037
PC1_ts.l2	0.071	0.024	2.955	0.004	Vol_ind_ts.l3	-0.448	0.263	-1.705	0.090
Vol_ind_ts.l2	0.195	0.072	2.696	0.008	Vol_ind_ts.l4	0.441	0.266	1.659	0.099
PC1_ts.l3	0.046	0.025	1.855	0.065	PC1_ts.l7	-0.174	0.087	-1.998	0.047
PC1_ts.l8	0.045	0.024	1.854	0.065	PC1_ts.l9	0.222	0.083	2.674	0.008
Vol_ind_ts.l9	0.150	0.073	2.070	0.040	PC1_ts.l10	0.198	0.073	2.717	0.007
Vol_ind_ts.l10	0.178	0.071	2.519	0.013	Vol_ind_ts.l10	0.602	0.253	2.382	0.018
Granger Causality				0.005	Granger Causality				0.152

				Lithu	uania				
	Vol_Ind~F	PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	I	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
PC1_ts.l1	0.146	0.033	4.475	0.000	PC1_ts.l1	-0.621	0.073	-8.502	0.000
Vol_ind_ts.l1	0.407	0.072	5.681	0.000	PC1_ts.l2	-0.186	0.087	-2.150	0.033
PC1_ts.l2	0.080	0.039	2.062	0.041	Vol_ind_ts.l2	-0.363	0.173	-2.095	0.038
PC1_ts.l5	-0.065	0.039	-1.668	0.097	PC1_ts.l3	0.177	0.088	2.028	0.044
Vol_ind_ts.l8	0.194	0.078	2.497	0.013	PC1_ts.l7	-0.217	0.087	-2.500	0.013
Vol_ind_ts.l10	0.131	0.073	1.805	0.073	PC1_ts.l8	-0.152	0.087	-1.748	0.082
Granger Causality				0.000	PC1_ts.l9	0.227	0.085	2.673	0.008
					PC1_ts.l10	0.196	0.076	2.566	0.011
					Vol_ind_ts.l10	0.305	0.163	1.874	0.062
					Granger Causality				0.161

				Nethe	erlands				
	Vol_Ind~[PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	ł	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.420	0.084	5.008	0.000	PC1_ts.l1	-0.589	0.081	-7.224	0.000
PC1_ts.l2	0.139	0.069	2.027	0.044	PC1_ts.l2	-0.249	0.096	-2.598	0.010
PC1_ts.l3	0.199	0.072	2.754	0.006	PC1_ts.l3	0.192	0.101	1.907	0.058
Vol_ind_ts.l6	0.183	0.092	1.988	0.048	Vol_ind_ts.l3	-0.389	0.122	-3.182	0.002
PC1_ts.l7	-0.144	0.061	-2.361	0.019	PC1_ts.l4	-0.198	0.102	-1.945	0.053
Granger Causality				0.056	PC1_ts.l8	-0.243	0.067	-3.629	0.000
					Granger Causality				0.153

				Port	ugal				
	Vol_Ind~I	PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	1	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.346	0.083	4.152	0.000	PC1_ts.l1	-0.600	0.081	-7.402	0.000
Vol_ind_ts.l5	0.148	0.085	1.742	0.083	PC1_ts.l2	-0.264	0.097	-2.726	0.007
Vol_ind_ts.l6	0.183	0.085	2.153	0.033	Vol_ind_ts.l3	-0.414	0.194	-2.131	0.034
PC1_ts.l7	-0.104	0.039	-2.709	0.007	PC1_ts.l4	-0.180	0.099	-1.815	0.071
Granger Causality				0.046	PC1_ts.l7	-0.147	0.088	-1.670	0.097
					PC1_ts.l8	-0.263	0.070	-3.763	0.000
					Granger Causality				0.377

				Sp	ain				
	Vol_Ind~F	PC1+Vol_I	nd			PC1~PC	1+Vol_Ind	1	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.454	0.079	5.747	0.000	PC1_ts.l1	-0.560	0.080	-7.036	0.000
PC1_ts.l2	0.096	0.050	1.930	0.055	PC1_ts.l2	-0.227	0.092	-2.478	0.014
PC1_ts.l3	0.127	0.052	2.461	0.015	PC1_ts.l3	0.195	0.096	2.044	0.042
Vol_ind_ts.l4	0.210	0.085	2.468	0.014	Vol_ind_ts.l3	-0.552	0.154	-3.573	0.000
Vol_ind_ts.l6	0.193	0.086	2.237	0.026	PC1_ts.l4	-0.169	0.097	-1.734	0.085
PC1_ts.l7	-0.134	0.050	-2.703	0.007	PC1_ts.l8	-0.181	0.085	-2.117	0.036
Vol_ind_ts.l9	0.157	0.080	1.969	0.050	Granger Causality				0.180
Granger Causality				0.023					

				Swe	eden				
	Vol_Ind~F	PC1+Vol_I	nd			PC1~PC	1+Vol_Inc	1	
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value
Vol_ind_ts.l1	0.407	0.082	4.947	0.000	PC1_ts.l1	-0.600	0.080	-7.497	0.000
PC1_ts.l2	0.159	0.079	2.009	0.046	PC1_ts.l2	-0.236	0.095	-2.481	0.014
PC1_ts.l3	0.263	0.083	3.178	0.002	PC1_ts.l3	0.196	0.099	1.970	0.050
Vol_ind_ts.l4	0.156	0.088	1.772	0.078	Vol_ind_ts.l3	-0.345	0.102	-3.372	0.001
PC1_ts.l6	-0.145	0.079	-1.830	0.069	PC1_ts.l4	-0.199	0.101	-1.973	0.050
Vol_ind_ts.l6	0.167	0.089	1.875	0.062	PC1_ts.l8	-0.236	0.067	-3.504	0.001
PC1_ts.l7	-0.219	0.071	-3.081	0.002	Granger Causality				0.220
PC1_ts.l8	-0.093	0.056	-1.658	0.099					
Granger Causality				0.005					

Switzerland										
Vol_Ind~PC1+Vol_Ind					PC1~PC1+Vol_Ind					
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value	
PC1_ts.l1	0.060	0.035	1.724	0.086	PC1_ts.l1	-0.562	0.079	-7.073	0.000	
Vol_ind_ts.l1	0.335	0.081	4.140	0.000	PC1_ts.l2	-0.211	0.095	-2.220	0.028	
PC1_ts.l2	0.077	0.042	1.856	0.065	PC1_ts.l3	0.214	0.098	2.175	0.031	
PC1_ts.l3	0.161	0.043	3.723	0.000	Vol_ind_ts.l3	-0.484	0.189	-2.561	0.011	
PC1_ts.l5	0.074	0.045	1.656	0.099	PC1_ts.l7	-0.151	0.088	-1.713	0.088	
PC1_ts.l6	-0.077	0.042	-1.815	0.071	PC1_ts.l8	-0.248	0.068	-3.619	0.000	
Vol_ind_ts.l6	0.233	0.086	2.698	0.008	Granger Causality				0.533	
PC1_ts.l7	-0.140	0.039	-3.620	0.000						
PC1_ts.l8	-0.084	0.030	-2.787	0.006						
Granger Causality				0.000						

United Kingdom											
Vol_Ind~PC1+Vol_Ind					PC1~PC1+Vol_Ind						
	Estimate	Std Error	t.value	p.value		Estimate	Std Error	t.value	p.value		
Vol_ind_ts.l1	0.472	0.078	6.046	0.000	PC1_ts.l1	-0.555	0.078	-7.082	0.000		
PC1_ts.l2	0.143	0.046	3.107	0.002	PC1_ts.l2	-0.218	0.089	-2.432	0.016		
PC1_ts.l3	0.194	0.048	4.020	0.000	PC1_ts.l4	-0.273	0.096	-2.851	0.005		
PC1_ts.l9	0.075	0.044	1.714	0.088	PC1_ts.l8	-0.216	0.091	-2.374	0.019		
Vol_ind_ts.l10	0.129	0.077	1.680	0.095	PC1_ts.l9	0.183	0.085	2.151	0.033		
Granger Causality				0.001	Granger Causality				0.521		