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The Idiosyncratic Volatility in Euro Zone Firms: Evolution, Cross-Sectional Relation with Returns

Ahmed K.F. SOLIMAN[1,2] & Erwan LE SAOUT[1,2]

[1] University Paris 1 Panthéon-Sorbonne, France

[2] PRISM Sorbonne, France

Correspondence: Erwan LE SAOUT, 17 rue de la Sorbonne 75231 Paris Cedex 5, France.

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Abstract

This paper discusses the behaviour of the time series and the pricing of the idiosyncratic risk in 10 Eurozone economies from January 2000 to June 2018. We identify as well factors upon which depend the idiosyncratic risk premium. Our results show evidence of a common component within these countries' aggregate idiosyncratic volatilities. Using Fama and MacBeth cross-sectional regressions, we observe a positive relationship between the idiosyncratic volatility and expected stock returns denying the idiosyncratic risk puzzle found by Ang et al. (2006). By performing Pooled OLS and radomn effects models, the results indicate that under-diversification proxies have a significant impact on the idiosyncratic risk premium.

Keywords: idiosyncratic risk, idiosyncratic premium, stock volatility, under diversification

JEL classification codes: G11, G12, G32, O16

1. Introduction

"If risk and reward make a ratio…. The denominator, risk, is bigger than generally acknowledged; and so the outcome is bound to disappear point." With these words, Mandelbrot highlights the importance of studying the risk (Hudson and Mandelbrot, 2006). Financial theorists have always been interested in studying risk, its components and its determinants. Eventually, the modern portfolio theory (Markowitz, 1952; Sharpe, 1964; Lintner, 1965) explains that stock volatility is composed of two types of risks: first, the systematic risk, which is non-diversifiable and related to market volatility, and second, an idiosyncratic risk which is specific to the firm. Modern portfolio theory shows that the investor can decrease or eliminate idiosyncratic risk through diversification. By including different stocks covering different sectors, the investor reduces the portfolio's exposure to idiosyncratic risk without reducing the expected returns. However, some studies have shown that idiosyncratic volatility has been the main component of stock and portfolio return volatilities (Nam, Khaksari and Kang, 2016). Furthermore, there are many factors, such as transaction costs (Constantinides, 1986), information costs (Merton, 1987; Brockman, Guo, Vivero, and Yu, 2022), and investor characteristics (Barber and Odean, 2001; 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 price of idiosyncratic volatility. While the theoretical framework suggests the elimination of the firm-specific risk, recent empirical studies prove otherwise.

Therefore, studying idiosyncratic risk is important because most investors, especially private investors (Goetzmann and Kumar, 2008), are exposed to this risk. Movements of idiosyncratic volatility and its relationship with returns will affect their investment strategies. In addition, following the theory of efficient markets, many portfolio managers lose interest in the active management of their portfolios. As a result, we are witnessing a shift towards passive portfolio management techniques, especially indexing. However, idiosyncratic volatility is a risk that will be present and will continue to affect the market portfolio if not fully eliminated. First, we explore the aggregate idiosyncratic volatility and its behavior presented in a sample of 10 European countries in the Eurozone. Next, we examine the presence of a common factor in their aggregate idiosyncratic volatilities. Finally, we examine the relationship between idiosyncratic volatility and the cross-section of returns and the determinants of the idiosyncratic risk premium.

This paper is organized as follows. Section 2 discusses the state of the art of idiosyncratic risk. Section 3 presents the models and the methodology of the estimation of commonly used risk measures: market portfolio volatility, average stock volatility and idiosyncratic volatility. Section 4 presents the empirical analysis. Its first subsection focuses on the behaviour of global and idiosyncratic volatility proxies. The second subsection discusses the relationship between idiosyncratic risk and cross-section of returns and presents under diversification proxies as determinants of the idiosyncratic risk premium. Finally, we conclude.

2. Analysis of Idiosyncratic Risk

This section revisits the main findings related to idiosyncratic volatility. We review the main theoretical and empirical studies that are related to idiosyncratic risk. This section concludes with a subsection discussing the identified relationships between idiosyncratic volatility and expected stock returns.

2.1 Origins of the Idiosyncratic Risk

The modern portfolio theory (Markowitz, 1952; Sharpe, 1964; Lintner, 1965) differentiates between market risk (systematic) and firm-specific risk (idiosyncratic). According to the theory, systematic risk should be priced and considered when estimating the required return rate. The idiosyncratic risk is supposed to be eliminated through optimal diversification. By definition, idiosyncratic volatility (risk) is the difference between the stock return and systematic volatility. It is the part of the stock volatility which cannot be explained by the common risk factors. However, the concept of idiosyncratic volatility differs according to different theories and perspectives. For example, in a valuation theory context, the firm-specific risk is affected by firm characteristics (Malagon et al., 2015). In other words, the idiosyncratic risk follows the firm fundamentals. On the other hand, the costly arbitrage theory considers that the idiosyncratic volatility reflects only the investor’s preferences. In this case, idiosyncratic volatility is the stock-specific risk and is not related to the firm’s characteristics.

The study of idiosyncratic risk was triggered by four main findings. First, the the idiosyncratic volatility series of the American firms have demonstrated positive trend identified by Campbell, Lettau, Malkiel and Xu (2001). Second, investors are deterred from maintaining a well-diversified portfolio due to market characteristics (Constantinides, 1986; Merton, 1987; Brockman et al., 2022), and investor characteristics (Barber and Odean, 2001; Malkiel and Xu, 2004). Third, the idiosyncratic risk puzzle proposed by Ang, Hodrick, Xing, and Zhang (2006; 2009) is based on their observation of a negative relation between idiosyncratic risk and stock returns for the United States market and 23 other developed markets. Thereby, idiosyncratic risk is negatively priced. Last but not least, the existence of a common factor within idiosyncratic volatilities (Herskovic et al., 2016; Nam et al., 2016; Caglayan, Xue, and Zhang, 2020).

Based on these four findings, we can identify three axes around which idiosyncratic volatility studies revolve: the estimation of the idiosyncratic risk and the behaviour of its time series, the determinants of idiosyncratic risk and the relation between the idiosyncratic risk and the required return, especially, the verification and the explanation of the negative relation between idiosyncratic risk and stock return.

2.2 Idiosyncratic Risk Estimation and Time Series Behaviour

Initially, the 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 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; Cox, Ingersoll and Ross, 1985). Malkiel and Xu (2004) tried to relax the perfectly diversified portfolio hypothesis. Campbell et al. (2001) developed a method to calculate firm idiosyncratic volatility without estimating every firm’s beta. Many studies employ the three-factor and five-factor models developed by Fama and French (2016), 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 poor earner relatively to a low book-to-market ratio. In addition, small firms experience longer periods of poor earnings than big firms do. Thus, they propose that firm size and the book-to-market ratio represent the cross-section of average returns. In the latest version of their multifactorial model, their five-factor model includes operating profitability and investment.

Debate on the behaviour 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 marketfrom 1962 to1997. They also found 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 Malkiel and Xu (2004), Fu (2009) and Abdoh and Varela (2017) have observed positive trends in the United States market. Fu (2009) shows that the idiosyncratic risk does not follow a random walk instead it is persistent. Herskovic et al. (2016) confirm the existence of a positive trend in the idiosyncratic volatility of American companies. They also provide proof of the existence of a substantial common factor among the idiosyncratic volatility across different industries. They argue that the common factor in idiosyncratic volatility is priced[1]. While Herskovic and colleagues link common idiosyncratic volatility[2] to the income risk faced by households.

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

Nam et al. (2016) explain aggregate idiosyncratic volatility (AIV) time series behavior as a change in the price interaction among stocks. Caglayan et al. (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 volatility[3].

Several studies have tried to find an explanation for the positive trend. Xu and Malkiel (2003) explain it as due to an increase in institutional ownership. Although Kitagawa and Okuda (2016) do not discuss the trend in idiosyncratic volatility, they find a similar positive relation between idiosyncratic volatility and foreign institutional ownership in the case of Japan. Abdoh and Varela (2017) suggest that increased product market competition is behind the increase in idiosyncratic volatility, while Fink, Fink, Grullon, and Weston (2010) observe a relation with the new listings. In a study of the Chinese stock market, Nartea, Wu, and Liu (2013) identify episodic behavior characterized by an autoregressive process of regime switches coinciding with reforms but they 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 period from 1962 to 1997. They point out to the increase of idiosyncratic volatility during attention-grabbing events and retail investor trading behaviors, such as splitting, which is associated with an increase 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 also suggested that the price interaction, which increases with the increase in the number of listed firms, has a positive relationship with idiosyncratic volatility.

2.3 The Relation between Idiosyncratic Risk and Returns

Due to its consequences for the portfolio investment strategy, the relation between idiosyncratic risk and stock returns has been strongly debated. According to financial theory, the higher the risk, the higher the return. However, there is no consensus on the direction of this relationship. Fama and MacBeth (1973) and Wei and Zhang (2005) reject the idea of a relationship between idiosyncratic risk and return. Similarly, Han and Lesmond (2011) find no association between idiosyncratic volatility and the expected return.[4] In a study of the MILA (Mercado Integrado Latino-Americano) markets, Berggrun, Lizarzaburu, and Cardona (2016) show that the relation between idiosyncratic volatility and returns is non-existent.

However, Ang et al.'s (2006) seminal paper provides evidence of a negative relation between idiosyncratic risk and stock returns in the case of the US stock market. This result is counter-intuitive and goes against the financial theory. Using the Fama and French three-factor model, Ang et al. (2006) estimated lagged idiosyncratic volatility to proxy for idiosyncratic risk. Fu (2009) critiqued their work, arguing that the negative relation was due to the idiosyncratic volatility series properties. He stated that the positive abnormal returns in months of high idiosyncratic volatility lead to negative abnormal returns in the case of small firms in the subsequent months. Thus, he showed that Ang et al.'s (2006) findings are driven by a subset of small firms. He proposed another method to estimate idiosyncratic risk, which is the expected idiosyncratic volatility, using the firm-specific conditional volatilities derived from the EGARCH (Exponential Generalized Autoregressive Conditional Heteroscedastic) model. Using his method, he finds a positive relation between idiosyncratic risk and firm returns. Brockman et al. (2022) replicated Fu's study for 57 countries over 21 years. He observed a significant positive relation as well. Several others confirm this positive relationship between idiosyncratic volatility and returns (Merton, 1987; Malkiel and Xu, 2004). Bali and Cakici (2010) find evidence of this positive relationship on the country specific idiosyncratic risk and the expected returns of the stock market. In the case of emerging markets, Nartea, Ward, and Yao (2011) report a positive relation between idiosyncratic volatility and cross-sectional returns for Indonesia, Malaysia, Singapore, and Thailand. Malagon, Moreno, and Rodriguez (2018) observe a positive relation between idiosyncratic risk and returns only during the period of recession.

Ang et al. (2006) responded by extending their sample to include 22 developed markets in addition to the US stock markets. They found the same relation between idiosyncratic risk and expected returns. Afterward, several other studies observed a negative relation (Stambaugh et al., 2015). For example, in the case of China, an emerging market, Nartea et al.

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[2] We call it aggregate idiosyncratic volatility.

[3] 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 idiosyncratic volatility.

[4] Han and Lesmond (2011) argue that there is a liquidity bias inducing the lagged idiosyncratic volatility estimated using daily data.

(2013) document a negative relation. Other studies that use Ang et al.'s (2006) methodology also find a negative relation for other markets. This has resulted in a focus on this idiosyncratic volatility puzzle and attempts to explain it. Stambaugh, Yu, and Yuan (2015) point to a conditional relation with mispricing. They suggest that the idiosyncratic risk-return relation is negative for overpriced stocks but positive for underpriced stocks. Since the negative relationship of the overpriced stocks is stronger than the relationship of underpriced stocks, the overall observed relationship for all firms listed in the market is negative.

3. Methodology and Variables Definitions

In this section, we describe the methods used to estimate each risk measure considered in this paper. First, we compute the market portfolio volatility and the average stock volatility to proxy for global market risk. We estimate idiosyncratic volatility using an EGARCH model in which the mean equation includes Fama and French's (2016) five-factor model and the momentum factor.

3.1 Estimation of Risk Measures

In this subsection, 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 an EGARCH model in which the mean equation includes Fama and French's (2016) five-factor model and the momentum factor.

3.1.1 Global Risk Measures

We compute the market portfolio volatility and average stock volatility as measures of the global stock market risk to assess their co-movement with idiosyncratic volatility. We estimate 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 for each month, based on the firms publicly traded on the stock market. We consider the 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.

We also find it useful to estimate the average stock volatility. We estimate the volatility of each stock as the square root of the average stock variance multiplied by the square root of the number of trading days in the month. Then, we consider the cross-sectional average over all listed companies.

3.1.2 Idiosyncratic Risk Measure

To examine the relation between the expected idiosyncratic volatility and the expected stock returns, we need to take into account the time-varying nature of the idiosyncratic volatility. We use Fu's[5] (2009) method and employ the EGARCH (p,q) model to estimate idiosyncratic volatility, which we call "conditional idiosyncratic volatility".

The ARCH (Autoregressive Conditional heteroskedasticity) model and its generalized models are recognized tools to model return volatility. The ARCH models were initially developed by Engle (1982) and became important in the field of financial economics because they provide a systematic framework to model volatility. Their main advantage is that they allowed joined modeling of variance and expected returns. The EGARCH model, proposed by Nelson (1991), has the same basic properties as the ARCH and GARCH (Bollersev, 1986, 1997) models in terms of clustering and fat tails. Thus, EGARCH (p,q) takes into account the leverage effect observed in the return volatility series. The EGARCH model that we use to estimate the expected idiosyncratic volatility is written as follows:

$$R_{it} - r_t = \alpha_{it} + \beta_{mi}(R_{mt} - r_t) + \beta_{SMBi}SMB_t + \beta_{HMLi}\,HML_t + \beta_{RMWi}\,MOM_t + \beta_{RMWi}\,RMW_t$$
$$+ \beta_{CMAi}\,CMA_t + \varepsilon_{it}$$
$$where\ \varepsilon_{it} \sim N(0, \sigma_{it-1}^2)$$

$$ln\sigma_{it}^2 = \alpha_i + \sum_{i=1}^{p} b_{it}\ ln\sigma_{it-1}^2 + \sum_{k=1}^{q} C_{ik}\left\{\theta\left(\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right) + \gamma\left[\left|\frac{\varepsilon_{it-k}}{\sigma_{it-k}}\right| - \sqrt{2/\pi}\right]\right\} \tag{1}$$

where R_{it} is the return on the stock *i* during the month t ; $r_t$is the risk free rate; $\alpha_{it}$is the intercept; $\beta_{mi}$is the market coefficient; R_{mt} is the value weighted European market return; β_{SMBi} is the size factor coefficient ; SMB_t is the portfolio return small minus big ; $\beta_{HMLi}$is the book-to-market coefficient; HML_t is the difference between the portfolio

[5] We follow Khaled Farouk Soliman (2021) who finds that it is more robust to follow Fu's (2009) estimation of the idiosyncratic risk using an EGARCH model than to follow Ang et al. (2006) methodology.

return, including the high book-to-market ratio firms and the low book-to-market ratio portfolio returns; MOM_t is the average return from high momentum portfolios minus the average return of low momentum portfolios; RMW_t is the average return on robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios; CMA_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. The model residual, ε_{it}, follows a normal distribution with zero mean and σ_{it}^2 variance. The variance depends on past residual variances for the (p) period and the return shocks for the (q) period, as shown in the formula. We tested several EGARCH (p,q) specifications on different stocks chosen randomly from our sample. The best specification is often based on the Akaike Information Criterion (AIC). In accordance with Brockman et al. (2022), no EGARCH setting has the needed AIC to dominate the others. Therefore, we follow Brockman et al. (2022) and use the EGARCH model (3, 1). The conditional 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.

In our study, we are interested in examining the possible existence of a certain common factor across firms' idiosyncratic volatilities. We show later that the market average of the idiosyncratic volatility moves synchronously with the all-share market index portfolio volatility. We run a one-factor regression to test for the existence of substantial common volatility in the idiosyncratic volatility. We regress each stock's conditional idiosyncratic volatility time series on the conditional idiosyncratic volatilities mean, estimated as the cross-sectional average of the idiosyncratic volatilities of all shares traded in the market.

$$IVol_{vit} = \alpha_i + \beta_{i\omega} AIV_{\omega t} + \varepsilon_{i\omega t} \quad (2)$$

IVol is the firm *i* conditional idiosyncratic volatility in the country *ω* during the month *t*; *AIV* is the average idiosyncratic volatility corresponding to each country in the sample. Afterwards we collect the regression coefficients and conduct a t-test. Finally, we report the coefficient values and the corresponding p-values from the t-test in table 5.

3.1.3 Control Variables

As for control variables, since there are certain deterrents to holding a fully diversified portfolio (Malkiel and Xu, 2004), and idiosyncratic volatility persists in the case of funds (Vidal-Gracia and Vidal, 2014), it is important to study the relation between idiosyncratic volatility and expected returns. Firm size is measured by total stock value. In the Bloomberg database, this is the variable current market cap. For each month, we average the daily market capitalization. The book-to-market ratio is the inverse of the market-to-book ratio (price-to-book ratio in Bloomberg). To control liquidity, we use stock turnover and the coefficient of variation of stock turnover. The monthly turnover, TURN, is the number of stocks traded divided by the number of shares outstanding. The other measure for liquidity is the coefficient of the variation in turnover in the previous 10 months. We introduce a measure for past returns to control for the momentum effect. Past returns (PR) (-2,-7), are the compounded past returns for each stock from month t-2 to month t-7 where t is the current month. We exclude the month t-1 returns to avoid a bid-ask bounce for the most frequently traded.

3.2 Cross-sectional Regressions

We present the cross-sectional regressions that we mobilize to test the existence of the idiosyncratic risk premium and identify the determinants of the idiosyncratic risk premium.

3.2.1 Pricing of the Idiosyncratic Risk

The cross-section regressions are the main tool we use to determine the sign and the magnitude of the relation between idiosyncratic risk and expected returns. To control autocorrelation, we perform cross-section regression, following the Fama-MacBeth approach. We regress the monthly excess returns on the five variables discussed in Section 3.1.3: firm size, book-to-market ratio, stock turnover, coefficient of variation in share turnover, and past returns. We include proxies for idiosyncratic volatility. We start by adding conditional idiosyncratic volatility derived from the EGARCH (3,1) model. Eventually, we test the idiosyncratic volatility coefficient to check whether the idiosyncratic risk is negatively or positively related to the expected return.

Multiple idiosyncratic risk studies adopt the portfolio approach to study the relationship between idiosyncratic risk and expected returns (Ang et al., 2006, 2009; Stambaugh et al., 2015; Malagon et al., 2018). These works observe a variation in the returns in addition to a variation in the idiosyncratic volatility. The problem with this type of approach is the following. It assumes that the idiosyncratic risk is totally wiped out by diversification. Consequently, the estimated idiosyncratic volatility will be less than the average of the stock idiosyncratic volatilities. Fu (2009) criticized portfolio-based studies for this reason. We use Fu's approach and estimate cross-section regressions where monthly expected returns are regressed on the idiosyncratic risk. Next, we average the coefficient estimates from these monthly regressions and we construct *t*-test statistics following Fama and MacBeth (1973). The monthly cross-section regressions are run as follows:

$$R_{i\omega t} = \gamma_{0\omega t} + \sum_{k=1}^{K} \gamma_{k\omega t} X_{ki\omega t} + \eta_{i\omega t} \; i = 1,2,\dots N, \omega = 1,2,\dots M, t = 1,2,\dots T \tag{3}$$

where $R_{i\omega t}$ is the return from stock i in country ω during the month; $\gamma_{k\omega t}$ are the coefficients of the explanatory variables; $X_{ki\omega t}$are the explanatory variables for the cross-section expected returns: Beta, firm value, book-to-market ratio, past returns, stock turnover, coefficient of variation of stock turnover; plus the addition of conditional idiosyncratic volatility. $\eta_{i\omega t}$ is the regression residual ; N is the total number of stocks; M is the total number of countries in the sample ; T is the maximum number of months that defer from stock to stock. We control the potential bias because of cross-sectional correlations among residuals. Fama and MacBeth (1973) test for statistical significance by averaging the coefficient estimates ($\gamma_{k\omega t}$) from the monthly regressions.

3.2.2 Underdiversification Effect on the Idiosyncratic Risk Premium

We need to test for factors affecting the idiosyncratic volatility premium. The hypothesis we test in this subsection is as follows. Factors reflecting the level of diversification in the market substantially influence the idiosyncratic volatility premium. The factors are grouped into two categories: information costs and investor characteristics.

We use panel data analysis to test the relation between under-diversification proxies and the idiosyncratic risk premium. We estimate the following panel data regression:

$$IdioPr_{\omega\tau} = \alpha + \beta_{SMB} SMB_{\tau} + \beta_{HML} HML_{\tau} + \beta_{MOM} MOM_{\tau} + \beta_{AIV} AIV_{\omega,\tau} + \beta_{AFE} AFE_{\omega,\tau} + \beta_{Inst\_Own} Inst\_own_{\omega,\tau} + \beta_{TURN} TURN_{\omega,\tau} + \beta_{FDI} FDI_{\omega,\tau} + \beta_{GDPk} GDPk_{\omega,\tau} + \varepsilon_{\omega,t} \tag{4}$$

Where α is the intercept; SMB, $HML$and MOM are those used in equation 1; $AIV$is the aggregate idiosyncratic volatility of country ω; AFE is earnings absolute forecast error; $Inst\_Own$ is the variation of the portion of capital held by institutional investors; $TURN$ is computed as the cross-sectional average of the stock turnover for all the firms listed on the market ; FDI is the amount of foreign direct investment; $GDPk$ is the GDP per capita represents the wealth of the investors in the market.

We add institutional ownership to proxy for investor characteristics. Institutional investors have more financial richness and more financial knowledge than individual investors. This variable represents the rate of change in the proportion of shares outstanding in an institutional investor's total market. It is calculated as the value of the outstanding shares held by institutional investors, divided by the sum of the market capitalization of all the listed firms in the stock market. The turnover variable proxies for investor tolerance. It is computed as the cross-sectional average of the stock turnover for all the firms listed on the market.

An increase in this variable denotes more risk-tolerant investors. GDP per capita represents the wealth of the investors in the market. Foreign direct investment proxy is for the presence of foreign investors in the market. For the information costs category, we compute earnings' absolute forecast error, following Veldkamp and Van Niewerburgh (2008), who propose it as a proxy for access to market information. It is the absolute value of the ratio of the difference between realized earnings and forecasted earnings to the values of forecasted earnings. If there is more publicly available information, this allows more precise estimates of firm earnings.

SMB, HML and MOM are used as control variables. Additionally, we include average idiosyncratic volatility as a control variable because of the presence of commonality in the market idiosyncratic volatility, which could have a substantial effect on the idiosyncratic volatility premium.

Table 1. Summary statistics

Country	Returns (SD) in % Individual firms	Firms Number	Cap
Austria	1.06 (12.3)	83	135 717
Belgium	1.12 (16.96)	347	394 408
Finland	0.79 (10.55)	151	142 961
France	1.56 (8.72)	1 188	2 086 940
Germany	1.3 (8.07)	611	2 038 038
Greece	1.49 (13.3)	189	45590
Italy	0.4 (8.43)	521	529110
Netherlands	1.08 (14.13)	147	991086
Portugal	1.85 (8.46)	59	68099
Spain	1.39 (7.58)	257	800754

Note: Table 1 shows summary statistics for the firms we are including in our sample. We report the number of firms per country, as well as the cross-sectional average and standard deviation of firms returns per country. All values of returns are in percentage. The last column (Cap) presents the market capitalization for each stock exchange in December 2018. Market capitalization values are in millions of euros.

4. Empirical Analysis

We dedicate this section to discuss all results. It contains three subsections. First, we present our sample and data used in our empirical tests. The second subsection focuses on time series behaviour of our risk proxies. We also highlight the presence of the common component of the idiosyncratic volatility and its relationship with national stock exchanges portfolio volatility. In the last subsection, we discuss the pricing of the idiosyncratic risk before identifying its determinants of its premium.

4.1 Data

We extract data from the Bloomberg market database from January 1st 2000 to June 31st 2018. We collect daily stock prices, return indexes, market values, the 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 3553 firms listed on 10 European stock markets: Austria, Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, and Spain. These countries account for over 90% of the gross domestic product of the Euro area.

Table 1 reports the average monthly firm and market portfolio returns. These firm returns are used to calculate the excess returns. The last column of table 1 shows considerable variation among countries in terms of market capitalization. In December 2018, the biggest stock market in Europe was Euronext Paris, with 2.087 trillion euros of market capitalization and the smallest market was the Athens Stock Exchange, with a market capitalization of 45 billion euros.

We present summary statistics of control variables in table 2. We next estimate correlations among the control variables, and between them and the conditional idiosyncratic volatility, for each country. The correlations matrix is provided in Appendix A. The cross-sectional correlations between the idiosyncratic volatility measures and the control variables are very weak for all countries. Correlations between conditional idiosyncratic volatility and expected returns are positive for the sample. This is consistent with Fu (2009) findings. However, the correlations between the idiosyncratic volatility measures and turnover are relatively high to other correlations. We would like to highlight that the correlation between the conditional idiosyncratic volatility and the market capitalization is always negative.

Table 2. Control variables summary statistics

Country	Log TURN MEAN (SD)	Log CVTURN MEAN (SD)	Log B/M MEAN (SD)	SIZE MEAN (SD)	PR[-2,-7] MEAN (SD)
Austria	5.705	0.689	-4.892	5.494	0.003
	(0.979)	(0.417)	(1.138)	(0.574)	(0.028)
Belgium	6.044	0.784	-0.274	5.119	0.001
	(0.754)	(0.39)	(0.458)	(0.607)	(0.031)
Finland	6.795	0.591	-0.546	5.182	0.001
	(0.927)	(0.431)	(0.521)	(0.612)	(0.041)
France	6.012	0.638	-0.439	4.803	0.001
	(0.997)	(0.407)	(0.516)	(0.67)	(0.039)
Germany	5.733	0.734	-0.416	4.583	-0.001
	(1.051)	(0.386)	(0.608)	(0.772)	(0.036)
Greece	6.067	0.375	-0.122	3.678	-0.001
	(1.591)	(0.433)	(0.722)	(0.994)	(0.069)
Italy	7.373	0.643	-0.345	5.767	-0.003
	(0.97)	(0.391)	(0.64)	(0.619)	(0.044)
Netherlands	6.965	0.819	-0.661	5.952	0.001
	(0.847)	(0.393)	(0.531)	(0.648)	(0.041)
Portugal	5.939	0.476	-0.213	4.454	-0.001
	(1.183)	(0.426)	(0.67)	(0.669)	(0.034)
Spain	7.231	0.669	-0.473	6.066	0
	(0.986)	(0.423)	(0.587)	(0.619)	(0.035)

Note: Our sample covers 3553 firms listed on 10 European stock exchange. The firm size is measured by total stock value. In the Bloomberg database, this is the variable current market cap. For each month, we calculate the natural logarithm of the average daily market capitalization. The book-to-market ratio is the natural logarithm of the inverse of the market-to-book ratio (price-to-book ratio in Bloomberg). The monthly turnover, TURN, is the number of stocks traded, divided by the number of shares outstanding. Then, we calculate its natural logarithm. Log CVTURN is the coefficient of variation in turnover in the previous 10 months. Past returns (PR) (-2,-7), are the compounded past returns for each stock from month t-2 to month t-7 where t is the current month. We exclude the month t-1 returns to avoid a bid-ask bounce for the most frequently traded.

4.2 Behavior of Different Risk Measures

First, we present the market portfolio volatility and average stock volatility results. Panel A of table 3 reports the summary statistics of the market portfolio volatility. While Greece has the highest portfolio volatility with an average standard deviation of 4.4% over the period of the study. Germany has the lowest portfolio volatility with an average standard deviation of 1.1% over the period of the study. Regarding the average stock volatility, Greece is ranked the highest, and Austria is ranked the lowest over the period of study.

In line with the Modern Portfolio Theory (Markowitz, 1952; Sharpe, 1964; Lintner, 1965), market portfolio volatility is less than the average stock volatility and the idiosyncratic volatility in each country. Graphs in figure 1 show that movements of volatility measures are synchronized and countercyclical, especially during recessions and crises. This suggests the existence of a common component that drives the idiosyncratic volatility and it is moving in harmony with market portfolio volatility. In addition, and in line with CLMX (2001), aggregate idiosyncratic volatility is the main component of average stock volatility. This suggests that idiosyncratic volatility is the main driver of stock volatility and could have an impact on the market portfolio volatility.

In panel C of table 3, we report summary statistics for the conditional idiosyncratic volatility (CIV). First, we compute statistics for every firm series and then we average them at the country level to obtain the mean for each country. Globaly, country rankings in terms of market portfolio volatility are close to their rankings in terms of idiosyncratic volatility. On average, over the whole period, while Greece exhibits the highest idiosyncratic volatility (10.88%), Austria is characterized by low values of idiosyncratic volatility (4.56%). AIV, estimated on the basis of CIV, are higher than the market portfolio volatility values for all countries, which demonstrates the benefits derived from diversification.

Table 3. Risk measures summary statistics

	Panel A: Market Portfolio Volatility			Panel B: Average Stock Volatility			Panel C: CIV		
Country	**Mean%**	**SD%**	**Median%**	**Mean%**	**SD%**	**Median%**	**Mean%**	**SD%**	**Median%**
Austria	1.6	0.6	1.4	4.8	0.7	4.7	4.56	0.62	4.49
Belgium	1.5	0.7	1.3	5.6	0.8	5.5	5.31	0.72	5.19
Finland	2.6	1.1	2.3	7.8	1.1	7.6	7.28	0.92	7.17
France	1.7	0.8	1.5	6.5	0.9	6.3	6.2	3.12	6.22
Germany	1.1	0.6	1	6.1	1.9	6.2	8.53	1.07	8.42
Greece	4.4	2.3	3.9	11.2	1.6	11.1	10.88	1.7	10.85
Italy	3.3	1.3	3	7.5	1.3	7.4	6.89	0.98	6.83
Netherlands	2.7	1.2	2.4	7.4	1.3	7.1	6.73	1.04	6.53
Portugal	2.1	0.8	2	6	0.9	6.1	5.72	0.73	5.78
Spain	2.5	1	2.4	5.9	1	5.9	5.44	0.72	5.4

Note: This table shows summary statistics for 10 European countries. We report the cross-sectional mean, standard deviation, and median (in percentage) for the market portfolio volatility (Panel A), the average stock volatility (Panel B), and the conditional idiosyncratic volatility (Panel C). The average stock volatility is the square root of the arithmetic mean of the stock variance defined in section 3.1.1. multiplied by the square root of the number of trading days in the month. To compute for monthly conditional idiosyncratic volatility, we multiply the standard deviation of idiosyncratic returns, estimated using an EGARCH model, over the month multiplied by the number of trading days in a month. The risk-free rate used to compute excess returns is the US one-month T-bill rate.

Figure 1 depicts the CIV behavior. We add market portfolio volatility and average stock volatility to the idiosyncratic volatility measures in the graphs. We observe four peaks that occur for all the volatility measures we use. The first occurs in the early 2000s and refers to the dot com bubble period and the telecoms crash. Additonally, in 2001, European countries suffered inflation because of imbalances following the introduction of the Euro in 1999. The second peak corresponds to the emergence of the global financial crisis in October 2008, which pushed the developed economies into recession. The third peak refers to the August 2010 sovereign debt crisis. Following this, nearly all countries in the sample experienced volatility increases. The fourth peak occurred in 2016 following the United Kingdom referendum resulting in its withdrawal from the European Union.

By inspecting graphs of figure 1, three stylized facts drew our attention because of their generality as they are found across all countries. First, idiosyncratic volatility accounts for around 90% of stock total volatility. Second, a substantial co-movement exists between each market's AIV and their market portfolio volatility. This points to the importance of re-assessing the correlation between AIV and market portfolio volatility in order to understand how idiosyncratic volatility impacts market portfolio volatility at the national level. Third, the existence of a synchronous movement of average cross-sectional idiosyncratic volatility across European countries.

4.3 Common Idiosyncratic Risk

We estimate correlations between all countries' common idiosyncratic volatility. We report these correlations in table 4. These correlations show that common idiosyncratic volatilities across countries are highly correlated. We observe very high correlations for Germany, Belgium, Finland, France and the Netherlands, ranging from 0.69 to 0.92. Note also that Italy, Portugal and Spain show fairly high correlations. These high correlations indicate the presence of a common Euro zone factor affecting countries' aggregate idiosyncratic risk.

We next regress the conditional volatility series for each firm on the stock market level average of the conditional idiosyncratic volatility (AIV). Table 5 presents the average common idiosyncratic volatility coefficients of the intercepts for each country. The intercept is not statistically significant and, if it becomes statistically significant, as in the case of Greece, its magnitude is small. In this case, Austria has the highest coefficient of average conditional idiosyncratic volatility and Greece has the lowest AIV coefficient. Our results show that the average idiosyncratic volatility could potentially be used to proxy for common idiosyncratic volatility. If we estimate the correlation between average idiosyncratic volatility conditional and market portfolio volatility, we find high correlation coefficients up to 0.8.[6]

[6] We believe that the common idiosyncratic volatility does not stem from the common systematic component because the cross-sectional correlations between the residuals are very low (not exceeding 0.2).

Table 4. Correlations between countries' common Idiosyncratic volatility

Country	Germany	Austria	Belgium	Denmark	Spain	Finland	France	Greece	Italy	Netherlands	Portugal
Germany	1										
Austria	0.274	1									
Belgium	0.894	0.416	1								
Denmark	0.46	0.689	0.564	1							
Spain	0.497	0.587	0.647	0.67	1						
Finland	0.807	0.439	0.844	0.612	0.68	1					
France	0.88	0.206	0.873	0.27	0.424	0.755	1				
Greece	0.519	0.249	0.485	0.521	0.402	0.433	0.361	1			
Italy	0.452	0.394	0.568	0.642	0.734	0.637	0.368	0.336	1		
Netherlands	0.909	0.294	0.918	0.488	0.564	0.866	0.883	0.462	0.579	1	
Portugal	0.344	0.314	0.459	0.471	0.637	0.54	0.305	0.274	0.738	0.458	1

This table reports the cross-sectional correlations between the common idiosyncratic volatility of the 10 Eurozone countries. First, we estimate the cross-section average of firms' idiosyncratic volatilities over a period of a month. Then, we use these values to construct the time series of the common idiosyncratic volatility for each country. Finally, we estimate Pearson coefficient of correlation between countries' common idiosyncratic volatility.

Table 5. Common idiosyncratic volatility regression results

Country	alpha	AIV
Austria	0	1.0503***
Belgium	0	0.9959***
Finland	-0,0018	1.0229***
France	0,0012	0.9942***
Germany	0	1***
Greece	0.0126***	0.906***
Italy	0,0007	0.9913***
Netherlands	-0,0019	1.0236***
Portugal	0,00041	1,15667
Spain	-0,0004	0.9794***

Table 5 presents results of the equation 2. AIV is the coefficient of the common idiosyncratic volatility. It shows the significance of the impact of the variation of the common idiosyncratic volatility on the firm's idiosyncratic volatility. AIV coefficients and alphas reported are the average of those obtained when the regression is performed for each firm.

4.4 Pricing of the Idiosyncratic Risk

We perform this regression at a country level. We test the relation between idiosyncratic risk and expected returns at the level of all fifteen European countries. Table 6 reports the cross-section regression results for conditional idiosyncratic volatility. It shows that almost all coefficients of conditional idiosyncratic volatility are positive. Consistently with Fu's (2009) and Brockman et al. (2022) findings, 8 out of10 countries have the expected positive result and statistically significant idiosyncratic volatility coefficients at 1% level. The highest coefficient is 3.98 (Greece) and the lowest coefficient is 0.173 (Austria).

At the sample level, the slope of the average conditional idiosyncratic volatility coefficient is 0.48 and the expected idiosyncratic volatility standard deviation is 1.04%. Thus, an increase of 1 standard deviation in a stock lead to a monthly increase in the expected returns of 0.48*1.04%=0.51%.[7] These results are in accordance with Fu (2009) and Brockman et al. (2022). Furthermore, the highly statistically positive relation between past and expected returns is evidence of a strong momentum effect in European stock markets.

4.5 Underdiversification Proxies as Determinants of the Idiosyncratic Risk Premium

Since we have evidence showing that idiosyncratic volatility is priced, we investigate the idiosyncratic risk premium. We adopt a trading strategy involving going long on the portfolio that includes stocks with the highest idiosyncratic volatility and going short on the portfolio with low idiosyncratic volatility.

[7] If we exclude Greece, the increase in the expected returns following an increase of 1 standard deviation is 0.267 * 1% = 0.27%.

For each country, we construct 10 portfolios, sorted according to their idiosyncratic volatility measure. Portfolios are rebalanced at the beginning of each month. Table 7 presents portfolio returns and returns from going long on the 10th and short on the 1st portfolios. For each country, we observe increased returns associated with an increase in the level of idiosyncratic volatility. In addition, the returns in column "10-1", are positive and statistically significant for all the countries in the sample. We would highlight that countries with a strong relationship between firm idiosyncratic volatility and cross-section average idiosyncratic volatility tend to show a lower idiosyncratic volatility premium.

Table 6. Fama and MacBeth cross-sectional regressions for Conditional Idiosyncratic Volatility

Country	*Log TURN*	*Log CVTURN*	*PR(-2,-7)*	*Log B/M*	*Log Size*	*CIV*
Austria	0,02	-0,32	0.369***	0,09	-0,09	0.173***
Belgium	0.36***	-0.52***	0.374***	0,15	-0.24***	0.23***
Finland	0.35***	-0,13	0.33***	-0,12	-0.2***	0.23***
France	0,40	-0,40	0.41***	-0,151	-0.38***	0,212***
Germany	0,35	-0,064	0.51***	-0,74	-0,0134	0.9***
Greece	0.19*	-0.39*	0.4***	0.24*	-0,10	3.99***
Italy	0.74***	-0.34**	0.34***	-0,11	-0.27***	0.615***
Netherlands	0,05	-0,12	0.32***	0,03	-0,07	0,141
Portugal	0.59***	-0,27	0.39***	0,34	-0,36	0,077
Spain	0.36***	-0.7***	0.34***	-0,19	-0.15***	0.39***

In this table, we report Fama and MacBeth cross-sectional regressions' results per country. Our sample covers 5335 firms listed on 10 European stock exchange. The conditional idiosyncratic volatility is the monthly standard deviation of residuals of an EGARCH (3,1) model. Common risk factors are added to the mean equation. We regress daily excess returns on European Fama and French five risk factors and the momentum factor. The firm size is measured by total stock value. In the Bloomberg database, this is the variable current market cap. For each month, we calculate the natural logarithm of the average of the daily market capitalization. The book-to-market ratio is the natural logarithm of the inverse of the market-to-book ratio (price-to-book ratio in Bloomberg). The monthly turnover, TURN, is the number of stocks traded, divided by the number of shares outstanding. Then, we calculate its natural logarithm. Log CVTURN is the coefficient of variation in turnover in the previous 10 months. Past returns (PR) (-2,-7), are the compounded past returns for each stock from month t-2 to month t-7 where t is the current month. We exclude the month t-1 returns to avoid a bid-ask bounce for the most frequently traded.

Table 7. The idiosyncratic risk premium

Country	1	2	3	4	5	6	7	8	9	10	10(-)1
Austria	0,06%	0,04%	0,10%	0,31%	0,22%	0,69%	0,86%	0,96%	0,61%	0,89%	0.815%***
Belgium	0,24%	0,84%	0,69%	0,92%	0,84%	0,56%	0,64%	0,66%	0,75%	1,41%	1.172%***
Finland	0,14%	0,35%	0,42%	0,75%	0,64%	0,24%	0,45%	0,81%	0,59%	0,75%	0.622%***
France	0,01%	-0,18%	0,26%	0,96%	0,93%	0,74%	0,98%	1,32%	1,06%	1,27%	1.200%***
Germany	0,13%	0,32%	0,48%	0,44%	0,84%	0,60%	0,82%	1,05%	0,75%	3,35%	3.198%***
Greece	-0,34%	-0,60%	-1,00%	-1,08%	-0,75%	-0,81%	0,03%	-0,06%	-0,52%	0,78%	1.087%***
Italy	-0,51%	-0,52%	-0,71%	-0,49%	-0,52%	-0,27%	-0,23%	-0,49%	-0,37%	0,57%	1.105%***
Netherlands	0,11%	0,62%	0,56%	0,72%	0,84%	0,59%	0,76%	0,57%	0,74%	0,75%	0.561%***
Portugal	0,04%	-0,10%	-0,26%	0,23%	0,28%	0,06%	0,28%	0,48%	0,65%	0,65%	0.613%***
Spain	0,02%	0,04%	0,69%	0,40%	0,51%	0,24%	0,36%	0,75%	0,61%	0,75%	0.737%***

For each country, we construct 10 portfolios, sorted according to their idiosyncratic volatility measure. Portfolios are rebalanced at the beginning of each month. Table 7 presents the portfolio returns and the returns from going long on the 10^{th} portfolio and short on the 1st portfolio.

Results of equation 4 used to test the significance of the effect of the under diversification proxies on the idiosyncratic risk premium are reported in table 8. Results of Models 1 and 2 show a significant effect of both investor characteristics and market information costs on the conditional idiosyncratic volatility premium. In Model 1 (Model 2), the Absolute Forecast Error (AFE) variable is significantly positive. An increase of 10% in the AFE leads to an increase of 1.721 (1.625) in the idiosyncratic volatility premium. This means that if the information is costly or unavailable, the experts cannot precisely predict earnings, which leads to an increase in the idiosyncratic risk premium. This is also confirmed by investors' distinctive characteristics. A change in institutional investor ownership has a negative effect, statistically significant at the 1% level, on the conditional idiosyncratic volatility premium. If the rate of change in institutional ownership increases by 1%, the idiosyncratic volatility premium decreases by -2.98% (-2.85%). This means that if institutional investors decide to hold more stocks, the conditional idiosyncratic volatility premium decreases. However, we do not find a significant effect of neither turnover nor FDI. The only negative statistically significant effect on the idiosyncratic volatility premium is for per capita GDP (Model 1). The estimated per capita GDP coefficient is -2.53%, which means that an increase of 1% in per capita GDP will lead to a decrease of -2.53% in the conditional idiosyncratic volatility premium. The coefficients of common idiosyncratic volatility are not statistically significant but they are negative.

To test for the rightness of the random effects, we use the Breusch Pagan Lagrangian multiplier and the Hausman tests. The Breusch Pagan test statistics is 117.07 for the conditional idiosyncratic volatility premium, both statistically significant at the 1% level. The Hausman test statistics is 5.529 but statistically insignificant, indicating the relevancy of the random effects model in our case.

Table 8. Effect of diversification variables on the idiosyncratic volatility

Model	**Model 1**	**Model 2**
SMB	2,682	2,792
	-1,856	-3,142
HML	9.686***	9.801*
	-3,331	-5,538
MOM	-3.701**	-3,696
	-1,529	-2,479
AIV	-2,496	-1,853
	-2,521	-2,848
AFE	1.721*	1.625*
	-0,900	-0,877
Inst_Own	-2.975***	-2.851***
	-0,967	-0,89
Turn	0,649	0,567
	-0,798	-0,813
FDI	-0,001	0,0004
	-0,001	-0,001
GDPk	-0.253**	-0,159
	-0,102	-0,134
Intercept	-1,487	-0,939
	-5,365	-5,288
$AdjR^2$	0,384	0,359
Method	Pooled	Random

Table 8 reports panel regressions results. It presents the results for models 1 and 2, which include conditional idiosyncratic volatility as the dependent variable. SMB is the portfolio return small minus big. HML 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 is the average return from high momentum portfolios minus the average return of low momentum portfolios. AFE is the absolute value of the ratio of the difference between realized earnings and forecasted earnings to values of forecasted earnings. Inst_Own change is the proportion of the market capitalization of all the listed firms held by institutional investors in the stock market. The turnover (TURN) is computed as the cross-sectional average of the stock turnover for all the firms listed on the market. FDI is the amount of foreign direct investment. GDPk is the GDP per capita representing the wealth of the investors in the market. AIV is the cross-sectional average of conditional idiosyncratic risk.

5. Conclusion

In this article, the reassessment of the relationship between idiosyncratic risk and stock returns, followed by the identification of determinants of the idiosyncratic risk premium after the adoption of the Euro in 10 Euro area economies is considered as the main contribution of this paper.

We find a proof of the presence of a common factor in firm’s specific volatilities. Our results show significant coefficients associated with high R^2. We highlight the presence of high correlations within eurozone countries’ aggregate idiosyncratic risk. These correlations indicate the potential presence of factors driving the aggregate idiosyncratic volatilities related to Euro Area. To the best of our knowledge, this is the first study indicating the presence of commonality between countries’ aggregate idiosyncratic volatility. Prior studies discussed the commonality between idiosyncratic volatilities of firms operating in the same country.

Regarding the idiosyncratic risk premium and its determinants, we show that the idiosyncratic risk is priced using Fama and MacBeth (1973) cross-sectional regressions and portfolio analysis. We accentuate the presence of a significant impact of under diversification proxies, especially the change in the institutional ownership and information cost, on the idiosyncratic risk premium.

For future work, the exploration of factors that significantly affect the indiosyncratic volatility is highly recommended as the firm-specific information must have an impact on the volatility of the idiosyncratic component of the stock return.

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Appendix A. Correlations between AIV and control variables per country

Panel A: Austria

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,051	1					
log_cvturn	-0,033	0,082	1				
log_bm	-0,033	-0,798	-0,151	1			
size	-0,029	0,097	0,213	-0,19	1		
Past_Ret	0,716	0,066	-0,025	-0,052	0,008	1	
Cond_vol	0,061	0,326	0,058	-0,232	0,113	0,061	1

Panel B : Belgium

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,099	1					
log_cvturn	-0,033	-0,029	1				
log_bm	-0,032	-0,022	-0,075	1			
size	-0,014	0,075	0,225	-0,454	1		
Past_Ret	0,74	0,09	-0,026	-0,072	0,034	1	
Cond_vol	0,029	0,167	-0,049	0,109	-0,158	-0,003	1

Panel C : Finland

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,114	1					
log_cvturn	-0,034	0,015	1				
log_bm	-0,037	-0,105	-0,103	1			
size	-0,014	0,047	0,167	-0,563	1		
Past_Ret	0,765	0,094	-0,035	-0,081	0,037	1	
Cond_vol	0,033	0,155	-0,068	0,124	-0,192	-0,013	1

Panel D : France

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,094	1					
log_cvturn	-0,019	0,018	1				
log_bm	-0,021	-0,017	-0,027	1			
size	-0,005	-0,033	0,169	-0,437	1		
Past_Ret	0,733	0,06	-0,01	-0,06	0,045	1	
Cond_vol	0,038	0,258	-0,081	0,025	-0,183	-0,001	1

Panel E: Germany

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,09	1					
log_cvturn	-0,019	0,012	1				
log_bm	-0,027	-0,022	-0,076	1			
size	-0,014	0,027	0,224	-0,461	1		
Past_Ret	0,7	0,039	-0,002	-0,075	0,041	1	
Cond_vol	0,026	0,227	-0,099	0,125	-0,249	-0,075	1

Panel F :Greece

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,071	1					
log_cvturn	-0,011	0,141	1				
log_bm	0,026	-0,291	-0,111	1			
size	-0,02	0,428	0,174	-0,521	1		
Past_Ret	0,786	0,039	-0,016	0,022	-0,018	1	
Cond_vol	0,077	0,164	0,039	0,088	-0,2	0,056	1

Panel G : Italy

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,196	1					
log_cvturn	-0,003	-0,078	1				
log_bm	-0,026	-0,149	0,035	1			
size	0,007	0,132	0,106	-0,519	1		
Past_Ret	0,789	0,123	0,03	-0,035	0,05	1	
Cond_vol	0,072	0,27	-0,051	0,168	-0,198	-0,037	1

Panel H : Netherlands

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,06	1					
log_cvturn	-0,024	-0,004	1				
log_bm	-0,032	-0,038	0,002	1			
size	-0,007	0,011	0,245	-0,368	1		
Past_Ret	0,753	0,037	0,001	-0,075	0,053	1	
Cond_vol	-0,051	0,085	-0,068	0,007	-0,139	-0,079	1

Panel I : Portugal

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,109	1					
log_cvturn	-0,033	0,039	1				
log_bm	-0,011	-0,097	0,014	1			
size	0,004	0,119	0,107	-0,531	1		
Past_Ret	0,707	0,083	-0,013	-0,048	0,069	1	
Cond_vol	0,062	0,244	0,027	0,126	-0,159	0,012	1

Panel J : Spain

	R	Log_Turn	log_cvturn	log_bm	size	Past_Ret	Cond_vol
R	1						
Log_Turn	0,079	1					
log_cvturn	-0,033	0,074	1				
log_bm	-0,049	-0,105	-0,013	1			
size	0,001	0,12	0,123	-0,435	1		
Past_Ret	0,786	0,051	-0,015	-0,075	0,055	1	
Cond_vol	0,012	0,214	0,032	0,137	-0,155	-0,059	1

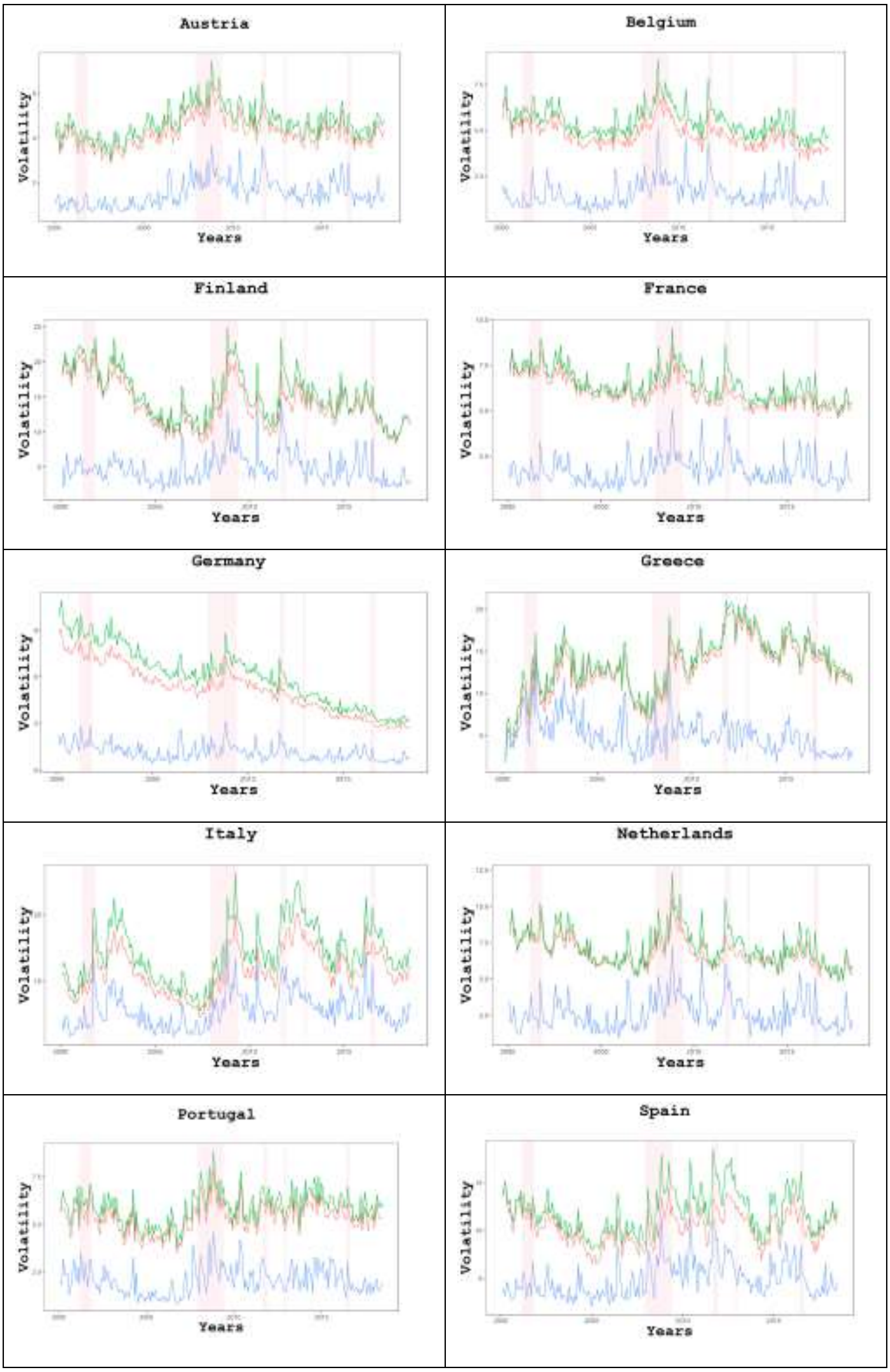

Figure 1. Conditional idiosyncratic volatility

Note: This figure displays the time series of average stock volatility, the market portfolio volatility and the cross-sectional average of the conditional idiosyncratic volatility. The sample covers 3553 listed firms on stock exchanges in 10 European countries from January 2000 to June 2018. We extract from Bloomberg market data. We collect daily stock prices, return indices, market values, number of shares outstanding, trading volumes, dividends and book-to-market ratio. All values are in Euros. Fama and French factors are obtained from the Kenneth French Website. The conditional idiosyncratic volatility is the monthly standard deviation of residuals of an EGARCH (3,1) model. Common risk factors are added to the mean equation. We regress daily excess returns on European Fama and French five risk factors and Carhart momentum factor. The shaded areas in the graph represents common recessions and crises between the European countries.