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Have European Stocks Become More Volatile? An Empirical Investigation of Idiosyncratic and Market Risk in the Euro Area

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An Empirical Investigation of Idiosyncratic and Market Risk in the Euro-Area

Abstract

We examine the dynamics of idiosyncratic risk, market risk and return correlations in European equity markets using weekly observations from 3515 stocks listed in the 12 Euro area stock markets over the period 1974-2004. Similarly to Campbell, Lettau, Malkiel and Xu (2001), we find a rise in idiosyncratic volatility, implying that it now takes more stocks to diversify away idiosyncratic risk. Contrary to the United States, however, market risk is trended upwards in Europe and correlations are not trended downwards. Both the volatility and correlation measures are pro-cyclical, and they rise during times of low market returns. Market and average idiosyncratic volatility jointly predict market wide returns, and the latter impact upon both market and idiosyncratic volatility. This has asset pricing and risk management implications.

1. Introduction

It is widely acknowledged that both single stock volatility and aggregate market volatility exhibit time varying behaviour. Within the capital asset pricing model (CAPM), the former is interpreted as idiosyncratic risk that can be diversified away, and empirical studies have traditionally focussed on the latter (see Bollersev, Chou and Kroner (1992), Hentschel (1995), Ghysel, Harvey and Renault (1996), Campbell, Lo and MacKinlay (1997) for surveys). But investors often hold incompletely diversified portfolios, and even if they are keen to diversify, they tend to hold a limited number of assets to reduce transaction costs (see Falkenstein (1996), Barber and Odean (2000) and Benartzi and Thaler (2001)). Barberis and Thaler (2003) provide a review of this 'insufficient diversification' puzzle. While systematic, market-wide volatility is most important to the holders of well-diversified portfolios, both total and idiosyncratic volatility are relevant for incompletely diversified investors. In this vein, Campbell, Lettau, Malkiel and Xu (2001), henceforth CLMX (2001), analyse long-term trends in both firm-level and market volatility in United States stock markets from 1962 to 1997. Using daily data on all stocks traded on the AMEX, the NASDAQ and the NYSE, they show that a decline in overall market correlations has been accompanied by a parallel increase in average firm-level volatility. In explaining their findings, CLMX (2001) suggest a number of possible causes, including the tendency for firms to access the stock market earlier in their development, executive compensation schemes that reward stock volatility, and the tendency for large conglomerates to be broken into smaller, less diversified corporations.

It is important to investigate whether the findings of CLMX (2001) on United States equity markets also feature in the equity markets of other countries. In this paper, we build on CLMX's (2001) methodology to study the aggregate firm level, industry level and systematic volatility of the 3515 stocks listed on the markets of the European Monetary Union[1] (Euro area) over the period from 1974 to 2004. We also study the closely related theme of average stock and industry correlations, and we develop an innovative methodology to construct average correlations series that is especially useful when large numbers of assets are under consideration. Our study is of interest to investors throughout the world who hold international equity portfolios, and it is particularly important for European individual and institutional investors who are recently tending to hold greater proportions of their portfolios in stocks[2]. We add to the literature by providing a more complete description of the relations between the systematic and idiosyncratic components of volatility and between these and stock market returns. To this end, we use a simple unconditional estimation methodology based on vector auto-regressions from which we recover structural relations between the systematic and idiosyncratic components of volatility, and between these and stock market returns, by imposing simple but theoretically motivated and intuitively appealing identifying restrictions. This allows us to highlight features of the multivariate distribution of stock returns that have important risk management implications, not only for naïve under-diversified investors, but also for investors engaging in long-short relative value trades.

We find that European stocks have indeed become more volatile, and that idiosyncratic risk is the largest component of this volatility. We also find that the potential benefit of diversification strategies in Europe remains substantial and relatively stable over time. Because of the larger idiosyncratic volatility of the typical stock, however, it now takes many more stocks to diversify it away. For example, the number of stocks required for residual idiosyncratic volatility to be reduced to 5 percent in a portfolio of European stocks has risen from 35 in 1974 to 166 in 2003. The low average stock correlation of about 20 percent implies a correspondingly low explanatory power for the market model. However, while CLMX (2001) report a declining explanatory power of the market model in the United States, there is no strong evidence of such a phenomenon in the Euro area. Market volatility forecasts both industry and firm-level volatility. This contrasts with CLMX (2001) who find that firm-level volatility predicts both market and industry-level volatility in the United States. We also find that market returns are positively related to lagged market variance and negatively related to lagged idiosyncratic variance. This confirms the findings of Guo and Savickas (2005) using comparable United States data, but we suggest that market and average idiosyncratic variance predict market returns because they jointly proxy for average correlation, and hence for a component of systematic risk. Finally, we find that there is a sizeable contemporaneous impact of market returns and market volatility on idiosyncratic volatility, suggesting that even positions constructed to remove market risk, such as long-short relative value trades, may prove more volatile during market downturns and at times of high market volatility.

Our paper is structured as follows. We begin in Section 2 by introducing a decomposition of average stock variance similar to CLMX's (2001) methodology, and we outline our methodology for the construction of our average correlation series. In Section 3, we describe our data set and we construct our variance and correlation series. In Section 4, we examine their long-run behaviour, and we then study their lead-lag relations with each other. In Section 5, we discuss possible explanations for the observed long-run trends in individual stocks volatilities and correlations. In Section 6, we discuss the portfolio management implications of our findings. In Section 7, we examine the interactions between our variance series and aggregate returns, and we test for the presence of predictive relations. In the final Section, we summarise our main findings and present our conclusions.

2. Variance Components and Average Correlation

Denote by $R_{i,t}$ the return on asset i included in portfolio P. Its return can be decomposed into the conditionally risk free rate, $R_{f,t}$, a portfolio-related component and an asset-specific component:

$$R_{i,t} = R_{f,t} + \beta_{i,p}(R_{p,t} - R_{f,t}) + u_{i,t} \qquad (1)$$

Here, $R_{p,t}$ is the return on the portfolio P, $\beta_{i,p}$ is a regression coefficient and $u_{i,t}$ is an idiosyncratic regression residual[3]. The variance of the asset can also be decomposed into a systematic and an idiosyncratic component:

$$Var(R_{i,t}) = \beta_{i,p}^2 Var(R_{p,t}) + Var(u_{i,t}) \tag{2}$$

Averaging across the assets, the variance of the typical asset can be approximately decomposed into a systematic and an idiosyncratic component:

$$\begin{aligned} Avg\left[Var(R_{i,t})\right] &= Avg\left[\beta_{i,p}^2 Var(R_{p,t})\right] + Avg\left[Var(u_{i,t})\right] \\ &= Avg\left(\beta_{i,p}^2\right) Var(R_{p,t}) + Avg\left[Var(u_{i,t})\right] \end{aligned} \tag{3}$$

Here, the operator $Avg(\cdot)$ denotes a weighted average across all the assets included in the portfolio. Using an elementary statistical result, and assuming that the cross-sectional variation of the beta coefficients, $CSV\left(\beta_{i,p}\right)$, is not too high, $Avg\left(\beta_{i,p}^2\right)$ in (3) can be conveniently rewritten as follows:

$$Avg\left(\beta_{i,p}^2\right) = Avg\left(\beta_{i,p}\right) Avg\left(\beta_{i,p}\right) + CSV\left(\beta_{i,p}\right) = 1 + CSV\left(\beta_{i,p}\right) \cong 1 \tag{4}$$

Using (4), the decomposition of the variance of the typical asset collapses into the sum of the portfolio variance and of the average idiosyncratic variance:

$$Avg\left[Var(R_{i,t})\right] \cong Var(R_{p,t}) + Avg\left[Var(u_{i,t})\right] \tag{5}$$

Turning to a larger scale analysis, the returns on the industry indices and on the individual stocks in the market portfolio are described in equations (6) and (7).

$$R_{j,t} = R_{f,t} + \beta_{j,m}(R_{m,t} - R_{f,t}) + \varepsilon_{j,t} \tag{6}$$

$$R_{ij,t} = R_{f,t} + \beta_{ij,m}(R_{m,t} - R_{f,t}) + \beta_{ij,j}\varepsilon_{j,t} + e_{ij,t} \tag{7}$$

Here, $R_{j,t}$ is the industry j return, $R_{ij,t}$ is the return on firm i in industry j, $R_{m,t}$ is the return on the market portfolio, $\beta_{j,m}$, $\beta_{ij,m}$ and $\beta_{ij,j}$, are regression coefficients and $\varepsilon_{j,t}$ and $e_{ij,t}$ are, respectively, industry and firm-level idiosyncratic regression residuals[4]. Letting $u_{ij,t} = \beta_{ij,j}\varepsilon_{j,t} + e_{ij,t}$, (7) can be rewritten as follows:

$$R_{ij,t} = R_{f,t} + \beta_{ij,m}(R_{m,t} - R_{f,t}) + u_{ij,t} \tag{8}$$

By construction, $R_{m,t}$, $e_{ij,t}$, and $\varepsilon_{j,t}$ are orthogonal, so $u_{ij,t}$ is orthogonal to $R_{m,t}$ and an idiosyncratic regression residual. It follows that (8) decomposes returns into pure market and idiosyncratic components, and (7) decomposes the latter into pure industry and firm level components[5].

Based on this model of returns and on (5), total stock variance can be decomposed into a systematic and an idiosyncratic component,

$$VAR_t = MKT_t + IDIO_t \tag{9}$$

where,

$$VAR_t = \sum_{j=1}^{n} w_{j,t} \sum_{i=1}^{k} w_{ij,t} Var(R_{ij,t})$$

$$MKT_t = Var(R_{m,t}) = \sum_{j=1}^{n} \sum_{i=1}^{k} w_{ij,t}^2 Var(R_{ij,t}) + \sum_{j=1}^{n} \sum_{i=1}^{k} w_{ij,t} Cov(R_{ij,t}, R_{m,t})$$

$$IDIO_t = \sum_{j=1}^{n} w_{j,t} \sum_{i=1}^{k} w_{ij,t} Var(u_{ij,t})$$

Here, k denotes the maximum number of stocks in each of the n industries, $w_{j,t}$ the weight of industry j in portfolio m, and $w_{ij,t}$ the weight of stock i in industry j, VAR_t is the weighted average total stock variance, MKT_t is the variance of the market portfolio, and $IDIO_t$ is the average idiosyncratic variance. Intuitively, VAR_t can be interpreted as the variance of the typical stock, and $IDIO_t$ as the variance born by the arbitrageur that holds a long position in the typical stock and a short position in the market portfolio.

Since this framework can be applied to any portfolio, we can also decompose the variance of the typical industry into its market and idiosyncratic components as follows:

$$VAR_t^{ind} = MKT_t + IND_t \tag{10}$$

where,

$$VAR_t^{ind} = \sum_{j=1}^{n} w_{j,t} Var(R_{j,t})$$

$$IND_t = \sum_{j=1}^{n} w_{j,t} Var(\varepsilon_{j,t})$$

Here, VAR_t^{ind} is average total industry variance and IND_t is the industry level average idiosyncratic variance. Intuitively, the former can be seen as the variance of the typical industry, and the latter as the typical variance born by an investor that holds a market neutral long-short position in an industry index. The idiosyncratic portion of average total variance can then be further decomposed into its industry and firm level components:

$$IDIO_t = IND_t + FIRM_t \tag{11}$$

where,

$$\begin{aligned} FIRM_t &= IDIO_t - IND_t \\ &= \sum_{j=1}^{n} w_{j,t} \left[\sum_{i=1}^{k} w_{ij,t} Var(u_{ij,t}) - Var(\varepsilon_{j,t}) \right] \\ &= \sum_{j=1}^{n} w_{j,t} \sum_{i=1}^{k} w_{ij,t} Var(e_{ij,t}) \end{aligned}$$

Here, $FIRM_t$ is the firm level average idiosyncratic variance. Intuitively, it can be interpreted as the variance born by an investor that holds a long position in the typical stock and a short position in the industry to which it belongs.

This variance decomposition is very similar to the methodology used by CLMX (2001), but it is based on returns instead of excess returns, and the main results are derived in a different, more intuitive manner. Since $u_{ij,t}$ can be seen as a CAPM idiosyncratic residual, (9) and (11) provide a CAPM-equivalent decomposition[6] of average total variance into market variance and average idiosyncratic variance and its industry and firm components, with the considerable advantage that it bypasses the need to estimate possibly time-varying *betas*.

Furthermore, define the average volatility of the stocks included in the market portfolio as $VOL_t = \sum_{j=1}^{n} w_{j,t} \sum_{i=1}^{k} w_{ij,t} \sigma_{ij,t}$, where $\sigma_{ij,t} = \sqrt{Var(R_{ij,t})}$ denotes the volatility of stock *i* drawn from industry *j*. Assuming that the market portfolio is well diversified, the average stock correlation can be obtained as the ratio of the market variance to the square of the average stock volatility:

$$CORR_t = \frac{MKT_t}{VOL_t^{\ 2}} \tag{12}$$

Here, $CORR_t$ is the level of correlation that, if assumed to hold for all pairs of assets, would give the same market volatility as the full correlation matrix. Equation (12) is based on a general and intuitively appealing result that, as proven in the Appendix, applies to any well diversified portfolio and that can therefore be used to simplify the construction of the average correlation time series of a large number of assets. In a similar way, defining $VOL_t^{ind} = \sum_{j=1}^{n} w_{j,t} \sigma_{j,t}$ as the average industry volatility, we can also construct a measure of average correlation for a diversified portfolio of industries as follows:

$$CORR_t^{ind} = \frac{MKT_t}{VOL_t^{ind\ 2}} \tag{13}$$

3. Data and Variable Construction

We use weekly returns and semi-annual capitalization data from *Datastream International* for the period December 1974 to March 2004. By using weekly returns, we lessen the importance of asynchronous trading across the Euro area stocks markets. Our firm level data comprises the total returns and market capitalisation for the 3,515 stocks listed on the equity markets of the countries that had adopted the Euro as of March 2004 (i.e., Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway and Spain). Our industry level data is obtained from *Datastream International Ltd* level 4 fixed history industry indices for the Euro area equity market[7]. Our market data comprises total returns on the *Datastream International Ltd* fixed history[8] index for the overall Euro area stock market[9].

We use unconditional estimators of variances based on sums and averages of return innovation squares and cross products. Many researchers such as Schwert (1989) and CLMX (2001) have used this approach because of its simplicity. The implicit assumption in this approach is that the variance of a process is observable, and as pointed out by Merton (1980), it can be estimated to any desired degree of accuracy by sampling the squared deviations of the process realisations from their means at sufficiently high frequency. We consequently define variances over a period T of length p as the average of the squared deviations of returns, R_t, $t = 1.... p$, from their mean $\overline{R}_T$. In all our computations, we apply the convention that each year comprises 52 weeks and each half-year or semester comprises 26 weeks. To estimate our semi-annual variance of weekly returns, we set p equal to 26. Formally:

$$Var(R_t)_T = \sum_{t=1}^{p}(R_t - \overline{R}_T)^2 \tag{14}$$

Using (14), we first construct our variance series using non-overlapping semi-annual periods for the individual stocks $Var(R_{ij,t})_T$, for the individual industries $Var(R_{j,t})_T$ and for the market portfolio $Var(R_{m,t})_T$. We then compute the average total variance time series, and using (9) we derive the average idiosyncratic variance time series as the difference between VAR_T and MKT_T. Turning to the decomposition of average idiosyncratic variance into its industry and firm level components, we use (10) to construct IND_T by subtracting MKT_T from $VAR^{ind}{}_T$ and, using (11), we derive $FIRM_T$ by subtracting IND_T from $IDIO_T$.

Using the square root of (14), we construct volatility series for each stock and industry, and we then compute the average stock volatility VOL_T and average industry volatility $VOL^{ind}{}_T$ series. Finally, applying (12) and (13) and using the constructed market volatility series and the average stock and industry volatility series, we compute the average correlation among the stocks and industries. This gives us 61 non overlapping semi-annual variance and correlation data points (T = 1, 2,..... 61) computed from the weekly returns data. The variance series are annualized by multiplying by 2 to minimise rounding errors and to display the results in a more intuitive form. While we construct both equally-weighted and value-weighted series, we focus mostly on the latter[10].

The industries and constructed series are described in Panels A and B of Table 1. The decomposition of the annualised value-weighted average total stock variance[11] into its market and idiosyncratic components is plotted in Panel A of Figure 1, and the ratio of firm to industry variance is plotted in panel B of the Figure. Panel C plots the value-weighted average stock and industry correlations. Inspection of Figure 1 reveals that total, idiosyncratic and market variance start off relatively low and tend to rise towards the end of the period. This tendency, however, is more pronounced for idiosyncratic variance and its firm-level component. Idiosyncratic variance is the largest component of average total variance, and average stock correlation is usually well below 50 percent with the noticeable exception of the 1974 oil crisis and the 1987 stock market crash. The potential benefit to diversification strategies is therefore substantial.

<< Insert Table 1 and Figure 1 here >>

These findings are broadly in line with those reported by CLMX (2001) for United States stocks. Contrary to CLMX (2001), however, industry level volatility is the largest component of idiosyncratic volatility for much of the 1970s and 1980s, as shown by Panel B of Figure 1. The reason for this is the limited cross-sectional dispersion within industries due to the small number of listed stocks. Unlike in the more mature United States markets, European industry indices initially comprised a small number of stocks with quite similar firms. In 1974, the number of stocks in the average industry index was less than 10, it rose to about 30 by the end of the 1980s, and since then it has grown steadily. In 2004 there were about 80 stocks in the average Euro area industry index. This also explains why, as reported in Panel B of Figure 1, the average correlation amongst Euro area industries is first initially very similar to the average correlation amongst Euro area stocks, but the former increased relative to the latter from the mid 1980s.

4. Time Series Analysis

We begin our formal time series analysis by providing descriptive correlations and autocorrelations and by testing for the presence of a long run trend. We then examine the short run interactions between our decomposed variance series. Table 2 presents descriptive correlations of the market variance, average idiosyncratic variance (and its components) and average correlation series with their own and each other's lags. Only average idiosyncratic variance and its firm and (to a lesser extent) industry-level components display substantial persistence. The low persistence of the market variance and correlation series is due to their construction from relatively low frequency (weekly) returns and to the semi-annual sampling period, and it suggests that they are unlikely to contain a unit root. This is also the case for the more persistent average idiosyncratic variance and its industry and firm-level components[12]. We therefore treat the constructed variance and correlation series as stationary and work in levels without differencing. All series display a negative correlation with stock market returns. They are also positively correlated with GDP growth, and hence are pro-cyclical.

<< Insert Table 2 about here >>

Long Run Trends

To test for the presence of a deterministic time trend, we estimate a dynamic model that includes among the regressors a constant and a lag of the dependent variable[13]. We then conduct a Wald-type test of the restriction that the deterministic time trend coefficient is zero. The results are reported in Panel A of Table 3. The trend coefficient is significant both in the average idiosyncratic variance, $IDIO_T$, and the market variance, MKT_T

series. These trends explain a substantial portion of the rise in these series over time. After 5 years, for example, the projected increase in market variance, MKT_T, and in idiosyncratic variance, $IDIO_T$, is 0.56 percent and 1.0 percent respectively. These values correspond to increases in market volatility and idiosyncratic volatility of the typical stock of about 7.5 and 10 percent respectively. Since the time trend is statistically insignificant for average industry–level idiosyncratic variance, IND_T, but highly significant for firm-level idiosyncratic variance, $FIRM_T$, the surge in idiosyncratic variance, $IDIO_T$ (which is the sum of both components from equation (9)), is attributable mostly to an upward trend in firm-level volatilities. The upward trend in idiosyncratic and firm-level variance is similar in magnitude to the upward trend in the corresponding United States series studied by CLMX (2001). Market volatility, however, is not trended upwards in the CLMX (2001) study.

The long run mean of average stock correlations, $CORR_T$, is close to 20 percent. The typical coefficient of determination, R^2, and hence the explanatory power of the market model with zero intercept, is therefore rather low at about 4 percent (calculated as the square of 20 percent). The trend coefficient of average stock correlations, $CORR_T$, is not statistically significant. This is not surprising, given that both market variance, MKT_T, and idiosyncratic variance, $IDIO_T$, are trended upwards by similar magnitudes. A consequence of this finding is that the explanatory power of the market portfolio is not trended downwards. This contrasts with the findings of CLMX (2001) who report a downward trend in average stock correlation and in the explanatory power of the market portfolio in the United States.

<< Insert Table 3 about here >>

Short Run Dynamics

There is a potentially rich set of short run dynamic interactions. Following the general-to-specific methodology (see, *inter alia*, Mizon (1995) and Kearney (2000)) we first specify a vector autoregression (VAR) model of the relation between overall market variance, MKT_t, industry variance, IND_t, and idiosyncratic firm variance, $FIRM_t$.

$$A(L)y_T = u_T \tag{15}$$

with

$$A(L) = I_3 - A_1L - A_2L^2 - ...... - A_QL^Q,$$

$$E(u_T) = 0, \quad E(u_Tu'_T) = \Sigma, \quad E(u_Tu'_S) = 0, \text{ for } T \neq S, \quad E(y_Tu_T) = 0$$

and

$$y_T = [\mathrm{MKT_T} \quad \mathrm{IND_T} \quad \mathrm{FIRM_T}]'$$

This is a reduced form VAR representation in which y_T is the vector of variables, I_3 is a (3×3) identity matrix, A_q are an (3×3) coefficient matrices, u_T is a (3×1) vector of white noise disturbance terms, and L^q denotes the lag operator (for example, $L^q y_T = y_{T-q}$). This model allows us to examine the full range of interaction between the variables in the y_T vector, i.e. the overall market variance, MKT_T, the industry variance, IND_T, and the idiosyncratic firm variance, $FIRM_T$. A convenient feature of the VAR representation in (15) is that it can be estimated by ordinary least squares, which yields consistent and asymptotically efficient estimates of the A_q matrices because the right-hand-side variables are predetermined and are the same in each equation of the model.

The first step in the estimation process is to decide on the appropriate lag length (Q). The Akaike Information Criterion (AIC) suggests the inclusion of 3 lags, and the Swartz Bayesian Criterion (SBC) suggests 1 lag. Since a Likelihood-Ratio test (LR) indicates that increasing the lag length from 1 to 3 produces a significant improvement in the overall model fit, we include 3 lags of each variable[14] (Q = 3). This lag length selection tests are reported in Panel A of Table 4. We next perform block-exogeneity tests on the MKT_T, IND_T and $FIRM_T$ series to determine whether lags of one variable Granger-cause any of the others. If all lags of one variable can be excluded from the equations of the other two variables, we can model the latter using a 2-variable VAR. We test these restrictions using a Likelihood Ratio (LR) statistic, modified by Sims's (1980) multiplier correction to improve the small sample properties of the test. This test statistic is distributed as chi-squared with degrees of freedom equal to the number of lags excluded from each equation in the restricted system. Panel B of Table 4 presents the results. The only block exogenous variable is $FIRM_T$[15]. Moreover, from Panel C of the Table, MKT_T Granger-causes IND_T whereas the latter Granger-causes both MKT_T and $FIRM_T$.

<< Insert Table 4 about here >>

Since the lags of both MKT_T and IND_T cannot be excluded from the equations of the other two variables, we must model the system as a tri-variate VAR. To identify the structural model from the estimated reduced form, we impose the restrictions that IND_T does not have contemporaneous effects on MKT_T, and $FIRM_T$ does not have contemporaneous effects on MKT_T and IND_T. Table 5 reports the corresponding variance decomposition of the Euro area market variance and average industry and firm level variance series. A large portion of the variance of IND_T and $FIRM_T$, over 30 percent one period ahead, is explained by variation in MKT_T, whereas only 5.7 percent of the latter is explained by variation in IND_T after 3 periods and none by $FIRM_T$.

<< Insert Table 5 about here >>

Comparing our findings to those reported by CLMX (2001), we can conclude that both systematic and industry level variance play a more important role in Europe than in the United States. Conversely, firm volatility appears to play a weaker role in driving the other volatility series in Europe than it does in the United States. This suggests that their role in forecasting exercises, which might be relevant in pricing applications and asset allocation decisions as suggested by Goyal and Santa Clara's (2003) work, is different depending on whether the stocks are drawn from a European rather than a United States sample.

5. What Might Explain Volatility and R^2 Trends?

CLMX (2001) and Wei and Zhang (2003), among others, suggest a number of circumstances that could explain the rise of idiosyncratic volatilities. The first obvious possible explanations are the tendency of conglomerates to break up into more specialized businesses, interpreted as a shift from internal to external capital markets, and to issue stocks at an earlier stage of the company life-cycle. Changes in executive compensation schemes that create an incentive to increase cash-flow volatility could also contribute to explain this phenomenon. These explanations could also account for why most of the increase has occurred in firm level rather than industry level volatilities. The argument that the tendency towards less diversified conglomerates might explain rising firm-level volatilities, however, applies less well to Euro area than to United States markets because it also implies a decrease in average correlations. Leverage is also an unlikely candidate to explain the rise in stock volatilities, because as a result of a secular tendency towards the disintermediation of financial transactions, it has declined over time both in the United States and in the Euro area.

Under a more behavioural perspective, divergence between institutional and individual investors' sentiment, coupled with the increasing institutionalization of equity ownership, could explain more trading and more volatile individual stock prices. For example, Xu and Malkiel (2003) find evidence of a positive relation between US idiosyncratic volatility and institutionalization of the ownership of United States stocks. Morck, Yeung and Yu (2000) and, more recently, Jin and Myers (2004), suggest a negative relation between the explanatory power of the market model and factors such as the degree of investor protection and the transparency of the agency relationships between insiders-managers and outsiders-investors. From this perspective, the finding of a low average correlation and hence of a low market R^2 is consistent with the generally good level of investor protection and transparency in Euro area stock markets.

A further possibility is that the rise of idiosyncratic volatility from the end of the 1990s to the first years of the present decade might be a one-off episode rather than the result of a long-run trend. A recent study by Brandt, Brav and Graham (2005) suggests that the rise of idiosyncratic volatility in the United States during the same period is related to a speculative episode, and that it can be explained on the basis of excess-trading by individual investors. Visual inspection of the idiosyncratic volatility time series in Panel A of Figure 2, however, suggests that while in the second semester of 2003 and the first semester of 2004 it reverted to its pre-1998 low levels, it did increase steadily over the entire sample period.

To formally test for the presence of a deterministic time trend in the pre-1998 period, just as we did for the full sample period, we estimate a dynamic model that includes among the regressors a constant and lags of the dependent variable[16]. We then conduct Wald-type tests of the restriction that the deterministic time trend coefficient is zero. We include only one lag in every case except in the model of $FIRM_T$. In the latter, since Durbin's *h* test rejects the null that the residuals are free of first-order autocorrelation, we re-estimate including a further lag. The results are reported in Panel B of Table 3. The point estimate of the deterministic time trend coefficient of $IDIO_T$ in the 1974-1997 sample period is half the 1974-2004 estimate, but it is still positive and statistically significant (even more so than in the full sample period). Interestingly, the time trend coefficient of the firm-level component of $IDIO_T$ is almost unchanged, whereas the trend coefficient of the industry-level component becomes negative, but remains statistically insignificant (both on the basis of the t-test and of the Wald test). The larger upward trend in idiosyncratic volatility in the post-1998 sample is therefore due to the surge of firm-level volatility relative to industry-level volatility in the second part of the sample period, as shown in Panel B of Figure 1, and thus to the fact that the more upwards-trending firm-level component represents a higher fraction of the overall idiosyncratic volatility.

<< Insert Figure 2 about here >>

6. Implications for Portfolio Management of Volatility Trends

A conventional rule of thumb, based on Bloomfield, Leftwich and Long (1977), suggests that a randomly chosen portfolio of 20 stocks produces most of the reduction in idiosyncratic risk that can be achieved through diversification. As remarked by CLMX (2001), however, the higher the average idiosyncratic variance, the larger the number of stocks needed to achieve a relatively complete diversification, given a random portfolio selection strategy. In Panel B of Figure 2, we report the residual portfolio idiosyncratic volatility as a function of the number of stocks included in equally-weighed portfolios formed by drawing randomly from our stock sample for various levels of average idiosyncratic risk at different points in time. It can be seen that it takes increasingly more stocks to reduce idiosyncratic risk to any given extent. It is worth noticing that a large portion of the increase has taken place in the second half of the sample period. To reduce idiosyncratic volatility to 5 percent, for example, 261 and 166 stocks were needed in the second semester of 2002 and 2003, respectively, and 154 stocks in the first semester of 2004 (our last data point). In comparison, just 35, 43 and 93 stocks were needed in the first semester of 1974 and in the second semester of 1989 and 1997, respectively. CLMX (2001)'s findings are similar. They report that a residual portfolio idiosyncratic volatility as low as 5 percent required 50 United States stocks in the period 1986-1997, but only about 20 stocks in the period 1974-1985[17].

On the other hand, the lower the correlation among stock returns, the higher the fraction of average total variance represented by idiosyncratic variance, and the higher the potential benefit from diversification. The low average correlation[18] suggests that diversification can be an important source of improvement in the portfolio risk-return ratio. The potential diversification benefit is fairly stable over time, because although average correlation is relatively noisy, it is not very persistent and it quickly reverts to its stationary long-run value (the half-life of a shock is 2.19 months).

The level of the equally-weighted average correlation is also important in determining the attractiveness of a simple asset allocation rule based on forming equally weighted portfolios of N assets, labelled the 'naïve $\frac{1}{N}$ strategy' by DeMiguel, Garlappi and Uppal (2005), relative to more sophisticated policies that determine optimal allocation weights based on asset expected returns and variance-covariance matrix estimates. The reason for this is that the smaller idiosyncratic volatility relative to systematic volatility, and thus the larger average correlation, the closer is the variance-covariance matrix of asset returns to being singular[19]. The impact of expected return estimates sampling error is therefore larger (mean-variance optimal portfolio weights are computed using the inverse of the returns variance-covariance matrix). This raises the optimal portfolio weight sampling error, and a longer estimation window is required to reduce it to any desired level. DeMiguel, Garlappi and Uppal (2005), in a simulation exercise where they assume 16 percent systematic volatility and 20 percent idiosyncratic volatility, show that it is highly unlikely for a mean-variance optimization policy to outperform the 'naïve $\frac{1}{N}$ strategy' in terms of out-of-sample Sharpe ratios using any reasonable estimation window, and thus over any reasonable investment horizon. Our evidence suggest, however, that at least for the portfolio of all European stocks, equally weighted average correlation is considerably lower than the value (39 percent) implied by the level of factor and idiosyncratic volatility assumed by DeMiguel, Garlappi and Uppal (2005). In fact, the mean equally weighted average correlation over the entire sample period is about 5 percent. This rekindles hope for a mean-variance optimization strategy to beat the 'naïve $\frac{1}{N}$ strategy'. Of course, it remains to be established whether this is empirically and practically the case, i.e. whether the equally weighted average stock correlation is low enough without having to invest in an unduly large number of stocks. This could be checked resorting to a simulation as in DeMiguel, Garlappi and Uppal (2005) but using different values for average correlation. Doing this would be a useful extension of the present work that we leave for future research.

7. The Dynamic Relation between Market Returns and Volatility

Having studied the relations between the market and idiosyncratic variance series, we now turn our focus to the causality between these series and the stock market returns. To this end, we estimate a simple VAR model of market returns, market variance and idiosyncratic variance (R_{mT}, MKT_T and $IDIO_T$). Both variance series are linearly de-trended. As reported in Panel A of Table 6, both the AIC (Akaike Information Criterion) and the SBC (Schwartz Bayesian Criterion) suggest the inclusion of one lag. We impose a set of identifying restrictions on the structural VAR in a manner that is consistent with asset pricing models that predict a linear relation between risk and expected returns, implicitly treating lags of the variance series as proxies for risk (expected variance). To this end, we rule out contemporaneous causal effects of market variance, MKT_T, on the market returns, R_{mT}. We also rule out contemporaneous effects of idiosyncratic variance, $IDIO_T$, on the other variance series[20], MKT_T, and on market returns, R_{mT}. The impulse response functions in Figure 3 depict the various impacts of shocks to each of the three series under consideration.

<< Insert Figure 3 about here >>

Shocks to both market and idiosyncratic variance have statistically significant effects on future returns. The effect of MKT_T is positive. This is broadly in line with a positive relation between market risk and expected market returns, and is therefore consistent with the findings of Turner, Startz and Nelson (1989) and Harvey (1989) among others. The effect of $IDIO_T$, however, is negative. How can we explain the negative relation between market returns and lagged idiosyncratic variance, $IDIO_T$? A positive shock to idiosyncratic variance, $IDIO_T$, implies, by (9) and (12), a decrease in average correlation, because we imposed the restriction that the former ($IDIO_T$) has no initial impact on market variance, MKT_T. The response functions, therefore, highlight, under this restriction, a positive relation between average stock correlation and one period ahead market returns. Since market variance is, by (12), proportional to average correlation, this is broadly in line with a positive relation between systematic risk and future returns.

This relation is also picked up by the regression of market returns on the lags of both market and idiosyncratic variance[21]. In Panel B of Table 6, we report predictive regressions of the market returns using a constant and lagged variance series as explanatory variables over the sample periods 1974-1997 and 1974-2004. The estimated market variance coefficient is always positive, but it is statistically insignificant in the longer sample period when idiosyncratic variance is excluded from the regression.

Moreover, while market variance and average idiosyncratic variance jointly predict market returns, the relation with lagged market variance is positive, whereas the relation with lagged idiosyncratic variance is negative. The latter is statistically significant at conventional levels in the 1974-2004 period, but not in the 1974-1997 period. Interestingly, this also obtains in the United States markets as reported by Guo and Savickas (2005). The significance levels of the reported t-statistics are confirmed by a bootstrap experiment.

<< Insert Table 6 about here >>

The impulse response functions in Figure 3 also highlight a sizeable and statistically significant contemporaneous negative impact of shocks to aggregate returns on both MKT_T and $IDIO_T$, i.e. both market and idiosyncratic volatility rise during market downturns. Finally, MKT_T has a considerable and statistically significant contemporaneous impact on $IDIO_T$, consistently with the Granger-causality relations[22] reported in Table 4. These two effects, the contemporaneous impact of market returns and market volatility on idiosyncratic volatility, suggest that even positions constructed to remove market risk may prove more volatile during market downturns and at times of high market volatility. Portfolios formed combining the typical stock and the market index, designed to hedge the local (time-varying) market beta of the stock, will display an asymmetric distribution (systematic co-skewness arising from a correlation of second moments with the market) with 'fat tails' (systematic co-kurtosis arising from a correlation of second moments with the market variance). In other words, relative-value investors will experience larger than usual gains or losses during market downturns and at times of high market volatility, because at least to a second and third order effect, the typical beta-hedged long-short position is not truly market-neutral[23].

8. Summary, Conclusions and Future Research

In this paper, we applied the variance decomposition proposed by CLMX (2001) to construct Euro area market and idiosyncratic variance series. We also proposed a methodology to simplify the construction of an average correlation measure. This is based on simple analytical result that links average correlation to market and average stock volatility. We first studied the salient empirical features of the constructed volatility and correlation series, we evaluated their predictive ability, and we discussed the implications of our main findings for portfolio management and asset pricing.

Regarding *long term* trends, our main findings are that, *first*, idiosyncratic volatility accounts for the main portion of the variance of the typical stock. The potential benefits to diversification strategies are, therefore, substantial. *Second*, the variance of the average European stock and of the Euro area stock market has increased over time, and a large portion of this increase is explained by a long-run deterministic trend. European stocks, therefore, have indeed become more volatile both at the individual and at the aggregate level. One consequence of the rise in average idiosyncratic risk is that it takes increasingly more stocks to capture the benefit of diversification. Investigating the determinants of these long-run trends in volatilities and correlations opens challenging opportunities for future research. Another possibility for future research, as discussed in Section 6, is to further explore the implications of the level and dynamics of market volatility, idiosyncratic volatility and average correlation for the attractiveness of the naïve equally-weighted diversification strategy relative to more sophisticated mean-variance optimization rules.

Regarding *short run* dynamics, we showed that there exists a rich set of interactions at different lags between the components of stock market. Euro area variance series are best forecast by market variance. This contrasts with the United States where, as reported by CLMX (2001), firm-level volatility predicts both market and industry-level volatility. Further investigating these relations using higher frequency data and exploring their economic explanation represents another possible extension of this work.

Finally, market and average idiosyncratic variance, as already documented by Goyal and Santa Clara (2003) and by Guo and Savickas (2005) using United States data, predict market-wide returns. We provide an alternative interpretation of this finding, consistent with a positive relation between aggregate expected return and systematic risk. Investigating the asset pricing implications of these findings, with special regards to the cross-section of average returns, is another fruitful area for future research. Idiosyncratic variance in turn is influenced, on a contemporaneous basis, by both the market variance and the market return. This has important implications for the risk management of supposedly market neutral, relative-value trades.

9. Appendix

Proposition: the average correlation between the stocks of a well diversified portfolio is asymptotically equal to the ratio between portfolio variance and the average variance of the constituent stocks.

Proof:

Consider the equation that expresses portfolio variance as a function of the weights, variances and co-variances of the constituent assets:

$$\begin{aligned}\sigma_{p,t}^2 &= \sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,t} w_{j,t} \sigma_{i,t} \sigma_{j,t} c_{ij,t} \\ &= \sum_{i=1}^{N} w_{i,t}^2 \sigma_{i,t}^2 + CORR_t \sum_{i=1}^{N}\sum_{\substack{j=1 \\ j\neq i}}^{N} w_{i,t} w_{j,t} \sigma_{i,t} \sigma_{j,t}\end{aligned} \tag{A1}$$

Here, $R_{p,t}$ denotes the return on portfolio P, $R_{i,t}$ is the return on the ith asset, N is the number of assets included in the portfolio, $\sigma_p = \sqrt{Var(R_p)}$ is the portfolio or systematic volatility, $\sigma_{i,t} = \sqrt{Var(R_{i,t})}$ is the volatility of asset i, $c_{ij,t}$ is the correlation between asset i and j, $CORR_t$ is the average asset correlation, i.e. the level of correlation that, if assumed to hold for all pairs of assets, would give the same portfolio volatility as the full correlation matrix.

For ease of algebraic manipulation and to facilitate intuition, it is convenient to define $\sigma_{ind,t}^2 = \sum_{i=1}^{N} w_{i,t}^2 \sigma_{i,t}^2$ as the variance that the portfolio would exhibit if all the assets were independent and $\sigma_{perf,t}^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,t} w_{j,t} \sigma_{i,t} \sigma_{j,t}$ as the portfolio variance if all the assets were perfectly correlated. Then we can rewrite (A1) as follows:

$$\sigma_{p,t}^2 = \sigma_{ind,t}^2 + CORR_t \left(\sigma_{perf,t}^2 - \sigma_{ind,t}^2 \right) \tag{A2}$$

Finally, solving (A2) for $CORR_t$,

$$CORR_t = \frac{\sigma_{p,t}^2 - \sigma_{ind,t}^2}{\left(\sigma_{perf,t}^2 - \sigma_{ind,t}^2 \right)} \xrightarrow{N} \frac{\sigma_{p,t}^2}{\sigma_{perf,t}^2} \tag{A3}$$

The last step in (A3) holds asymptotically for a well diversified portfolio, because $\sigma_{ind,t} \xrightarrow{N} 0$ by the law of large numbers. Since the volatility of a portfolio made up of perfectly correlated assets is equal to the average volatility of the constituent assets, we have $\sigma_{perf,t}^2 = \left(\sum_{i=1}^{N} w_{i,t} \sigma_{i,t} \right)^2$ and the average correlation of a large, well diversified portfolio can be rewritten as follows:

$$CORR_t = \frac{\sigma_{p,t}^2}{\sigma_{perf,t}^2} = \frac{\sigma_{p,t}^2}{\left(\sum_{i=1}^{N} w_{i,t} \sigma_{i,t} \right)^2} = \frac{\text{Portfolio Variance}}{\left(\text{Average Total Volatility} \right)^2} \tag{A4}$$

The expression in (A4) thus provides a measure of average stock correlation that is asymptotically valid for large, well diversified portfolios. It is very similar to an estimator of average correlation used by RiskMetrics™ and discussed by Finger (2000). This result is particularly useful for portfolio managers because it simplifies the construction of the average correlation time series amongst a large number of assets. It also has the interesting analytical implication that the variance of a diversified portfolio can be modelled in either a univariate or a simple bivariate setting by studying the process followed by its average correlation, its average volatility, and their interaction.

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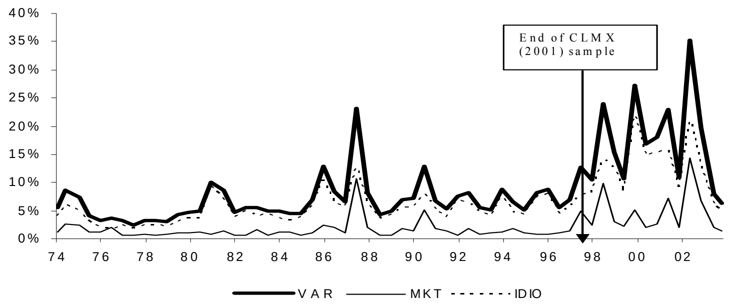
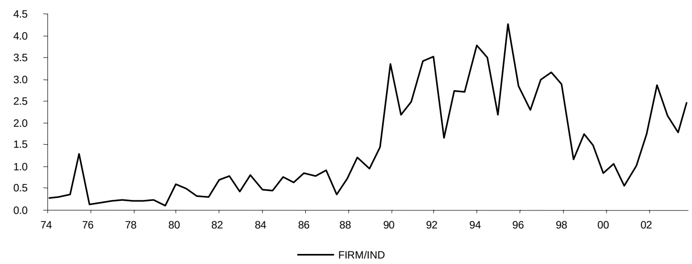
Figure 1:
Systematic and Idiosyncratic Variance
and Average Correlations of Euro area Stocks, 1974 – 2004

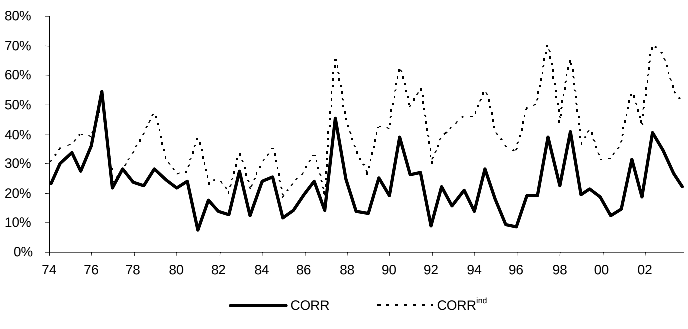
Panel A



Panel B



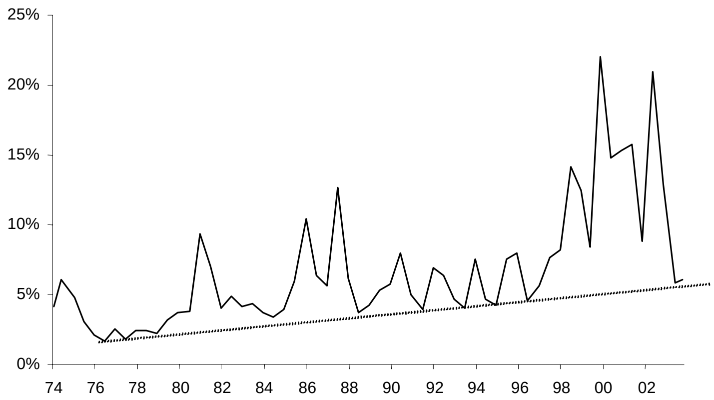
Panel C



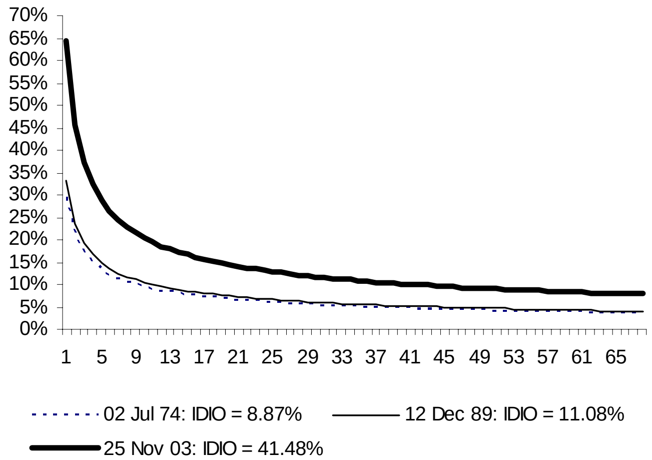
***Note*.** Panel A plots the decomposition of the total variance of the typical Euro area stock into its systematic and idiosyncratic component. Panel B plots the ratio of firm to industry level average variance. Panel C plots the value-weighted average correlation amongst the 3515 firms ($CORR_T$) and amongst the 35 Datastream Level 4 industry indices ($CORR_T^{ind}$). The sample period is 1974 - 2004.

Figure 2:
Idiosyncratic Volatility

Panel A
(Idiosyncratic Variance)

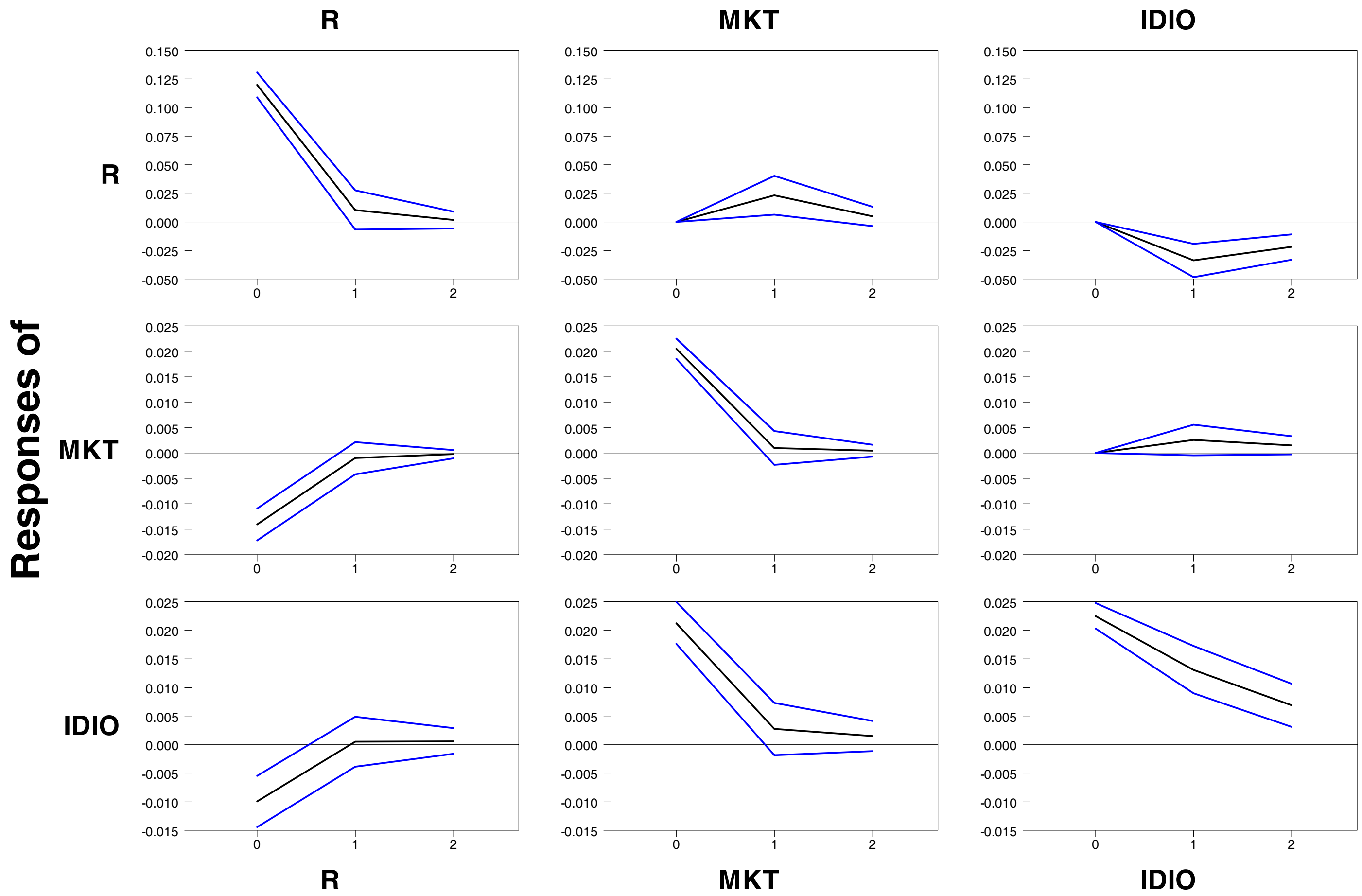


Panel B
(Residual Portfolio Idiosyncratic Volatility)



Notes. Panel A of this figure plots idiosyncratic variance over the period 1974-2004. Panel B plots the residual undiversified idiosyncratic volatility as a function of the number of stocks included in equally-weighted portfolios formed by randomly drawing from our stock sample at different points in time with varying levels of average

Figure 3:
Impulse Responses of Market Return and Variance Series



Notes. This figure plots the impulse response functions of the R_{mT}, MKT_T and $IDIO_T$ series (denoted by R, MKT and IDIO, respectively) to shocks to each other. The variance series are linearly detrended. The model is estimated under the restriction that MKT_T has no contemporaneous effect on $R_{m,T}$ and $IDIO_T$ has no contemporaneous effect on MKT_T and $R_{m,T}$. The sample period is 1974-2004. The 95% confidence bands are constructed using a Montecarlo integration procedure (the RATS code is available from the authors upon request).

Table 1
Data and Variables Definitions

Panel A

Industries – Datastream Level 4			
1	Mining	19	Retail, General
2	Oil & Gas	20	Leisure & Hotels
3	Chemicals	21	Media, Entertainment
4	Cons.. & Bldg. Mat.	22	Support Services
5	Forestry & Paper	23	Transport
6	Steel &Oth. Metals	24	Food & Drug Retailers
7	Aerospace, Defence	25	Telecom Services
8	Diversified Industrials	26	Electricity
9	Electric Equipment	27	Other Utilities
10	Eng.&Machinery	28	Inf. Tech. Hardw.
11	Auto & Parts	29	Software & Comp. Serv.
12	H'Hld GDS&Textls	30	Banks
13	Beverages	31	Insurance
14	Food PrDr./PrCr.	32	Life Assurance
15	Health	33	Investment Cos.
16	Per.Care&Hshld	34	Real Estate
17	Pharm. & Biotech	35	Spc. & Other Finance
18	Tobacco		

Panel B

Variables		
1	R_{jT}	Weekly return on industry j
2	$R_{i,jT}$	Weekly return on stock i from industry j
2	R_{mT}	Weekly return on the stock market portfolio
3	VAR_T	Average total variance of stock returns
4	MKT_T	Annualised semi-annual variance of R_{mT}
5	$IDIO_T$	$VAR_T – MKT_T$
6	VAR_T^{ind}	Average total variance of industry returns
7	IND_T	$VAR_T^{ind} – MKT_T$
6	$FIRM_T$	$VAR_T – VAR_T^{ind}$

Notes. Panel A of this table reports the industries included in our sample based on the Datastream Level 4 classification. Panel B summarizes the main variables. The market portfolio is the Datastream index for the Euro area. All returns are total returns (they include accrued dividends). All indices are "fixed history" (they are not recalculated following modifications to the index composition).

Table 2
Descriptive Correlations

	q	MKT_{T+q}	$IDIO_{T+q}$	IND_{T+q}	$FIRM_{T+q}$	$CORR_{T+q}$	$(R_m\text{-}R_f)_{T+q}$	GDP_{T+q}
MKT_T	1	0.22	0.32	0.14	0.38	0.10	0.04	-0.05
	0	1	0.74	0.55	0.70	0.61	-0.52	0.14
	-1	*0.22*	0.35	0.19	0.39	-0.06	-0.08	-0.08
	-2	0.24	0.35	0.23	0.35	0.08	-0.11	0.27
	-3	0.18	0.50	0.50	0.36	-0.12	0.10	0.10
$IDIO_T$	1	0.35	0.62	0.45	0.59	-0.01	-0.19	0.01
	0	0.74	1	0.81	0.88	0.08	-0.35	0.16
	-1	0.32	*0.62*	0.45	0.59	-0.14	-0.10	0.12
	-2	0.23	0.54	0.37	0.53	-0.11	0.03	0.29
	-3	0.34	0.60	0.49	0.53	-0.03	-0.02	0.18
IND_T	1	0.19	0.45	0.53	0.27	-0.06	-0.16	0.10
	0	0.55	0.81	1.00	0.45	0.07	-0.33	0.15
	-1	0.14	0.45	*0.53*	0.27	-0.19	-0.07	0.12
	-2	0.10	0.39	0.40	0.28	-0.10	0.13	0.23
	-3	0.26	0.40	0.44	0.26	0.07	0.14	0.10
$FIRM_T$	1	0.39	0.59	0.27	0.69	0.04	-0.17	-0.08
	0	0.70	0.88	0.45	1.00	0.06	-0.26	0.11
	-1	0.38	0.59	0.27	*0.69*	-0.07	-0.10	0.08
	-2	0.28	0.52	0.25	0.60	-0.09	-0.06	0.26
	-3	0.32	0.61	0.41	0.62	-0.10	-0.14	0.20
$CORR_T$	1	-0.06	-0.14	-0.19	-0.07	0.18	0.19	0.03
	0	0.61	0.08	0.07	0.06	1	-0.30	0.20
	-1	0.10	-0.01	-0.06	0.04	*0.18*	-0.01	-0.15
	-2	0.08	-0.03	-0.08	0.01	0.23	-0.03	0.14
	-3	0.00	0.12	0.20	0.03	0.00	0.33	0.01

Note. This table reports descriptive correlations of the variables reported in the first column with leads q of the variables reported at the top of the other columns. No series is de-trended. The proxy for the risk free rate is the semi-annual average of the 1 Month Euro-Mark. *GDP* is the GDP growth rate. The sample period is 1974-2004

Table 3
Long Run Trends

y_T	***α*** **(*t-stat.*)**	***δ*** **(*t-stat.*)**	***β₁*** **(*t-stat.*)**	***β₂*** **(*t-stat.*)**	***h-stat.*** **(*sign.*)**	***Wald-stat.*** **(*sign.*)**
			Panel A (1974-2004)			
$IDIO_T$	1.16	0.10	35.86		0.52	6.25
	(1.81)	(2.50)	(3.35)		(.470)	(.012)
$FIRM_T$	-0.42	0.11	12.79		2.30	12.90
	(-0.89)	(3.59)	(1.10)		(.130)	(.000)
IND_T	1.10	0.01	50.00		1.47	0.81
	(2.49)	(0.90)	(5.16)		(.220)	(.36)
MKT_T	0.35	0.056	5.91		0.35	5.60
	(0.69)	(2.36)	(0.57)		(.550)	(.017)
VAR_T	1.67	0.17	21.32		0.33	6.99
	(1.61)	(2.64)	(1.97)		(.560)	(.008)
$CORR_T$	20.50	-0.04	16.98		2.37	0.35
	(6.22)	(-0.59)	(1.62)		(.120)	(.553)
			Panel B (1974-1997)			
$IDIO_T$	2.31	0.05	28.69		1.58	9.34
	(3.64)	(3.05)	(3.64)		(.208)	(.002)
$FIRM_T$	-0.04	0.09	13.94		3.98	26.10
	(-0.16)	(5.10)	(1.11)		(.05)	(.000)
	-0.19	0.12	16.12	-0.28	2.77	22.81
	(-0.67)	(4.77)	(1.13)	(-2.37)	(.24)	(.000)
IND_T	2.07	-0.01	37.20		0.20	2.61
	(3.95)	(-1.61)	(3.78)		(.648)	(.105)
MKT_T	1.16	0.01	4.37		0.10	1.14
	(3.51)	(1.06)	(0.80)		(.744)	(.285)
VAR_T	3.64	0.07	18.14		0.85	7.17
	(4.02)	(2.67)	(2.22)		(.356)	(.007)
$CORR_T$	24.40	-0.17	11.04		0.43	2.68
	(5.91)	(-1.63)	(0.97)		(.509)	(.101)

Notes. This tables reports estimates of the parameters of the model of the variance and correlation series with a deterministic time trend. All the variables are defined as in the text. All the series are semi-annual (annualised). The point estimates of the α, δ, and β parameters are multiplied by 100 to improve legibility. The rightmost columns report the Durbin's *h*-statistic of the null that the dynamic model residuals are not first-order serially correlated and the Wald statistic (in both cases with the associated significance levels) of the restriction that δ is equal to zero. All the Wald and t-test statistics, standard errors and significance levels have been computed using a Newy-West adjusted variance-covariance matrix with Parzen weights to correct for error heteroschedasticity and autocorrelation. The estimated model is the following form (u_T denotes and error term):

$$y_T = \alpha + \delta T + \beta_1 y_{T-1} + \beta_2 y_{T-2} + u_T$$

Table 4
Short Run Volatility Components Dynamics
Reduced Form Model

Panel A
(Lag-length Selection)

Lags	AIC	SBC	LR	p-value
1	-23.702	-23.243*		
2	-23.558	-22.755	10.785	0.290
3	-23.900*	-22.753	35.122	0.000
4	-23.777	22.286	11.861	0.221
5	-23.674	-21.839	12.852	0.169
6	-23.586	-21.406	13.591	0.137

Panel B
(Block-exogeneity Tests)

Variable	$ln\|\Sigma_{UR}\|$	$ln\|\Sigma_R\|$	Chi-Squ.(6)	Sig.
MKT_T	-16.751	-16.525	11.730	0.068
IND_T	-16.693	-16.350	17.847	0.006
$FIRM_T$	-16.458	-16.315	7.431	0.282

Panel C
(Granger Causality Tests)

Dep. Variable	Lags	F-Statistic	Sig.
MKT_T	MKT_{T-q}	1.713	0.176
	IND_{T-q}	7.176	0.000
	$FIRM_{T-q}$	0.130	0.941
IND_T	MKT_{T-q}	2.822	0.048
	IND_{T-q}	8.812	0.000
	$FIRM_{T-q}$	1.596	0.202
$FIRM_T$	MKT_{T-q}	0.120	0.947
	IND_{T-q}	3.947	0.013
	$FIRM_{T-q}$	1.188	0.324

Notes. Panel A of this table reports, for the trivariate VAR system of MKT_T, IND_T and $FIRM_T$ the AIC, the SBC and the Likelihood Ratio (LR) test statistics. The latter is constructed as the change in the likelihood function each time the lag length is incremented. The p-value refers to the LR statistic. Panel B reports the log-determinants of the unrestricted ($ln|\Sigma_U|$) and restricted ($ln|\Sigma_R|$) 2-variable VAR systems where the variable specified in the left-most column is restricted to be block-exogenous. The Chi-Squared statistic is computed as $(T - c)(ln|\Sigma_R| - ln|\Sigma_U|)$, where $T = 61$ and c is Sims' (1980) multiplier correction. Panel C reports Granger-causality tests of the null that all the lags of a variable can be excluded from the equation of the dependent variable. All the variables are linearly de-trended. The sample period is 1974-2004.

Table 5
Short Run Volatility Components Dynamics
Structural Model

Series	St. Error	Step	MKT_T	IND_T	$FIRM_T$
MKT_T	1.95	1	100.0	0.0	0.0
		2	99.3	0.2	0.4
		3	93.6	5.7	0.6
IND_T	1.96	1	40.3	59.6	0.0
		2	32.9	65.8	1.1
		3	29.3	67.1	3.4
$FIRM_T$	2.02	1	37.5	1.1	61.2
		2	37.5	1.1	61.2
		3	37.5	2.2	60.2

Notes. This table reports, for the trivariate VAR system of MKT_T, IND_T and $FIRM_T$ the percentage of the variance of the series reported in the first column explained by the series reported at the top of each row. The variance decomposition imposes the restriction that IND_T has no contemporaneous effect on MKT_T and $FIRM_T$ has no contemporaneous effect on MKT_T and on IND_T. All the variables are linearly de-trended. The sample period is 1974-2004.

Table 6
Predicting the Market Return

Panel A
(VAR of R_{mT}, MKT_T and $IDIO_T$ - Lag-length Selection)

Lags	AIC	SBC
1	-19.298*	-18.839*
2	-19.137	-18.334
3	-19.165	-18.018
4	-19.209	-17.718
5	-19.206	-17.370
6	-19.047	-16.867

Panel B
(Market Return Predictive Regressions)

$$R_{mT} = const. + \beta_{MKT}\, MKT_{T-1} + \beta_{IDIO} IDIO_{T-1} + u_T$$

Restriction	β_{MKT}	β_{IDIO}	Adj. R^2
	1974-1997		
$\beta_{IDIO} = 0$	0.96		0.02
	(1.97)		
$\beta_{MKT} = 0$		-0.03	0.00
		(-0.06)	
	1.59	-0.78	0.03
	(2.02)	(-1.15)	
	1974-2004		
$\beta_{IDIO} = 0$	0.42		0.01
	(0.62)		
$\beta_{MKT} = 0$		-0.69	0.04
		(-2.28)	
	1.95	-1.55	0.12
	(2.67)	(-3.83)	

Notes. Panel A reports, for the trivariate VAR system of R_{mT}, MKT_T and $IDIO_T$, the AIC and the SBC. MKT_T, $IDIO_T$ are linearly de-trended. The sample period is 1974-2004. Panel B reports coefficient estimates and coefficients of determination (R^2 adjusted for degrees of freedom) of predictive regressions of Euro area market returns. In brackets are t-statistics adjusted for heteroskedasticity and auto-correlation and regressions always include a constant.

Footnotes

[1] In this study we neglect the country level, traditionally prominent in the literature on volatility and correlations in European markets (see, for example, Baele (2002) and Cappiello, Engle and Sheppard (2003)) and we focus instead on the firm, industry and aggregate level of the Euro area stock market as a whole. This choice is motivated by the considerable evidence on a substantial degree of equity market integration, which has gathered pace in Europe since the mid-1990s (Hardouvelis, Malliaropulos and Priestley (2000) and Fratzschler (2002)). Moreover, following the introduction of the Euro, equity markets of the countries that have adopted the new currency have become almost perfectly correlated, as reported by Cappiello, Engle and Sheppard (2003) and by Kearney and Potì (2005).

[2] The desire to supplement social security benefits and public pension provisions, shrinking because of a rapidly ageing population, contributes towards this shift in investment habits. See Guiso, Haliassos and Jappelli (2002) for an extensive review of the empirical evidence on increasing stock market participation in Europe and the importance of its demographic determinants.

[3] Notice that idiosyncratic residuals are not assumed to be uncorrelated across all pair of firms and industries (our reference model is the CAPM, not the APT). They are, however, orthogonal on average. In other words, since they are regressions residuals of models that include the same set of regressors, their average correlation is by construction zero.

[4] Notice that idiosyncratic residuals are not assumed to be uncorrelated across all pair of firms and industries (our reference model is the CAPM, not the APT). They are, however, orthogonal on average. In other words, since they are regressions residuals of models that include the same set of regressors, their average correlation is by construction zero.

[5] Moreover, letting $\beta_{ij,m} = \beta_{ij,j}\beta_{j,m}$ and substituting from (6) into (7), $R_{ij,t} = R_{f,t} + \beta_{ij,j}\,(R_{j,t} - R_{f,t}) + e_{ij,t}$.

[6] As implied by (4), this is an approximate decomposition. In particular, $IDIO_t$ is only approximately equal to the average variance of the CAPM idiosyncratic residuals. CLMX (2001), however, show that their difference is negligible if the cross-sectional variance of the beta coefficients is not too volatile.

[7] Datastream Level 4 Industry Indices classify Euro area stocks into 35 industries (Panel A in Table 1), thus providing enough cross-sectional variation to be able to discriminate their behaviour from sources of variation common to all the stocks (e.g. the market).

[8] The choice of using fixed history indices is necessary to ensure consistency with our average variance computation methodology and with the procedure followed by CLMX (2001).

[9] We constructed a value-weighted index of all the stocks included in our dataset for the shorter period 1st semester 1997 – 1st semester 2004 and found that its correlation with the Datastream Euro area market index was almost perfect (96.8 percent) over this period and over various sub-periods. We felt that, since we could use the excellent proxy represented by the Datastream Euro area market index (that represents at least 75% of the capitalization of the Euro area equity market), it was not necessary to construct the value-weighted index of our stocks for the entire 1974-2004 sample period, a computationally very intensive task that would have likely lead to errors.

[10] The results are almost identical, and all are available on request from the authors.

[11] The equally-weighted average total variance series (not reported but available upon request) is much higher, thus suggesting that the greater the capitalization, the smaller, on average, stock volatility. However, since the equally-weighted market variance is smaller than the value-weighted one, small-capitalization stocks are on average less correlated than large-capitalization ones.

[12] While they are more auto-correlated, they appear far from containing a unit root. To double check on whether the series are stationary, however, we also conduct Dickey-Fuller and augmented Dickey-Fuller tests and we analyse the spectral density function of the series. These results are available upon request.

[13] We include among the regressors only one lag of the regressand because, from Table 2, higher order auto-correlations do not appear to be important. We check however that the estimated residuals from this model are serially uncorrelated. To do this we use Durbin's *h* statistic because, in the presence of a lagged value of the dependent variable among the regressors, the Durbin-Watson test is biased towards

acceptance of the null of no autocorrelation. We use the generalised version of Durbin's *h*-test, developed by Godfrey and Breusch, based on a general Lagrange Multiplier test. Even though this procedure can detect higher order serial correlation, we test only test the null of no first-order residual autocorrelation.

[14] Moreover, a Likelihood Ratio test does not reject the restriction that the lag length is one instead of two (the Chi-squared statistics is 7.83 with significance level 0.550).

[15] The significance level of MKT_T is only slightly higher than the 5 percent level.

[16] We include among the regressors only one lag of the regressand because, from Table 2, higher order auto-correlations do not appear to be important. To check that the estimated residuals from this model are serially independent we use the Durbin's *h* statistic because, in the presence of a lagged value of the dependent variable among the regressors, the *DW* test is biased towards acceptance of the null of no autocorrelation. We use the generalised version of Durbin's *h*-test, developed by Godfrey and Breusch, based on a general Lagrange Multiplier test. Even though this procedure can detect higher order serial correlation, we test only test the null of no first-order residual autocorrelation.

[17] It would also have taken about the same number of stocks in the earlier 1962-1973 period.

[18] Especially in the equally-weighted case, not reported to save space but available upon request.

[19] In particular, when average idiosyncratic volatility is zero, average correlation is equal to 1 and the returns variance-covariance matrix has rank one.

[20] We do this using a Cholesky decomposition of the VAR variance-covariance matrix and the ordering of the endogenous variables $R_m \rightarrow$ MKT $\rightarrow$ IDIO.

[21] Average idiosyncratic variance, controlling for market variance, appears to proxy for the predictable portion of average correlation and market variance. This follows from the persistence of the predicted market return. Details on the latter are not reported to save space but they are available upon request.

[22] MKT_T Granger-causes IND_T, which in turn Granger-causes $FIRM_T$ and thus, ultimately, MKT_T Granger-causes $IDIO_T$ (because the latter is made up of IND_T and $FIRM_T$).

[23] Some of these ideas were already put forth and discussed by Richards (1999) in an (to my knowledge) unpublished manuscript.

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