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Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk

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Abstract

This paper examines the volatility of common stocks of the Athens Stock Exchange at the market, industry and firm level. Over the period from 1988 to 2009 there has been a considerable increase in firm-level volatility relative to the market volatility, which implies that it takes increasingly more stocks to diversify away idiosyncratic risk. All volatility series move together and they are trended upwards. All three volatility measures show a countercyclical behavior relative to GDP growth, and they all help to forecast GDP. Correlations among individual stocks have increased over the sample period, yet the explanatory power of the market model for a typical stock is still relatively low. All three volatility series rise during times of low returns. Factors that may be responsible for these findings are suggested.

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1) Previews Literature

Volatility is a key variable which permeates most financial instruments and plays a central role in many areas of finance. For example, volatility is crucially important in asset pricing models and dynamic hedging strategies as well as in the determination of options prices. From an empirical standpoint, it is therefore of utmost importance to carefully model any temporal variation in the volatility process. Over the last four decades a substantial part of the empirical finance literature has been devoted to modelling and forecasting stock prices and their volatility.

Black (1976) and Christie (1982) were the first to find that individual firms' stock return volatility rises after stock prices fall. In other words, they found a negative relationship between changes in volatility and stock returns. Two of the most popular explanations for this well-known relation are leverage effect and time varying risk-premia. **Black (1976)** argued that a fall in a firm's stock value relative to the market value of its debt causes a rise in its debt-equity ratio and increases its stock volatility, or simply the leverage effect points that a firm's stock price decline raises the firm's financial leverage, resulting in an increase in the volatility of equity.

Christie (1982) examined the relation between the variance of equity returns and several explanatory variables and found that equity variances have a strong positive association with both financial leverage and, contrary to the predictions of the options literature, interest rates. To a substantial degree, the negative elasticity of variance with respect to the value of equity that is part of the market folklore is found to be attributable to financial leverage. A maximum likelihood estimator has been developed for this elasticity that is substantially more efficient than extant estimation procedures.

Duffee (1995) argued that the negative relation between individual firms' stock return volatility and stock prices is largely due to a positive contemporaneous relation between firm stock returns and firm stock return volatility. The relation between firm returns and one-period-ahead volatility is much weaker. It is positive at the daily frequency and negative at the monthly frequency. These relations largely explain the finding of Black, Christie, and Cheung and Ng that firm stock returns and changes in volatility are negatively correlated. The positive relation between firm stock returns and firm stock return volatility is strongest for both small firms and firms with little financial leverage. Smaller firms exhibit a greater positive contemporaneous relation between returns and volatility than do larger firms. In addition, this contemporaneous relation is much greater for firms that are eventually delisted. Therefore, a survivorship bias has an important effect on the results of earlier empirical work. The behaviour of returns near the time that a firm is delisted is responsible for much of the difference between delisted firms and survivors. At the aggregate level, the sign of this contemporaneous relation is reversed.

Merton (1980) analysed three models of equilibrium expected market returns which reflect the dependence of the market return on the interest rate. He used estimation procedures which incorporate the restriction that equilibrium expected excess returns on the market must be positive and he applied them to return data for the period 1926-1978. The principal conclusions are that in estimating models of the expected market return, the non-negativity restriction of the expected excess return should be explicitly included as part of the specification, and estimators which use realized returns should be adjusted for heteroscedasticity. He stressed that variances of realized stock returns are large in relation to the likely variance of expected returns and this low 'signal-to-noise' ratio makes it difficult to detect variation in expected stock returns. He also noted that in a model of capital market equilibrium where a 'representative investor' has constant relative risk aversion, there are conditions under which the expected market risk premium will be approximately proportional to the ex ante variance of the market return.

Poterba and Summers (1986) evaluated the changing risk premium hypothesis and examined the influence of changing stock market volatility on the level of stock prices. By using a two-step procedure (the estimates were based on both actual and ex ante volatilities), they argued that shocks to the U.S. stock market are only short-lived, with a half-life of less than six months. For multiperiod assets, like stocks, shocks have to persist for a long time for a time-varying risk premium to be able to explain the large fluctuations observed in the stock market. If volatility changes are only transitory, no significant adjustments to the risk premium will be made by the market, and therefore no significant changes in the discount factor or the price of a stock as determined by the net present value of the future expected cash flow will occur. As a result, they rejected Malkiel's (1979) and Pindyck's (1984) hypothesis that shocks to the investment environment during the early and mid-seventies were the most important factor in explaining the market plunge during the mid-seventies. However, on using a GARCH(1, 11-M model, Chou (1988) reports a very different result on the persistence of volatility, with the average half-life for volatility shocks being about one year, consistent with the changing risk premium hypothesis. These markedly different findings are most likely due to the difference in estimation methodology.

French, Schwert, and Stambaugh (1987) examined the relation between stock returns and stock market volatility. They used daily returns to the Standard & Poor's (S&P) composite portfolio to estimate monthly volatility from 1928 to 1984 and they found evidence that the expected market risk premium on common stocks is positively related to the predictable volatility of stock returns. There is also a strong negative relation between the unpredictable component of stock market volatility and excess holding period returns. If expected risk premiums are positively related to predictable volatility, then a positive unexpected change in volatility (and an upward revision in predicted volatility) increases future expected risk premiums and lowers current stock prices. The magnitude of the negative relation between contemporaneous returns and changes in volatility is too large to be attributed solely to the effects of leverage discussed by Black (1976) and Christie (1982) so they interpreted this negative relation as evidence of a positive relation between expected risk premiums and ex ante volatility.

Schwert (1989) analyzed the relation of stock volatility with real and nominal macroeconomic volatility, economic activity, financial leverage, and stock trading activity using monthly data from 1857 to 1987. An important fact, previously noted by Officer (1973), is that stock return variability was unusually high during the 1929-1939 Great Depression. While aggregate leverage is significantly correlated with volatility, it explains a relatively small part of the movements in stock volatility. The amplitude of the fluctuations in aggregate stock volatility is difficult to explain using simple models of stock valuation, especially during the Great Depression.

Schwert's paper analyzes many factors related to stock volatility, but it does not test for causes of stock price volatility. Rather, the hypotheses involve associations between stock volatility and other variables. For example, the analysis of the volatility of bond returns, inflation rates, money growth, and industrial production growth, along with stock volatility, seeks to determine whether these aggregate volatility measures change together through time. In most general equilibrium models, fundamental factors such as consumption and production opportunities and preferences would determine all these parameters (e.g., Abel (1988)). Nevertheless, the process of characterizing stylized facts about economic volatility helps to define the set of interesting questions, leading to tractable theoretical models.

Schwert and Seguin (1990) showed that heteroskedasticity in stock returns is a pervasive phenomenon. Using five portfolios of stocks sorted by firm size, they showed that there is a common "market" factor in the heteroskedasticity of monthly stock returns. They used daily returns to the Standard & Poor's composite portfolio to measure aggregate monthly stock volatility. The volatility of monthly returns to the size portfolios is highly related to autoregressive predictions of this market volatility factor. They also documented implications of heteroskedasticity and time-varying betas for tests of the capital asset pricing model (CAPM) (they showed how tests of the capital asset pricing model are affected by a simple weighted least squares heteroskedasticity correction). Accounting for heteroskedasticity increases the evidence that risk-adjusted returns are related to firm size. They also estimated a constant correlation model. Portfolio volatilities predicted by this model are similar to those predicted by more complex multivariate generalized-autoregressive-conditional-heteroskedasticity (GARCH) procedures.

Andersen et al. (1999) constructed model-free estimates of daily exchange rate volatility and correlation using high-frequency data on Deutschemark and Yen returns against the dollar. In addition to being model-free, their estimates were also approximately free of measurement error under general conditions, which helped them treat the exchange rate volatilities and correlations as observed rather than latent. By doing so, they characterized their joint distribution, both unconditionally and conditionally. Noteworthy results include a simple normality-inducing volatility transformation, high contemporaneous correlation across volatilities, high correlation between correlation and volatilities, pronounced and highly persistent temporal variation in both volatility and correlation, clear evidence of long-memory dynamics in both volatilities and correlation, and remarkably precise scaling laws under temporal aggregation.

Economists have built increasingly sophisticated statistical models to capture the time variation in volatility, from simple filters such as the rolling standard deviation used by Officer (1973) to parametric ARCH or stochastic-volatility models.

Robert Officer (1973) used the method of rolling standard deviation to explain the cause of the decline in the variability of the market factor over the period 1926 to 1960. Using data from a number of indexes in order to represent the market factor (Dow-Jones Industrial Average (later Dow-Jones), NYSE, Fisher Arithmetic Index (later Fisher) and Scholes Daily Price File), Officer created a series of rolling standard deviations. The series was obtained by estimating the standard deviation of the market factor for the first 12 months of data, then the first month was dropped and the thirteenth month added to obtain a new estimate. Each estimate was centered at its approximate midpoint, for example, 6 months. This procedure was followed until the last month of data was included in an estimate, so that the last estimate of the standard deviation, containing 12 observations of the market factor, covered the period May 1968-June 1969. The main conclusion of the study was that the decline in variability observed by other studies is better described as a return to the "normal" level of variability that existed before the great depression of the 1930s.

Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model in an attempt to generalize the assumption of traditional econometric models of a constant one-period forecast variance. While it had been recognized for quite some time that the uncertainty of speculative prices, as measured by the variances and covariances, are changing through time (Mandelbrot (1963), Fama (1965)), it was not until the 80's that applied researchers in financial and monetary economics started explicitly modelling time variation in second- or higher-order moments. Since the introduction of the ARCH model several hundred research papers applying this modeling strategy to financial time series data have appeared

Bollerslev, Chou, and Kroner (1992) gave an overview of some of the developments in the formulation of ARCH models and a survey of the numerous empirical applications using financial data.

Hentschel (1995) developed in his paper a parametric family of models of generalized autoregressive heteroskedasticity (GARCH). The family nests the most popular symmetric and asymmetric GARCH models, thereby highlighting the relation between the models and their treatment of asymmetry. Furthermore, the structure permits nested tests of different types of asymmetry and functional forms.

Much of modern finance theory is cast in terms of continuous time stochastic differential equations, while virtually all financial time series are available at discrete time intervals only. This apparent gap between the empirically motivated ARCH models and the underlying economic theory is the focus of **Nelson (1990b)**, who shows that the discrete time GARCH(1, 1) model converges to a continuous time diffusion model as the sampling interval gets arbitrarily small. Along similar lines, **Nelson (1992)** showed that if the true model is a diffusion model with no jumps, then the discrete time variances are consistently estimated by a weighted average of past residuals as in the GARCH(1, 1) formulation.

Aggregate volatility (the volatility experienced by holders of aggregate index funds) is very important in almost any theory of risk and return. But the aggregate market return is only one component of the return to an individual stock. Industry-level and idiosyncratic firm-level shocks are also important components of individual stock returns, for the following reasons.

First, many investors have large holdings of individual stocks. They may fail to diversify in the manner recommended by financial theory, or their holdings may be restricted by corporate compensation policies. These investors are affected by shifts in industry-level and idiosyncratic volatility, just as much as by shifts in market volatility.

Second, some investors who do try to diversify do so by holding a portfolio of 20 or 30 stocks. Conventional wisdom holds that such a portfolio closely approximates a well-diversified portfolio in which all idiosyncratic risk is eliminated. However, the adequacy of this approximation depends on the level of idiosyncratic volatility in the stocks making up the portfolio.

Third, arbitrageurs who trade to exploit the mispricing of an individual stock (as opposed to a pattern of mispricing across many stocks) face risks that are related to idiosyncratic return volatility, not aggregate market volatility. Larger pricing errors are possible when idiosyncratic firm-level volatility is high. **Shleifer and Vishny (1997)** described the workings of markets in which specialized arbitrageurs invest the capital of outside investors, and where investors use arbitrageurs' performance to ascertain their ability to invest profitably. They showed that such specialized performance-based arbitrage may not be fully effective in bringing security prices to fundamental values, especially in extreme circumstances. More generally, specialized, professional arbitrageurs may avoid extremely volatile "arbitrage" positions. Although such positions offer attractive average returns, the volatility also exposes arbitrageurs to risk of losses and the need to liquidate the portfolio under pressure from the investors in the fund. The avoidance of volatility by arbitrageurs also suggests a different approach to understanding persistent excess returns in security prices. Specifically, one would expect anomalies to reflect not some exposure of securities to difficult-to-measure macroeconomic risks, but rather, high idiosyncratic re-turn volatility of arbitrage trades needed to eliminate the anomalies. In sum, this more realistic view of arbitrage can shed light on a variety of observations in securities markets that are difficult to understand in more conventional models.

Fourth, firm-level volatility is important in event studies. Events affect individual stocks, and the statistical significance of abnormal event-related returns is determined by the volatility of individual stock re-turns relative to the market or industry (Campbell et al. (1997)).

Finally, the price of an option on an individual stock depends on the total volatility of the stock return, including industry-level and idiosyncratic volatility as well as market volatility.

Disaggregated volatility measures also have important relations with aggregate output in some macroeconomic models. Models of sectoral reallocation, following Lilien (1982), imply that an increase in the industry-level volatility of productivity growth may reduce output as resources are diverted from production to costly reallocation across sectors. Models of "cleansing recessions" (Caballero and Hammour (1994), Eden and Jovanovic (1994)) emphasize similar effects at the level of the firm. An exogenous increase in the arrival rate of information about management quality may temporarily reduce output as resources are reallocated from low-quality to high-quality firms; alternatively, a recession that occurs for some other reason may re-veal information about management quality and increase the pace of real-location across firms.

Lilien (1982) characterized a substantial fraction of cyclical unemployment as fluctuations of the "frictional" or "natural" rate than as deviations from some relatively stable natural rate. Shifts of employment demand between sectors of the economy necessitate continuous labor reallocation. Since it takes time for workers to find new jobs, some unemployment is unavoidable. His paper presents evidence that most of the unemployment fluctuations of the seventies were induced by unusual structural shifts within the U.S. economy. Simple time-series models of layoffs and unemployment are constructed that include a measure of structural shifts within the labor market. These models are estimated and a derived natural rate series is constructed.

Caballero and Hammour (1994) investigated industry response to cyclical variations in demand. Production units that embody the newest process and product innovations are continuously being created, and outdated units are being destroyed. Although outdated units are the most likely to turn unprofitable and be scrapped in a recession, they can be "insulated" from the fall in demand by a reduction in creation. The structure of adjustment costs plays a determinant role in the responsiveness of those two margins. The calibrated model matches the relative volatilities of the observed manufacturing job creation and destruction series, and their asymmetries over the cycle.

Eden and Jovanovic (1994) argued that the degree of asymmetry in information is a variable that can influence stock prices and that some of the volatility of stock prices in excess of fundamentals result from fluctuations in the amount of public information over time. Their model assumes that dividends and consumption are constant in the aggregate but that there are good firms and bad firms whose identity may be unknown to the public, as in Akerlof's "lemons" problem. In that case, the collective valuation of the constant dividend stream depends in the degree of informational asymmetry. They showed that endogenous fluctuations in public information can lead to fluctuations in the stock market value of all firms even though aggregate dividends and aggregate consumption are constant. The market value equals the value buyers place on aggregate future consumption. Market value is higher, and the rate of return is lower when information is less precise, because in this case uninformed buyers get less future consumption and at the margin they value it more.

There is surprisingly little empirical research on volatility at the level of the industry or firm. A few papers use disaggregated data to study the "leverage" effect, the tendency for volatility to rise following negative returns (Black (1976), Christie (1982), Duffee (1995)). Engle and Lee (1993) use a factor ARCH model to study the persistence properties of firm-level volatility for a few large stocks. Some researchers have used stock market data to test macroeconomic models of reallocation across industries or firms (Loun-gani, Rush, and Tave (1990), Bernard and Steigerwald (1993), Brainard and Cutler (1993)), or to explore the firm-level relation between volatility and investment (Leahy and Whited (1996)). Roll (1992) and Heston and Rouwen-horst (1994) decompose world market volatility into industry and country-specific effects and study the implications for international diversification. Bekaert and Harvey (1997) construct a measure of individual firm dispersion to study the volatility in emerging markets. More specifically:

Loungani, Rush, and Tave (1990), tested the sectoral shifts hypothesis, advanced by Lilien (1982) and Davis (1987), which suggests that unemployment is, in part, the result of resources being reallocated from declining to expanding sectors of the economy. Using US data from 1931 to 1987 and by constructing an index measuring the dispersion among stock prices from different industries, they found that lagged values of this index significantly affect unemployment and that the stock market dispersion index is less contaminated by aggregate demand influences than Lilien's employment dispersion index.

Brainard and Cutler (1993) developed a new measure of reallocation shocks based on the variance of industry stock market excess returns to assess the contribution of sectoral reallocation to unemployment in the postwar U. S. economy. They used the Beveridge Curve relationship to establish that this series isolates reallocation shocks. Reallocation shocks are found to explain only a moderate share of the fluctuations in aggregate unemployment on average over the period. However, reallocation accounted for a substantial share of increases in unemployment in several episodes, particularly the mid-1970s. Reallocation shocks also account for a larger share of fluctuations in unemployment of longer durations than of shorter durations. Their findings confirm that cross-section volatility is reallocational as opposed to cyclical in nature.

Leahy and Whited (1996) tried to establish some stylized facts concerning the relationship between uncertainty and investment and to evaluate the various theories in light of these results. Their results indicate that an increase in uncertainty decreases investment, primarily through its effect on marginal product of capita . In addition, they found no evidence for a positive effect via the channel of the convexity of the marginal product of capital or for the presence of a CAPM-based effect of risk, leaving irreversible investment as the most likely explanation for the observed correlation between investment and uncertainty.

Roll (1992) compared stock price indices across countries in an attempt to explain why they exhibit such disparate behavior. There are large differences in volatilities across markets, even after nominal and inflation differences are taken into account by converting returns into common currency units at prevailing exchange rates. Roll documented three separate explanatory influences. First, part of the behavior can be attributed to a technical aspect of index construction; some indices are more diversified than others. Second, each country's industrial structure plays a major role in explaining stock price behavior. Roll reported that, on average across countries, global industry factors, computed strictly from returns in other countries, explain about 40% of the variance of country index returns Third, for the majority of countries, a portion of national equity index behavior can be ascribed to exchange rate behavior. Exchange rates explain a significant portion of common currency denominated national index returns, although the amount explained by exchange rates is less than the amount explained by industrial structure for most countries.

Heston and Rouwenhorst (1994) examined the influence of industrial structure on the cross-sectional volatility and correlation structure of country index returns for 12 European countries between 1978 and 1992. By separately measuring country and industry effects, they were able to examine why country stock indices differ in volatility and why correlations between stock indices are so low. Country indices are generally more volatile and less highly intercorrelated than industry indices. This might simply be explained by the fact that industries are more diversified across countries than countries are diversified across industries. They found that industrial structure explains very little of the cross-sectional difference in country return volatility, and that the low correlation between country indices is almost completely due to country-specific sources of return variation. Diversification across countries within an industry is a much more effective tool for risk reduction than industry diversification within a country.

Bekaert and Harvey (1997) constructed a measure of individual firm dispersion to study the volatility in emerging markets. Understanding volatility in emerging capital markets is important for determining the cost of capital and for evaluating direct investment and asset allocation decisions. The goal of their paper was to broaden the understanding of the behavior of volatility in emerging equity markets.

They provided an approach that allows the relative importance of world and local information to change through time in both the expected returns and conditional variance processes. Their time-series and cross-sectional models analyze the reasons that volatility is different across emerging markets, particularly with respect to the timing of capital market reforms. They found that capital market liberalizations often increase the correlation between local market returns and the world market but do not drive up local market volatility.

Systematic, market-wide volatility is very important to the holders of well-diversified portfolios. However, both total and idiosyncratic volatility are important as well for incompletely diversified investors. In this vein,

Campbell, Lettau, Malkiel and Xu (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, Campbell, Lettau, Malkiel and Xu (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 Campbell, Lettau, Malkiel and Xu (2001) on United States equity markets also feature in the equity markets of other countries. In this paper, we build on their methodology to study the aggregate firm level, industry level and systematic volatility of the 255 stocks listed on the Athens Stock Exchange over the period from 1988 to 2009. We use a decomposition of volatility that does not require the estimation of covariances or betas for industries or firms and use daily data within each month to construct sample variances for that month. A substantial literature has questioned the findings of Campbell, Lettau, Malkiel and Xu (2001) about an upwards trend in volatility and attribute it to a sample specific finding. We embrace this view and proceed with our study.

We find that Greek stocks have indeed become more volatile, and that idiosyncratic risk is the largest component of this volatility. Therefore, the potential benefit of diversification strategies is substantial. However, it now takes more stocks to diversify away any given amount of portfolio risk. Firm-level volatility displays the largest and significant positive trend. This finding is robust to variations in the number of firms in the sample, or using weekly or monthly returns instead of daily returns to estimate volatility. The low average stock correlation of about 26 percent implies a correspondingly low explanatory power for the market model of 7 percent, calculated as the square of 26 percent. However, contrary to Campbell, Lettau, Malkiel and Xu (2001), we find that correlations among individual stocks, and consequently the explanatory power of the market model for a typical stock, have increased over the sample period. Granger-causality tests suggest that firm-level volatility helps to predict both market and industry level volatility, similar to the findings of Campbell, Lettau, Malkiel and Xu (2001). We also find that market returns are positively related to lagged market and industry level variance and negatively related to lagged firm level variance. All three volatility measures increase in economic downturns and help to forecast GDP growth.

The paper is structured as follows. In Section 2 we present the basic decomposition of volatility into market, industry and firm level components, according to the methodology of Campbell, Lettau, Malkiel and Xu (2001). In Section 3, we measure trends in volatility. In section 4, we examine correlations across individual stocks, the explanatory power of the market model for individual stocks and the number of stocks needed to achieve a satisfactory level of diversification. In Section 5, we study the lead-lag relations of the three volatility measures and their cyclical behavior. In Section 6, we discuss some possible explanations for the observed long-run trends in individual stocks volatilities. Finally, Section 7 presents some concluding comments.

2. Estimation of Volatility Components

2.1 Volatility Decomposition

In this paper we will follow the volatility decomposition proposed by Campbell, Lettau, Malkiel and Xu (2001). We use daily returns from the Thompson Datastream for the period January 1988 to October 2009. Our firm-level data comprises the total returns and market capitalization for the 255 Stocks listed in the Athens Stock Exchange during the sample period.

We use unconditional estimators of variances based on sums and averages of return innovation squares and cross products. Many researchers have used this approach because of its simplicity. The implicit assumption of 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.

The return on a "typical" stock is decomposed into three components: the market-wide return, an industry-specific residual, and a firm-specific residual. The goal is to construct time series of volatility measures of the three components for a typical firm based on this return decomposition and to define volatility measures that sum to the total return volatility of a typical firm, without having to keep track of covariances and without having to estimate betas for firms or industries.

Let i be the notation for industries and j the notation for individual firms. R_{jit} is the excess return (over the risk-free rate) of a firm j that belongs to industry i in period t. Finally, let w_{jit} be the weight of firm j in industry i.

The excess return of industry i in period t is given by

$$R_{it} = \Sigma_{j\in i} w_{jit} R_{jit}$$

The same methodology is used for industries. If *wit* is the weight of industry *i* in the total market, the excess market return is

$$R_{mt} = \Sigma_i w_{it} R_{it}$$

The next step is the decomposition of firm and industry returns into the three components.

According to the CAPM the return of industry *i* is:

$$R_{it} = \beta_{\iota\mu} R_{mt} + \bar{\varepsilon}_{it} \qquad (1)$$

Where β_{im} is the beta for industry *i* with respect to the market return and $\tilde{\varepsilon}_{it}$ is the industry-specific residual, while the return of individual firm *j* is:

$$R_{jit} = \beta_{ji} R_{it} + \tilde{\eta}_{jit} = \beta_{ji} \beta_{im} R_{mt} + \beta_{ji} \tilde{\varepsilon}_{it} + \tilde{\eta}_{jit}$$

(2)

Where β_{ji} is the beta of firm *j* in industry *i* with respect to its industry, and $\tilde{\eta}_{jit}$ is the firm-specific residual.

$\tilde{\eta}_{jit}$ is orthogonal by construction to the industry return R_{it}. Therefore, it is also orthogonal to the components R_{mt} and $\tilde{\varepsilon}_{it}$:

$$\beta_{jm} = \beta_{ji} \beta_{im}$$

The weighted sums of the different betas equal unity:

$$\sum_i w_{it} \beta_{im} = 1 \ , \qquad \sum_{j \in i} w_{jit} \beta_{jim} = 1 \qquad (3)$$

The CAPM decomposition (1) and (2) guarantees that the different components of a firm's return are orthogonal to one another. That means that all covariance terms are zero, which makes the computation of the industry and firm variance easier:

$$Var(R_{it}) = \beta_{im}^2 Var(R_{mt}) + Var(\tilde{\varepsilon}_{it}) \tag{4}$$

$$Var(R_{jit}) = \beta_{jm}^2 Var(R_{mt}) + \beta_{ji}^2 Var(\tilde{\varepsilon}_{it}) + Var(\tilde{\eta}_{jit}) \tag{5}$$

The problem with this decomposition, however, is that it requires knowledge of firm --specific betas that are difficult to estimate and may well be unstable over time. For this reason a simplified model that does not require any information about betas is necessary.

The simplified industry return decomposition that drops the industry beta coefficient β_{im} from equation (1) is:

$$R_{it} = R_{mt} + \varepsilon_{it} \tag{6}$$

Equation (6) defines εit as the difference between the industry return R_{it} and the market return R_{mt}. Campbell et al. (1997, Chapter 4, p. 156) refer to equation (6) as a "market-adjusted-return model" in contrast to the market model of equation (1).

Comparing equations (1) and (6), we have

$$\varepsilon_{it} = \tilde{\varepsilon}_{it} + (\beta_{im} - 1)R_{mt} \tag{7}$$

The market-adjusted-return residual ε_{it} equals the CAPM residual of equation (4) only if the industry beta β_{im}=1 or the market return $R_{mt} = 0$.

The drawback of the decomposition (6) is that R_{mt} and ε_{it} are not orthogonal, and the covariance between them remains when computing the variance of the industry return yields :

$$\begin{aligned} Var(R_{it}) &= Var(R_{mt}) + Var(\varepsilon_{it}) + 2Cov(R_{mt}, \varepsilon_{it}) = \\ &= Var(R_{mt}) + Var(\varepsilon_{it}) + 2(\beta_{im} - 1)Var(R_{mt}) \end{aligned} \tag{8}$$

In equation (8) the covariance term once again introduces the industry beta into the variance decomposition.

Although the variance of an individual industry return contains covariance terms, the weighted average of variances across industries is free of the individual covariances:

$$\sum_i w_{it} Var(R_{it}) = Var(R_{mt}) + \sum_i w_{it} Var(\varepsilon_{it}) = \sigma^2_{mt} + \sigma^2_{\varepsilon t} \tag{9}$$

where $\sigma^2_{mt} \equiv Var(R_{mt})$ and $\sigma^2_{\varepsilon t} \equiv \Sigma_i w_{it} Var(\varepsilon_{it})$. The terms involving betas aggregate out because from equation (3) $\Sigma_i w_{it} \beta_{im} = 1$. Therefore we can use the residual ε_{it} in equation (6) to construct a measure of average industry- level volatility that does not require any estimation of betas. The weighted average $\Sigma_i w_{it} Var(R_{it})$ can be interpreted as the expected volatility of a randomly drawn industry (with the probability of drawing industry *i* equal to its weight wit).

The same fashion is used for individual firm returns. A firm return decomposition that drops β_{ji} from equation (2) is:

$$R_{jit} = R_{it} + \eta_{jit} \tag{10}$$

where η_{jit} it is defined as

$$\eta_{jit} = \tilde{\eta}_{jit} + (\beta_{ji} - 1)R_{it} \tag{11}$$

The variance of the firm return is

$$Var(R_{jit}) = Var(R_{it}) + Var(\eta_{jit}) + 2Cov(R_{it}, \eta_{jit}) = \\ = Var(R_{it}) + Var(\eta_{jit}) + 2(\beta_{ji} - 1)Var(R_{it}) \tag{12}$$

The weighted average of firm variances in industry i is therefore

$$\sum_{j \in i} w_{jit} Var(R_{jit}) = Var(R_{it}) + \sigma^2_{\eta it} \tag{13}$$

where $\sigma^2_{\eta it} \equiv \Sigma_{j \in i} w_{jit} Var(\eta_{jit})$ is the weighted average of firm-level volatility in industry i.

If equation (9) is used to compute the weighted average across industries, we can have a beta-free variance decomposition:

$$\begin{aligned} \sum_i w_{it} \sum_{j \in i} w_{jit} Var(R_{jit}) &= \sum_i w_{it} Var(R_{it}) + \sum_i w_{it} \sum_{j \in i} w_{jit} Var(\eta_{jit}) = \\ &= Var(R_{mt}) + \sum_i w_{it} Var(\varepsilon_{it}) + \sum_i w_{it} \sigma^2_{\eta it} = \\ &= \sigma^2_{mt} + \sigma^2_{\varepsilon t} + \sigma^2_{\eta t} \end{aligned} \tag{14}$$

Where $\sigma^2_{\eta t} \equiv \Sigma_i w_{it} \sigma^2_{\eta it} = \Sigma_i w_{it} \Sigma_{j \in i} w_{jit} Var(\eta_{jit})$ is the weighted average of firm-level volatility across all firms. As in the case of industry returns, the simplified decomposition of firm returns (10) yields a measure of average firm-level volatility that does not require estimation of betas.

When we use the CAPM in industry and firm level (epuations 4 and 5) we find that:

$$\sigma^2_{\varepsilon t} = \tilde{\sigma}^2_{\varepsilon t} + CSV(\beta_{im}) \sigma^2_{mt} \tag{15}$$

where $\tilde{\sigma}^2_{\varepsilon y} \equiv \Sigma_i w_{it} Var(\tilde{\varepsilon}_{it})$ is the average variance of the CAPM industry shock fit, and $CSV_t(\beta_{im}) \equiv \Sigma_i w_{it}(\beta_{im} - 1)^2$ is the cross-sectional variance of industry betas across industries. Similarly,

$$\sigma^2_{\eta t} = \tilde{\sigma}^2_{\eta t} + CSV_t(\beta_{im})\sigma^2_{mt} \tag{16}$$

where $\tilde{\sigma}^2_{\eta t} \equiv \Sigma_i w_{it} \Sigma_{j \in i} w_{jit} Var(\tilde{\eta}_{jit})$, $CSV_t(\beta_{jm}) \equiv \Sigma_i w_{it} \Sigma_j w_{jit}(\beta_{jm} - 1)^2$ is the cross-sectional variance of firm betas on the market across all firms in all industries, and $CSV_t(\beta_{ji}) \equiv \Sigma_i w_{it} \Sigma_j w_{jit}(\beta_{ji} - 1)^2$ is the cross-sectional variance of firm betas on industry shocks across all firms in all industries.

Equations (15) and (16) show that cross-sectional variation in betas can produce common movements in our variance components σ^2_{mt}, $\sigma^2_{\varepsilon t}$ and $\sigma^2_{\eta t}$ even if the CAPM variance components $\tilde{\sigma}^2_{\varepsilon t}$ and $\tilde{\sigma}^2_{\eta t}$ do not move at all with the market variance σ^2_{mt}.

2.2 Estimation of volatility components

The following procedure is used to estimate the three volatility components in equation (14). Let *s* denote the interval at which returns are measured. We will use daily returns for most estimates but also consider weekly and monthly returns to check the sensitivity of our results with respect to the return interval. Using returns of interval *s*, we construct volatility estimates at intervals *t*. Unless otherwise noted, *t* refers to months. To estimate the variance components in equation (14) we use time-series variation of the individual return components within each period *t*. The sample volatility of the market return in period *t*, which we denote from now on as MKTt, is computed as

$$MKT_t = \hat{\sigma}^2_{mt} = \sum_{s \in t} (R_{ms} - \mu_m)^2 \qquad (17)$$

where μ_m is defined as the mean of the market return Rms over the sample. we construct the market returns as the weighted average using all firms in the sample in a given period. The weights are based on market capitalization. For weights in period *t* we use the market capitalization of a firm in period *t* - 1 and take the weights as constant within period *t*.

For volatility in industry *i*, we sum the squares of the industry-specific residual in equation (6) within a period *t*:

$$\hat{\sigma}^2_{\varepsilon it} = \sum_{s \in t} \varepsilon^2_{is} \qquad (18)$$

We have to average over industries to ensure that the covariances of individual industries cancel out. This yields the following measure for average industry volatility

$$IND_t = \sum_i w_{it} \hat{\sigma}^2_{\varepsilon it} \qquad (19)$$

Estimating firm-specific volatility is done in a similar way. First we sum the squares of the firm-specific residual in equation (10) for each firm in the sample:

$$\hat{\sigma}^2_{\eta jit} = \sum_{s \in t} \eta^2_{jis} \tag{20}$$

Next, we compute the weighted average of the firm-specific volatilities within an industry:

$$\hat{\sigma}^2_{\eta it} = \sum_{j \in i} w_{jit} \hat{\sigma}^2_{\eta jit} \tag{21}$$

And lastly we average over industries to obtain a measure of average firm- level volatility

$$FIRM_t = \sum_{i} w_{it} \hat{\sigma}^2_{\eta it} \tag{22}$$

As with industry volatility, this procedure ensures that the firm-specific covariances cancel out.

3. Measuring Trends in Volatility

3.1 Graphical Analysis

In this section we examine whether the volatility of the stock market has increased over time. We build on the methodology of Campbell, Lettau, Malkiel and Xu (2001) to study the aggregate firm level, industry level and systematic volatility of 255 stocks listed on the Athens Stock Exchange.

In figure 1 we plot the volatility of the market returns for the period 1/1/1988-30/10/2009. We use data from the Thompson Datastream. For consistency with Schwert (1989) and Campbell, Lettau, Malkiel and Xu (2001), we compute monthly standard deviations based on daily data. The figure shows huge spikes in volatility during the period 1998-2002, at the time of the stock market bubble, as well as in 2006-2008. In general, however, there is no discernible trend in market volatility. The average standard deviation for the sample period is 0,000000332.

Figures 2 to 4 plot the three variance components, estimated monthly, using daily data over the period 1988 to 2009: market volatility MKT, industry-level volatility IND, and firm-level volatility FIRM. The top panels show the raw monthly time series and the bottom panels plot a lagged moving average of order 12. All the vertical scales differ in each figure and cannot be compared with Figure 1, because they are now plotting variances rather than a standard deviation.

Figure 2 reveals that market volatility starts off relatively low and tends to rise towards the end of the sample period. Comparing the monthly series with the smoothes version in the bottom panel suggests that market volatility has a slow-moving component along with a fair amount of high-frequency noise. Market volatility was particularly high during 1998-2002 and 2006-2008. The stock market bubble in 1999 caused an enormous spike in market volatility. The value of MKT in April 2000 is 0,00763 and in October 2008 it is 0,00752.

Next, we will examine the behavior of industry volatility IND plotted in Figure 3. Compared with market volatility, industry volatility is higher on average.

There is a slow-moving component and some high-frequency noise. IND was particularly high during 1998-2000 and 2006-2008. In November 1999 IND was 0,037 and in May 2007 it was 0,015.

Figure 4 plots firm-level volatility FIRM. FIRM was particularly high during 1999-2000 and 2005-2008. In November 1999 FIRM was 0,0235 and in October 2007 it was 0,021. However, during 1999-2000 IND was higher than FIRM. An important characteristic of FIRM is that it trends up over the sample (particularly from 1998 and thereafter) in a more clear vision than MKT and IND. This indicates that the stock market has become more volatile on a firm-level basis, particularly since 2001.

In figure 5 we look at the three volatility components together, as well as the total volatility computed from equation (14). It is clear that the different volatility measures tend to move together. More specifically, Figure 5 reveals that total, idiosyncratic (IND and FIRM) and market variance start off relatively low, they rise during 1998-2001, with a peak at 1999, at the time of the stock market "bubble" in the Athens Stock Exchange, and again during 2004-2008. The tendency to rise is more pronounced for idiosyncratic variance and its firm-level component. Idiosyncratic variance is the largest component of total variance.

These findings are broadly in line with those reported by Campbell, Lettau, Malkiel and Xu (2001) for United States stocks. Contrary to Campbell, Lettau, Malkiel and Xu (2001), however, industry level volatility is the largest component of idiosyncratic volatility during 1998-2000, as shown in Figure 5. The reason for this is the limited-cross sectional dispersion within industries due to the small number of listed stocks. Unlike in the most 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. In the Athens Stock Exchange the average number of stocks listed during the 1998-2000 period was 160, whereas during the 2004-2008 period it was 250.

3.2 Stochastic versus Deterministic Trends

Figures 2 to 4 suggest the possibility of an upward trend in idiosyncratic volatility. Therefore, an important question is whether such a trend is of stochastic or deterministic nature. The possibility of stochastic trend is suggested by the persistent fluctuations in volatility shown in the figures.

Table 1 reports autocorrelation coefficients for the three volatility measures. All these series exhibit high serial correlation. The autocorrelation coefficients die off after a large number of lags, which is a sign that the series obey a low-order autoregressive process. The high serial correlation raises the possibility that they contain unit roots.

To check this, in Table 2 we employ augmented Dickey and Fuller (1979) tests, based on regressions that include a constant or a constant and a time trend. The number of lags is determined by the Schwarz Criterion. The hypothesis of a unit root is rejected for MKT and IND at the 5 percent level, whether a deterministic time trend is allowed or not. Therefore, MKT and IND are stationary. However, Firm contains a unit root. Since the computed ADF test-statistics (-1.663.189 when a constant is included and -2,110932 when a constant and a linear trend are included) are greater than the critical values (-3,455289 , -2,872413 and -2,572638 at 1%, 5% and 10% respectively when a constant is included, and -3,993608 , -3,427137 and -3,136859 at 1%, 5% and 10% respectively when a constant and a linear trend are included) we cannot reject the null hypothesis. This means that FIRM has a unit root problem and, therefore, it is a non-stationary series. This indicates that shocks to FIRM may have permanent effects which do not decay as they would if the series were stationary.

In Table 3 we report some descriptive statistics and trend regressions. The top panel presents results for volatility series based on daily returns and the two following panels report results for volatility series based on weekly and monthly returns, respectively. First we will examine the volatility components in our benchmark sample based on daily returns. The mean of MKT is 0,045, IND has a higher mean of 0,379, and finally FIRM has the largest mean of 0,424.

All three series exhibit substantial variation over time. The second row in each panel of Table 3 reports unconditional standard deviations of the variance series. Industry and firm volatility are more variable over time than market volatility. However, a large portion of the time-series variation in market volatility is due to the 1999 bubble.

We will proceed by testing the hypothesis of the existence of a deterministic linear time trend. Table 3 reports also the trend coefficient from a simple OLS regression of volatility on time, as well as the F-statistic and p-value for the null hypothesis that coefficients are zero. On the top panel, which reports results for the monthly volatility series estimated from daily data, the trend regression confirms the visual evidence from the plots. MKT and IND have a small positive but significant trend coefficient, whereas FIRM has the larger, trend coefficient, which is also significant.

Table 3 also reports standard deviations of the detrended volatility series. A time trend biases the unconditional time-series variation upwards. Because FIRM has the largest trend among the three measures, the standard deviation decreases the most when the data is detrended. The effects of detrending are modest for MKT and IND. For the detrended data, IND exhibits the greatest time-series variation.

Daily stocks exhibit significant short-run serial correlation, which might affect the volatility series, in particular if the pattern of serial correlation changes daily. To check the robustness of the results based on daily data, we construct volatility series based on weekly and monthly returns for which autocorrelation is much weaker. In order to do so, we change the time interval s in equations (17), (18) and (19) from daily to weekly and monthly, while still keeping the time interval t equal to one month. The second and third panel in Table 3 show that the means of the three volatility measures decrease somewhat for longer horizon returns. The trend coefficients in the weekly and monthly volatility series also decrease somewhat but are still sufficient.

The forth panel on table 3 reports volatility series for large firms. In order to check the firm size effect, since many smaller firms are now listed on the stock market raising the number of firms in the data set, we compute the volatility series using only the 76 largest firms based on market capitalization. MKT and IND are not affected by the exclusion of smaller firms. However, the mean and trend for FIRM have slightly decreased.

In the last panel of Table 3 we report results for equally weighted series, as another way to check the effect of firm size. MKT is again not affected. IND and FIRM exhibit a small increase. IND and FIRM have a mean of 0,3915 and 0,4318 respectively. The linear trend of IND has slightly increased, whereas the linear trend of FIRM is not affected.

3.3 Individual industries

Up until now IND represented volatility averaged over industries and provided information about an average industry. However, there is a great deal of variation through industries, because the nature and composition of industries in our sample differ tremendously. The industry and firm-level volatility in each sector behave differently. Therefore, we will proceed to examine the 10 industries of the Athens Stock Exchange (as presented in the Thompson Datastream) separately. Each industry includes a number of sectors. The composition of each industry is presented in Table 4.

In order to construct volatility series for individual industries, we need to adjust our estimation procedure. In section 1 we showed that the three return components in equation (10) are orthogonal when we average over firms and industries. However, when we examine individual industries we no longer average over industries. So we need to alter the return composition in a way that includes a beta for each industry.

$$R_{it} = \beta_{im} R_{mt} + \tilde{\varepsilon}_{it} \tag{24}$$

$$R_{jit} = \beta_{im} R_{mt} + \tilde{\varepsilon}_{it} + \eta_{jit} \tag{25}$$

R_{mt} and $\tilde{\varepsilon}_{it}$ are by construction orthogonal. Therefore the volatility of the industry return is

$$Var(R_{it}) = \beta_{im} Var(R_{mt}) + \tilde{\sigma}_{it}^2 \tag{26}$$

Where $\tilde{\sigma}_{it}^2$ is the variance of $\tilde{\varepsilon}_{it}$. We still sum over all firms in the industry, so for the average firm volatility in industry *i* from equation (13) we have:

$$Var(R_{jit}) = \beta_{im} Var(R_{mt}) + \tilde{\sigma}_{it}^2 + \sigma_{\eta it}^2 \tag{27}$$

Where $\sigma_{\eta it}^2$ is defined as before. We use the residuals $\tilde{\varepsilon}_{it}$ in equation (24) and η_{jit} in equation (25) to construct industry and firm-level volatility for individual industries without having to estimate covariances or firm-level betas. We only have to estimate the industry betas on the market β_{im} . So we use OLS regressions assuming that the betas are constant over the sample. The results, as well as the industries' weights and betas, are presented in Table 5.

Table 5 shows that Financials is the largest industry in our sample with an average share of 46% of the total market capitalization over the whole sample period followed by consumer good and consumer savings. Most of the industries have substantially low betas (close to zero), with the exception of Telecommunication firms, which have a beta of 1,13, and Utility firms, which have a negative beta(yet close to zero).

Next we examine the descriptive statistics of industry and firm-level volatility. As in the aggregated data, FIRM is slightly larger than IND. The means of IND and FIRM vary much from industry to industry, yet their values in each industry differ very little, with firm-level volatility being a little larger than industry-level volatility. Overall, industries with high average industry-level volatility tend to have high firm-level volatility. The correlation of the means of IND and FIRM across industries is 0,99. Moreover, large industries tend to have low IND and FIRM on average. For example, the financial industry, which has the biggest weight (46%), has the smallest mean (0,004236 in industry-level volatility and 0,004706 in firm-level volatility). The correlations of industry weights with the means of IND and FIRM are 0,31 and -0,01 respectively. This may be attributed to the fact that shocks to large industries move the market as a whole, so MKT reflects shocks to these industries.

We will proceed to examine whether individual industries also exhibit significant trends in volatility. First we perform unit root tests on all industry and firm volatility series using the Akaike Information Criterion. The results are reported in Table 6. We can see that we cannot reject the unit root hypothesis for a number of industries. In regressions of a linear time trend, all the industries show a significant positive time trend in IND and FIRM. The consumer savings and the industrial sectors exhibit the largest upward trend both in industry and firm level volatility. Table 6 presents the F-statistics and p-values of the null hypothesis that trend coefficients are zero, which is rejected in all cases.

Figure 6 reports the correlations among the industries by calculating all pairwise correlations among industries. Correlations are calculated annually using monthly data and we compute an equally-weighted average of these correlations. The figure shows that correlations tend to decline over time, apart from a huge upward movement in 2008. The average stock correlation is close to 55 percent. The typical coefficient of determination, R^2, and hence the explanatory power of the market model with zero intercept is rather low at about 30 percent, calculated as the square of 55 percent.

4. Portfolio implications of the increase in idiosyncratic volatility

Panel A of Figure 7 presents the evolution of correlations among individual stocks. We calculate all pairwise correlations among stocks traded on the Athens Stock Exchange during January 1988 to October 2009, using both daily and monthly data. Correlations using daily data are calculated each month, using the previous 12 months of daily observations, or as many months are available at the beginning of the data set. The number of stocks in the sample at each month ranges from about 25 to 255, so the number of pairwise correlations ranges from 325 to 32.640. Correlations using monthly data are again calculated each month, but they use the previous 60 months of monthly returns.

The figure shows that correlations among individual stocks have a tendency to rise, contrary to the finding of Campbell, Lettau, Malkiel and Xu (2001) about the United States. Correlations based on daily data increase from 0,08 in 1988 to 0,25 in 2009, and correlations based on monthly data increase from 0,02 in 1988 to 0,22 in 2009.

Panel B of Figure 7 presents the coefficient of determination, R^2, and hence the explanatory power of the market model with zero intercept, calculated as the square of each correlation calculation and using the same stocks as Panel A. The explanatory power of the market portfolio is trended upwards, contrary to the findings of Campbell, Lettau, Malkiel and Xu (2001) about the United States. The average stock correlation, calculated using daily data, is close to 26 percent, which implies that the average R^2 is rather low at about 7 percent, calculated as the square of 26 percent.

We have seen that idiosyncratic volatility accounts for the main portion of the variance of a typical stock. Therefore, the potential benefits to diversification strategies are substantial. An investor who holds only one stock bears the full risk of the individual stock, whereas an investor who holds a sufficient number of stocks bears only market risk. Bloomfield, Leftwich and Long (1977) suggest that a randomly chosen portfolio of 20 stocks produces most of the reduction in idiosyncratic risk that can be achieved through diversification. This is the conventional rule of thumb. As remarked by Campbell, Lettau, Malkiel and Xu (2001), however, the higher the average idiosyncratic variance, the larger the number of stocks needed to achieve a relative complete diversification, giver a random portfolio selection strategy. We will try to illustrate this in Figure 8, by investigating the standard deviations of portfolios containing different number of randomly selected stocks.

Figure 8 shows the annualized standard deviation each year, calculated from daily data during the year, of equally weighted portfolios containing 2, 5, 20 and 50 stocks. Stocks are randomly grouped into portfolios and a simple average of portfolio standard deviations is calculated across portfolios. The figure shows that the standard deviation of a typical 2-stock portfolio is much larger that that of a typical 50-stock portfolio. All the standard deviations of all the portfolios exhibit a substantial increase during the 1998-2001 period, thus we assume that the cause of this increase is the stock market bubble at the time. It can be seen that it takes more stocks to reduce idiosyncratic risk to any given extent.

5. Short-run volatility dynamics

5.1 Covariation and lead-lag relationships

We have seen that there are trends in volatility over time. However, as we can see in figures 2 to 4, there are many short-run movements around these trends, and these movements tend to be correlated across our three volatility measures. We examine this in Table 7, in which we present the correlation structure of our volatility series, both for raw and detrended data. In series with trend, the correlation of MKT with IND and FIRM is about 0,4, whereas the correlation of IND and FIRM is very high, at 0,92. For the detrended data, the correlation of MKT with IND and FIRM is negative, whereas the correlation between IND and FIRM is again positive and very high, at 0,82.

Next we will examine what percentage of the variance of each volatility component is explained by the other volatility series. In order to do so, we must model the system as a trivariate VAR. We use the Schwartz Bayesian Criterion and include 3 lags in the VAR. Table 8 reports the variance decomposition of the three volatility series. Only a very small portion of IND and FIRM is explained by variation in MKT, whereas a large portion of FIRM is explained by variation in IND. Therefore idiosyncratic volatility plays a more important role in the Greek market than systematic volatility.

In Table 9 we present a mean and variance decomposition of the three volatility measures, in order to examine how important they are relative to the total volatility of an average firm. To compute the shares of MKT, IND and FIRM in the total mean and variance of the volatility of a typical stock, we use the following methodology. We define the volatility of a typical stock as

$$\sigma_{rt}^2 = MKT_t + IND_t + FIRM_t$$

Then to compute the mean of volatility we have

$$1 = E(MKT_t)/E\sigma_{rt}^2 + E(IND_t)/E\sigma_{rt}^2 + E(FIRM_t)/E\sigma_{rt}^2$$

And for the variance of volatility

$$\begin{aligned}1 &= Var(MKT_t)/Var(\sigma_{rt}^2) + Var(IND_t)/Var(\sigma_{rt}^2) + Var(FIRM_t)/Var(\sigma_{rt}^2)\\ &+ 2Cov(MKT_t, IND_t)/Var(\sigma_{rt}^2) + 2Cov(MKT_t, IND_t)/Var(\sigma_{rt}^2)\\ &+ 2Cov(IND_t, FIRM_t)/Var(\sigma_{rt}^2)\end{aligned}$$

Let's first consider the mean. Over the whole sample, market volatility accounts for 5% of the unconditional mean of total volatility, whereas industry volatility accounts for 45% and firm volatility for 50%.

The variance decomposition shows that most of the time-series variation in total volatility is due to variation in IND and FIRM. About 70% of the total variation is due to variance and covariance terms of FIRM. The market component by itself is much less important, only 0,7% of the total variation in volatility. IND and FIRM show almost the same time-series variation.

In order to isolate the longer-run movements we need to smooth the series. One way to do so is to decompose each volatility series into an expected and an unexpected part:

$$u_t = E_{t-1}u_t + \xi_t$$

where $u \in \{MKT, IND, FIRM\}$. We compute the conditional expectation of each volatility series by regressing it on its own lag. We choose a lag length of 1 when computing the conditional expectations.

On the bottom panel of Table 9 we report a variance decomposition of the conditional expectations of the volatility series. About 70% of the total variation is due to variance and covariance terms of FIRM. The contribution of MKT is about 4% and of IND is more or less the same as in the raw data.

Next we will examine whether the volatility measures help to forecast each other. In Table 10 we present Granger-causality tests. The top panel reports p-values for bivariate VARs and the bottom panel reports p-values for trivariate VARs including all three series. The null hypothesis is that lags 1 through *l* of the series indicated in the row do not help to forecast the series indicated in the column, conditional on the other variables in the VAR. The data are detrended and the VAR lag length was chosen using the Akaike information criterion. In bivariate VARs, FIRM appears to Granger-cause both MKT and IND at very high significant levels. MKT does not help to predict IND or FIRM, but IND helps to forecast FIRM at a very high significant level. In the trivariate VARs, MKT Granger-causes IND at a very high significant level. FIRM Granger-causes IND at the same high significance, but in this case it Granger-causes MKT at lower significant levels than in the bivariate case. Finally, IND helps to forecast both MKT and FIRM at high significant levels. Overall, FIRM helps to predict market volatility.

Next, we conduct impulse response functions in order to test the causality between these series and the stock markets returns. We estimate a simple VAR model of market returns, market variance, industry-level variance and firm-level variance (Rm_t, MKT_t, IND_t and $FIRM_t$). All variances are linearly detrended. We use the Schwarz Criterion and include 3 lags in the VAR. Figure 9 reports the impulse response functions of the variables.

An impulse response function traces the effect of a one-time shock to one of the variables on current and future values of the other variables. Shocks to market, industry and firm level variance have statistically significant effects on future returns. The effect of MKT_t and IND_t is positive. The positive effect of MKT_t is 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 $FIRM_t$ is negative. This negative relation could be interpreted as follows: a positive shock to $FIRM_t$ implies a decrease in the average correlation, therefore the response functions highlight a positive relation between average stock correlation and one period ahead market returns.

Figure 9 also suggests a statistically significant contemporaneous negative impact of shocks to aggregate returns on all volatility series. This means that both systematic and idiosyncratic volatility rise during market downturns. MKT_t has a statistically significant contemporaneous impact on IND_t, but no impact on $FIRM_t$. These findings are consistent with the Granger-causality relations reported in Table 8. The contemporaneous impact of market returns and market volatility to idiosyncratic volatility suggest that even positions constructed to reduce market risk may prove more volatile during market downturns and at times of high market volatility.

5.2 Cyclical behavior of aggregate volatility measures

In this section we study the cyclical behavior of volatility with GDP data. GDP is measured on a quarterly frequency, so we construct volatility series on that frequency, using daily returns within each quarter. The quarterly series behave much like the monthly ones. Table 11 reports correlations of volatility with GDP growth up to a lead and a lag of one year. MKT is negatively correlated with GDP growth in all leads and lags, therefore MKT is countercyclical to GDP. IND and FIRM, however, do not show a clear pattern. Correlations of leads and lags up to two quarters are positive and the rest are negative. However, in absolute values, the negative correlations are greater than the positive correlations, which are close to zero. Therefore we assume that IND and FIRM show generally a countercyclical behavior.

Next, we will examine whether the three volatility measures have any ability to forecast GDP growth. Table 12 reports the results of OLS regressions with GDP growth as the dependent variable. As regressors, we use lagged GDP growth, the lagged return of the market portfolio R_m and combinations of lagged volatility series. All t-statistics are Newey-West corrected. Regressing GDP growth with its own lag and the lagged market index yields an R^2 of 70,4%. Next, we add each of the lagged volatility measures in turn. R^2 increases most when the lagged MKT is introduced. Next, we include pairs of volatility variables as regressors. The p-values of the F-tests are all zero, therefore we reject the null hypothesis that coefficients are zero for all volatility variables. The R^2 increases to 71,8% when MKT and IND are included in the regression. Finally, we include all three volatility measures in the regression. The volatility series are jointly significant, as the p-value of the F-test is zero. R^2 increases the most (72,5%). There is no conclusive evidence indicating which of the three volatility measures has the most forecasting power, but overall we can say that the three volatility measures help to forecast GDP growth.

6. What Might Explain Increasing Idiosyncratic Volatility?

We have documented that idiosyncratic volatility of stock returns of the Athens Stock Exchange has increased over the past two decades. In this section we discuss some possible reasons for this increase.

Campbell, Lettau, Malkiel and Xu (2001) and Wei and Zhang (2003) suggest a number of circumstances that could explain the rise of idiosyncratic volatility.

Stock returns are affected by shocks to expected future cash flows, discounted at a constant rate, and shocks to discounted rates. Therefore, an increase in volatility results from an increase in the variance of cash-flow shocks, an increase in the variance of discount-rate shocks, or an increase in the covariance between the two types of shocks. Campbell (1991) provides an approximate loglinear accounting framework that can be used to break stock market volatility into these components.

According to the strict random-walk model of stock prices, stock returns are unforecastable. Since discount rates are constant, stock returns are driven entirely by expected future cash flows. The random walk theory also implies that all unexpected movements in stock prices must be due to news about future dividends. However, modest predictability of stock returns can generate important volatility apart from that coming from shocks to cash flows. Campbell (1991) argues that unexpected stock returns can be interpreted by breaking them into components which are attributable to "news about future dividends" and "news about future returns". The objective is to decompose prices into a 'transitory' and a 'permanent' component. The movements of the former are associated with changing rational expectations of returns, but the movements of the latter are not.

The relative importance of the two components depends not only on the forecastability of stock returns, but also on the time-series properties of the forecastable component of returns. If predictable returns are highly persistent, then a small degree of predictability will have a drastic effect on the interpretation of returns. The variability and persistence of expected stock returns account for a considerable degree of volatility in unexpected returns. Campbell estimates that over the full sample period, the variance of news about future cash flows accounts for only a third to a half of the variance of unexpected stock returns. The remainder of the stock return variance is due to news about future expected returns. This suggests that an economic explanation of stock market volatility must also be an explanation of short-term predictability in returns. News about future returns is not independent of news about cash flows. Increases in future expected cash flows tend to be associated with decreases in future expected returns, a correlation which amplifies the volatility of stock returns.

Vuolteenaho (1999) applies a similar methodology to individual stock returns and estimates that shocks to individual firms' cash flow have a variance about twice that of shocks to individual firms' discount rates. The cash flow shocks are less highly correlated across firms than are the discount rate shocks, however, so cash flow news plays a smaller role at the aggregate level.

There are several possible reasons why the variance of idiosyncratic shocks to cash flows might have increased over the past decades.

In corporate governance, there has been a strong tendency to break up conglomerates and replace them with more focused companies specializing in a single industry or economic activity. This can be interpreted as a shift from external to internal capital markets (Gertner, Scharfstein, and Stein (1994), Stein (1997)). It implies that firms are now separately listed, and their idiosyncratic risks separately measured, whereas previously they might have traded as a single conglomerate that was itself a diversified portfolio of activities. The argument that the tendency towards less diversified conglomerates might explain rising firm-level volatilities, however, applies less well to the Athens Stock Exchange case than to United States markets because it also implies a decrease in average correlations.

Another possible reason is that companies have begun to issue stock earlier in their life cycles, often at a stage where profitability is not yet clearly established and there is considerable uncertainty about long-run prospects

Changes in executive compensation may also play a role in these developments. Executives who are compensated through stock options have incentives to manage firms in ways that maximize firm market value. Since options increase in value with the volatility of the underlying stock, executive stock options provide managers with incentives to take actions that increase firm level risk. Cohen, Hall, and Viceira (2000) study a panel of large firms and find that executives respond to these incentives and that there is a statistically significant relationship between increases in option holdings by executives and subsequent increases in firm risk. However, they conclude that although options appear to increase firm risk, there is no evidence that this effect is either large or damaging to shareholders.

Leverage is another factor that can affect the volatility of cash flows to equity investors (Black (1976), Christie (1981)). When leverage increases, stockholders bear a greater share of the total cash-flow risk of the firm, and the volatility of the stock return increases accordingly. However, it is 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.

Another possible reason for the increase in idiosyncratic volatility (not just because idiosyncratic cash flows are now separately traded) is the fact that information about these cash flows is now disseminated far more rapidly. Information technology has certainly helped to make firm-specific information available on a more timely basis. However, if discount rates are constant, improved information about future cash flows actually decreases volatility rather than increasing it. The reason was explained by West (1988), following Shiller (1981) and LeRoy and Porter (1981). Improved information about future cash flows increases the volatility of the stock-price level, but it reduces the volatility of the stock return because news arrives earlier, at a time when the cash flows in question are more heavily discounted.

The opening of new derivative markets may also have affected the availability of information about future cash flows. As argued by Ross (1976) and John (1984), options can complete an otherwise incomplete market and can have a significant impact on the price behavior of the underlying securities. Grossman (1989) argued that derivatives markets increase information and therefore reduce volatility. However, according to Stein (1987), it is possible for new derivatives markets to change the pattern of trading by informed speculators in such a way that the information content of prices is reduced, and volatility is increased. Empirically, however, there is little evidence that this perverse effect is important. Kumar, Sarin, and Shastri (1998) and earlier studies cited there, notably Conrad (1989) and Skinner (1989), report that optioned stocks, on average, experience a statistically significant decline in volatility relative to the market as a whole. More specifically, Kumar, Sarin and Shastri (1998) find that option listings are associated with a decrease in the variance of the pricing error and the bid-ask spread, and increases in depth, trading volume, transaction size, and trading frequency. These findings are consistent with the notion that option listings result in a lower level of information asymmetry and are evidence of a greater pricing efficiency and of a higher market quality. Conrad (1989) argues that the introduction of individual options causes a permanent price increase in the underlying security and a decrease in excess returns volatility, while systematic risk is unchanged. Skinner (1989) examines the variance of returns on common stocks around the time exchange-traded options are listed on these stocks and finds that stock return variance declines after options listing, and that this phenomenon is not fully explained by contemporaneous shifts in market volatility. He also finds that stock market trading volume increases, on average, after options are listed on firms' stocks. Thus there is little scientific support for the popular belief that the proliferation of derivative instruments increases volatility.

Having discussed some possible reasons of the increase in idiosyncratic variance due to shocks to cash flows, we will examine the case of shocks to discount rates.

Shocks to investors' discount rates can also affect idiosyncratic volatility. Within the framework of the CAPM, for example, changes in betas can move discount rates and, hence, prices. If betas are now more volatile, this would explain increased firm-level volatility. There are ambiguous findings about this matter. Braun, Nelson, and Sunier (1995) find little evidence that beta shocks are important for volatility of industry and size portfolios, but Cho and Engle (1999) obtain more encouraging results for a sample of nine large individual stocks.

Under a more behavioural perspective, discount rates are determined by the interactions of heterogeneous groups of investors, so 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. Malkiel and Xu (1999) explore this effect in a sample of S&P 500 stocks and find that the proportion of institutional ownership is correlated with volatility, and that institutional ownership helps to forecast volatility in industry portfolios formed from S&P 500 stocks. 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. Morck, Yeung, and Yu (2000) study variation across countries in the explanatory power of the market model, using each country's own stock index as the market index. They find that the market model has much greater explanatory power in less-developed markets with weak legal protection for outside investors. They argue that such markets rely more heavily on internal finance, with cross-holdings and cross-subsidization that prevent individual firms' stock prices from reflecting information about the values of their core operations. From this perspective, the finding of a low average correlation and hence of a low market R^2 presents a generally good level of investor protection and transparency in the Athens Stock Exchange

7. Concluding Comments

In this paper, we have applied the variance decomposition proposed by Campbell, Lettau, Malkiel and Xu (2001) to construct variance series at the market, industry and firm levels of the stocks listed on the Athens Stock Exchange. This decomposition does not require the estimation of covariances or betas for industries or firms. In order to be consistent with recent literature questioning the findings of Campbell, Lettau, Malkiel and Xu (2001), we note that all findings are sample specific.

We have used daily data within each month to construct sample variances for that month. Our main results are as follows. First, in out 1988 to 2009 sample period, there is a significant positive deterministic trend in all volatility series, with that of firm level volatility being the largest. This finding is robust to variations in the number of firms in the sample, or the time basis of the data used to construct the volatility series (using weekly or monthly returns).

Second, we have used the same methodology on the level of individual industries, but this time we have used estimates of industry betas on the aggregate market (estimation of firm-level betas was not required). The results are similar to those before.

Third, correlations among individual stocks, and consequently the R^2 of the market model for a typical stock, have increased over the sample period. However, the explanatory power of the market model for a typical stock is still rather low. Moreover, the number of stocks needed for diversification has increased.

Forth, firm level volatility is the largest component of total volatility and helps to predict both market and industry level volatility. Market returns are positively related to lagged market and industry level variance and negatively related to lagged firm level variance. All three volatility measures increase in economic downturns.

Finally, we have seen that all three volatility measures show a countercyclical behaviour relative to GDP growth and they all help to forecast GDP.

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Figure 1

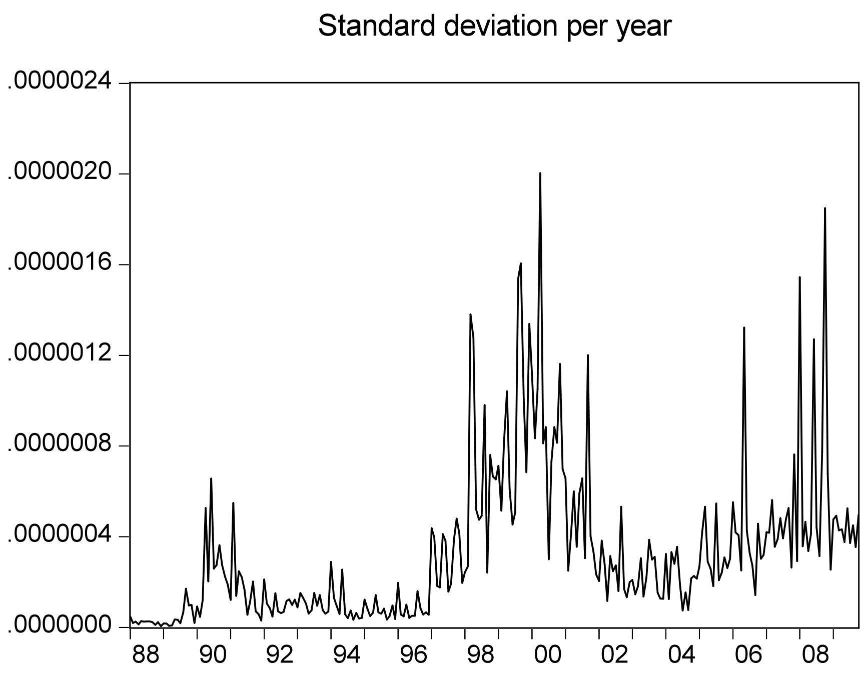


Figure 1. Standard deviation of value-weighted stock index. The standard deviation of monthly returns within each year is shown from 1988 to 2009.

Figure 2

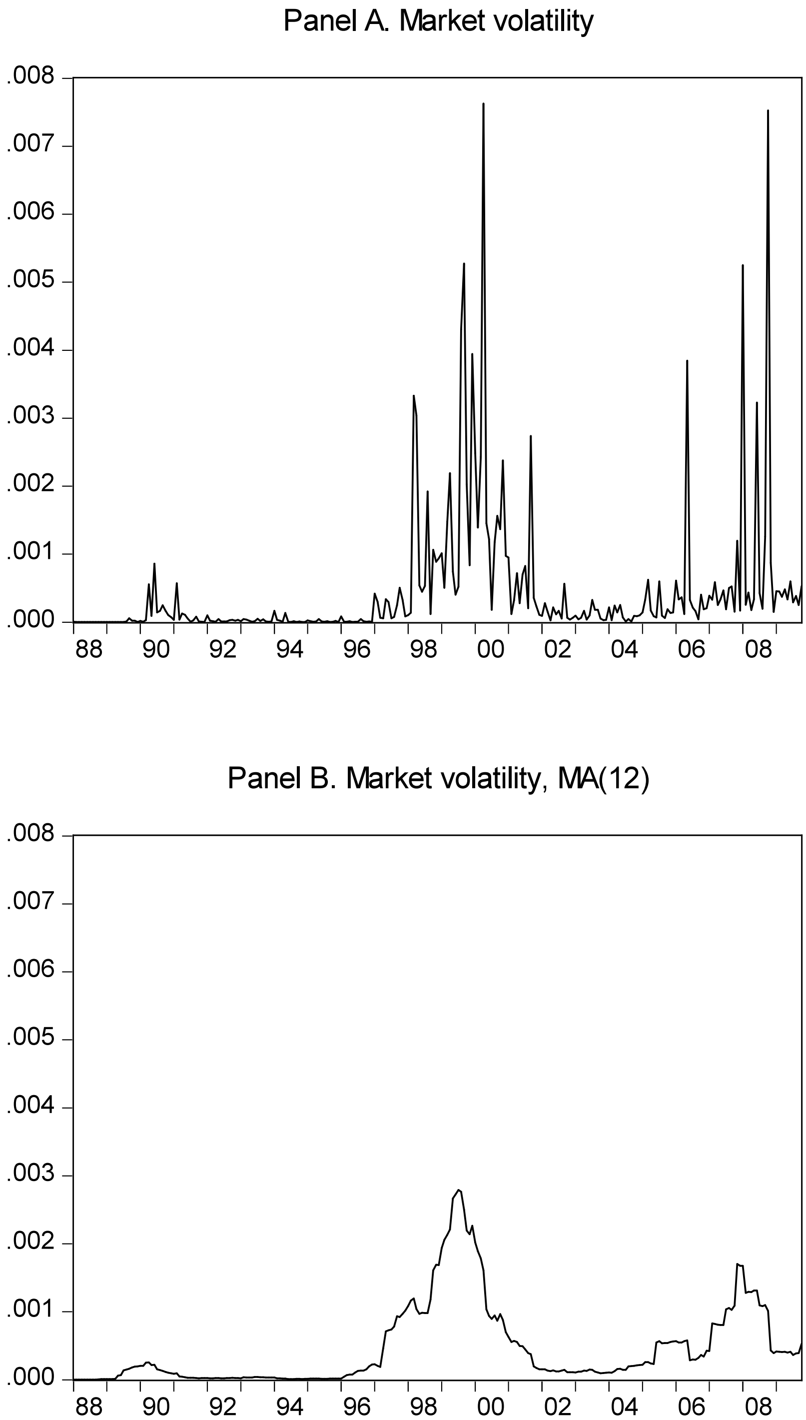
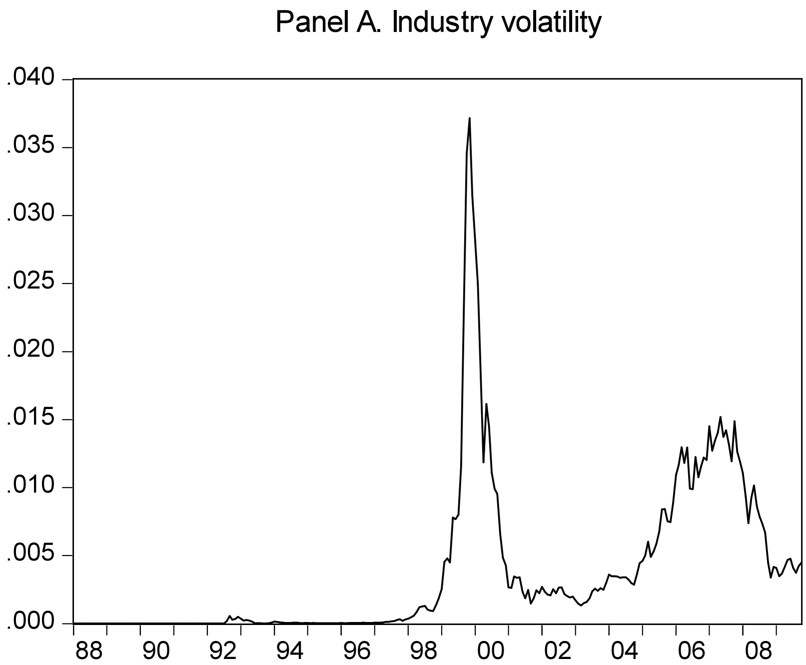


Figure 2. Annualized market volatility MKT. The top panel shows the annualized variance within each month of daily market returns, calculated using equation (17), for the period January 1988 to October 2009. the bottom panel shows a backwards 12-month moving average of MKT.

Figure 3



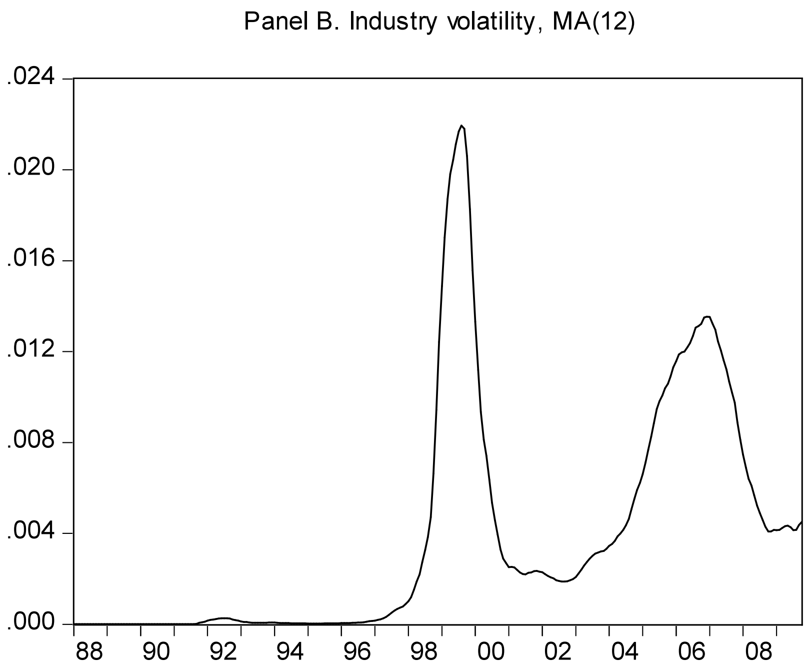
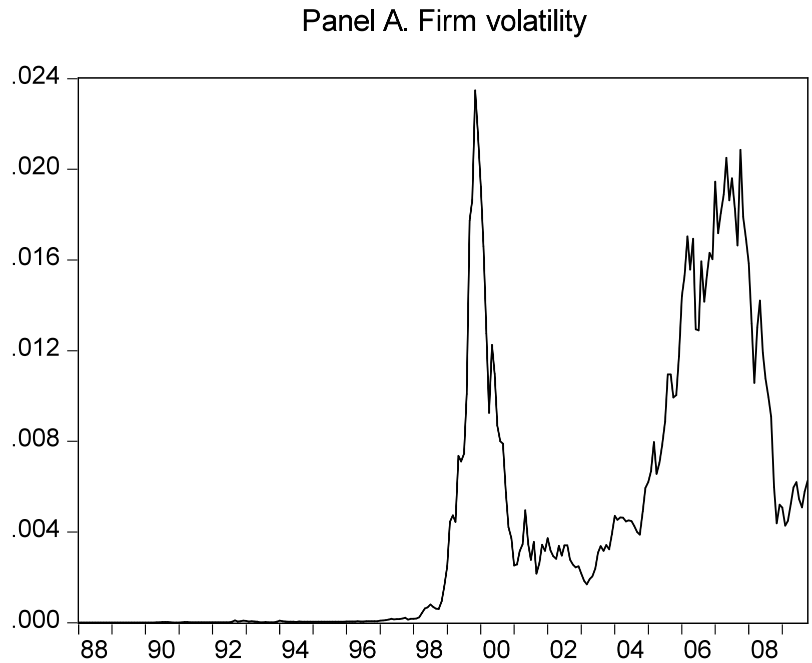


Figure 3. Annualized industry-level volatility IND. The top panel shows the annualized variance within each month of daily industry returns relative to the market, calculated using equations (18) and (19), for the period from January 1988 to October 2009. The bottom panel shows a backwards 12-month moving average of IND.

Figure 4



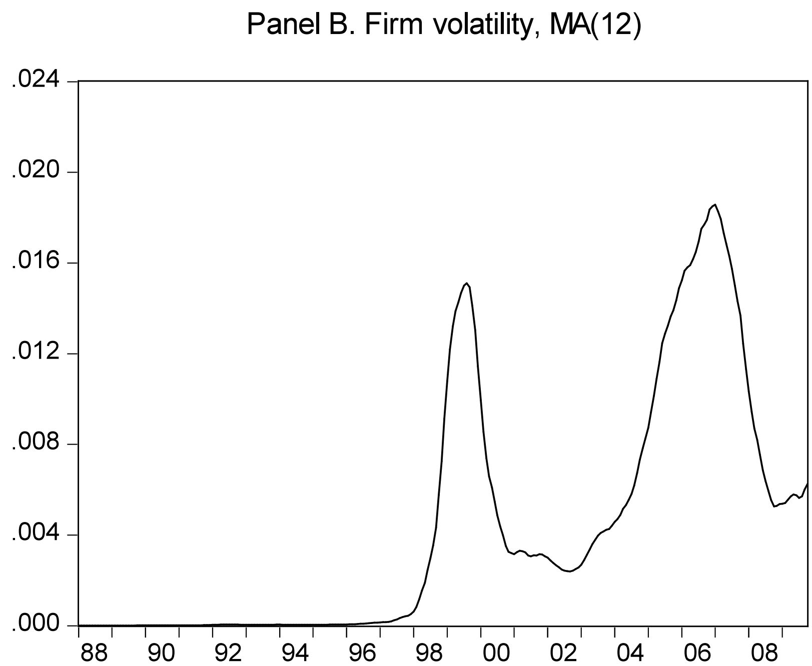


Figure 4. Annualized firm-level volatility FIRM. The top panel shows the annualized variance within each month of daily firm returns relative to the firm's industry, calculated using equations (20)-(22), for the period from January 1988 to October 2009. The bottom panel shows a backwards 12-month moving average of FIRM.

Figure 5

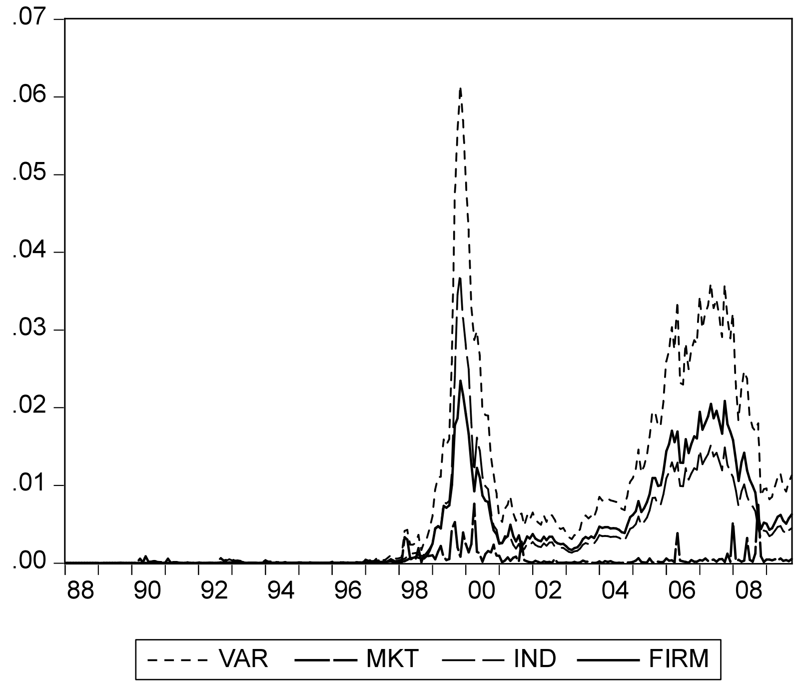


Figure 5. Multiple graph of total volatility, MKT, IND and FIRM. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22).

Figure 6

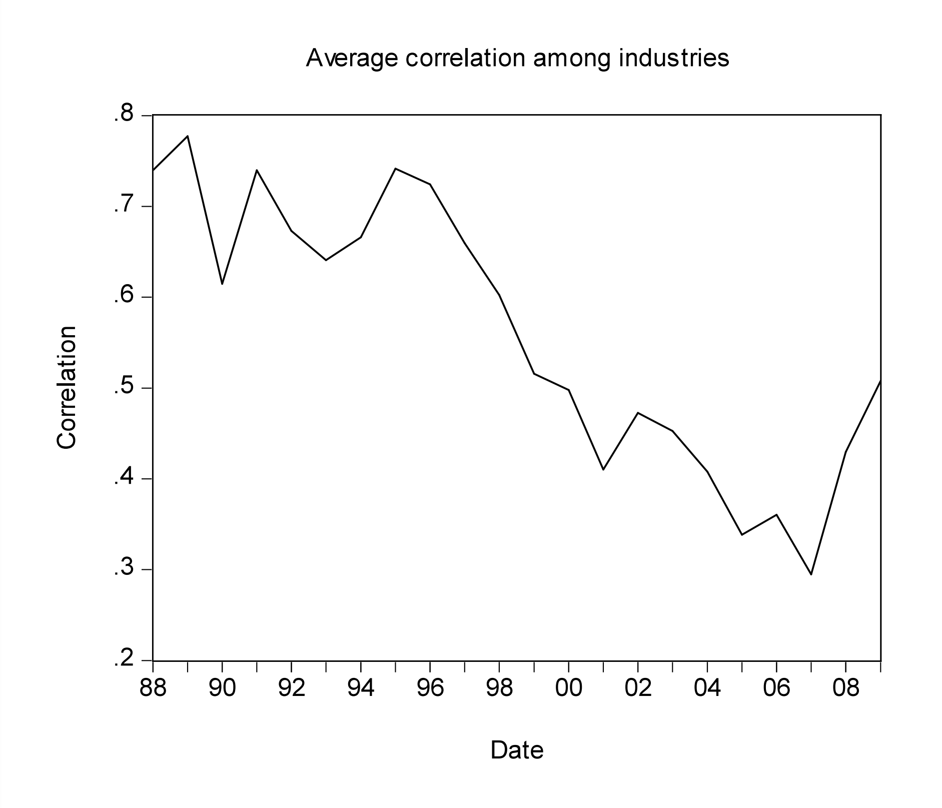
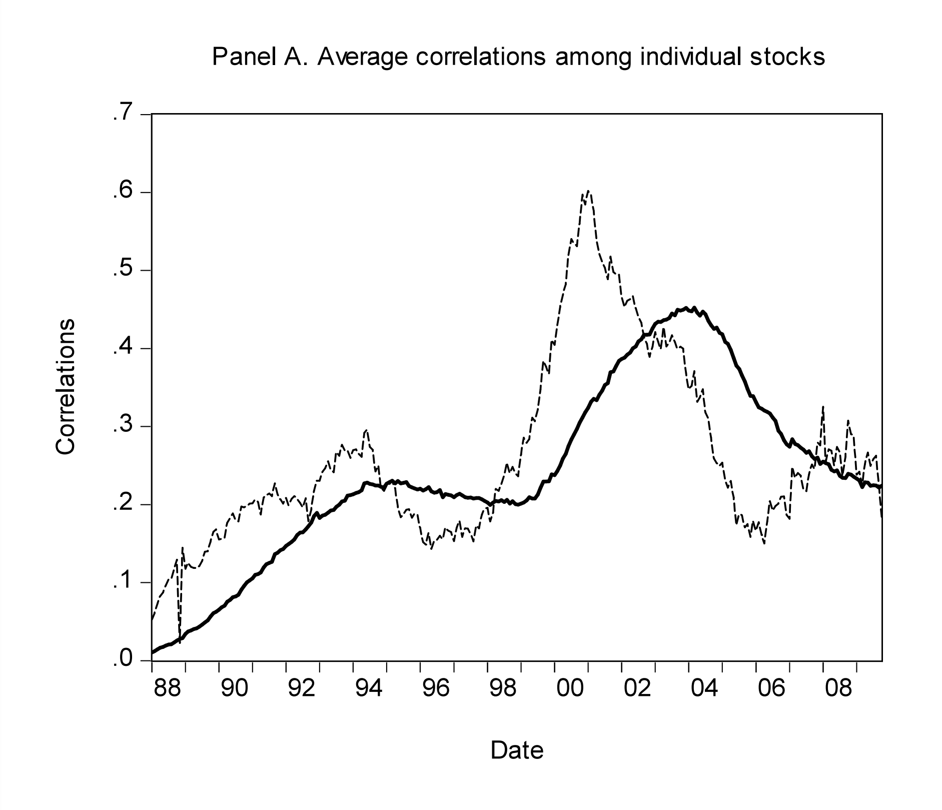


Figure 6. Average correlation among industries. The line is the average correlation over the past 60 months of monthly data.

Figure 7



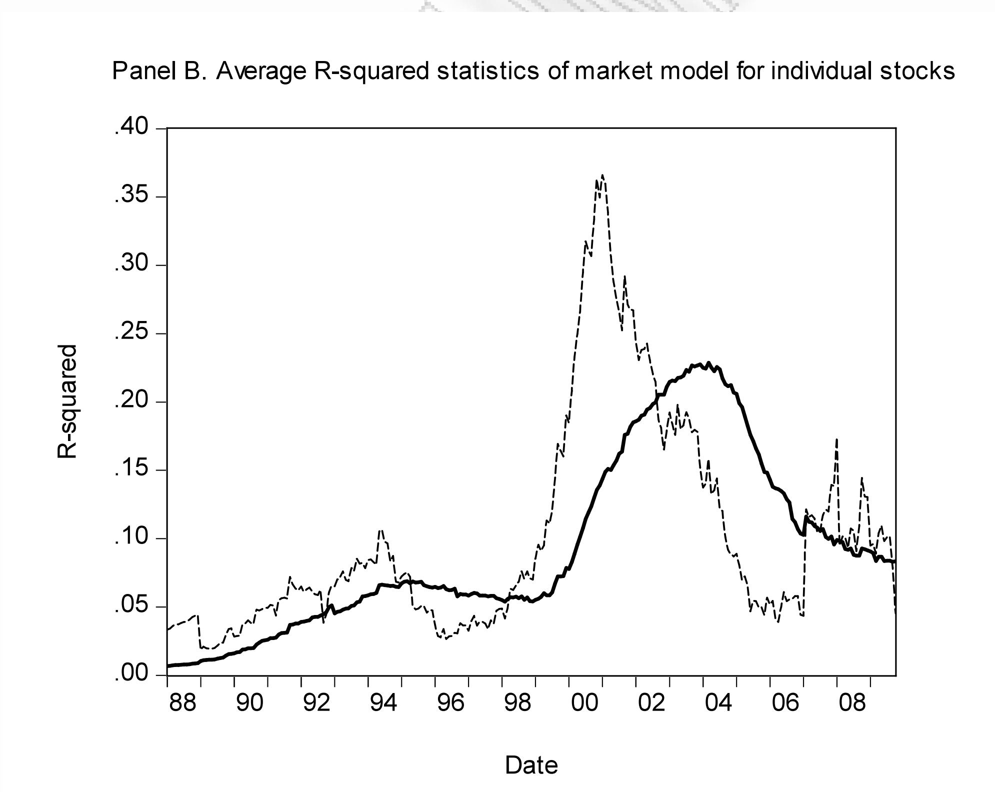


Figure 7. Average correlations and R^2 statistics of market model for individual stocks. The top panel reports the equally weighted average pairwise correlation across stocks traded on the ASE, estimated using the past 60 months of monthly data (solid line) or

the past 12 months of daily data (dotted line). The bottom panel reports the equally weighted average R^2 statistic of a market model, estimated using the past 60 months of monthly data(solid line) or the past 12 months of daily data (dotted line).

Figure 8

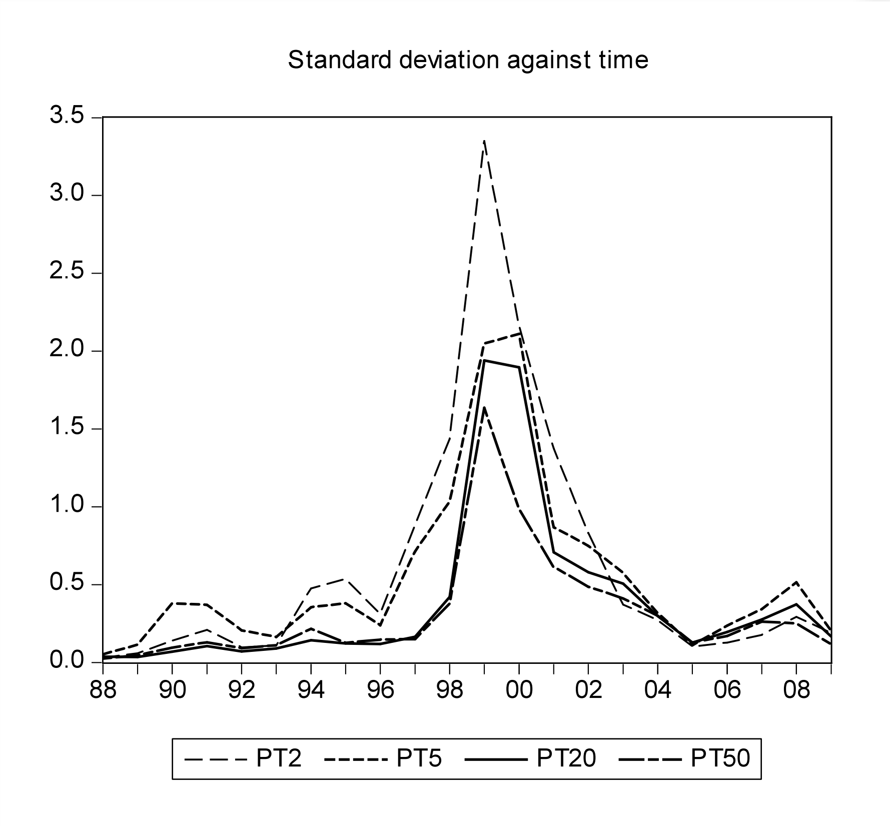


Figure 8. Standard deviation against time calculated each year from daily data within the year, for randomly selected portfolios containing 2 stocks, 5 stocks, 20 stocks and 50 stock.

Figure 9

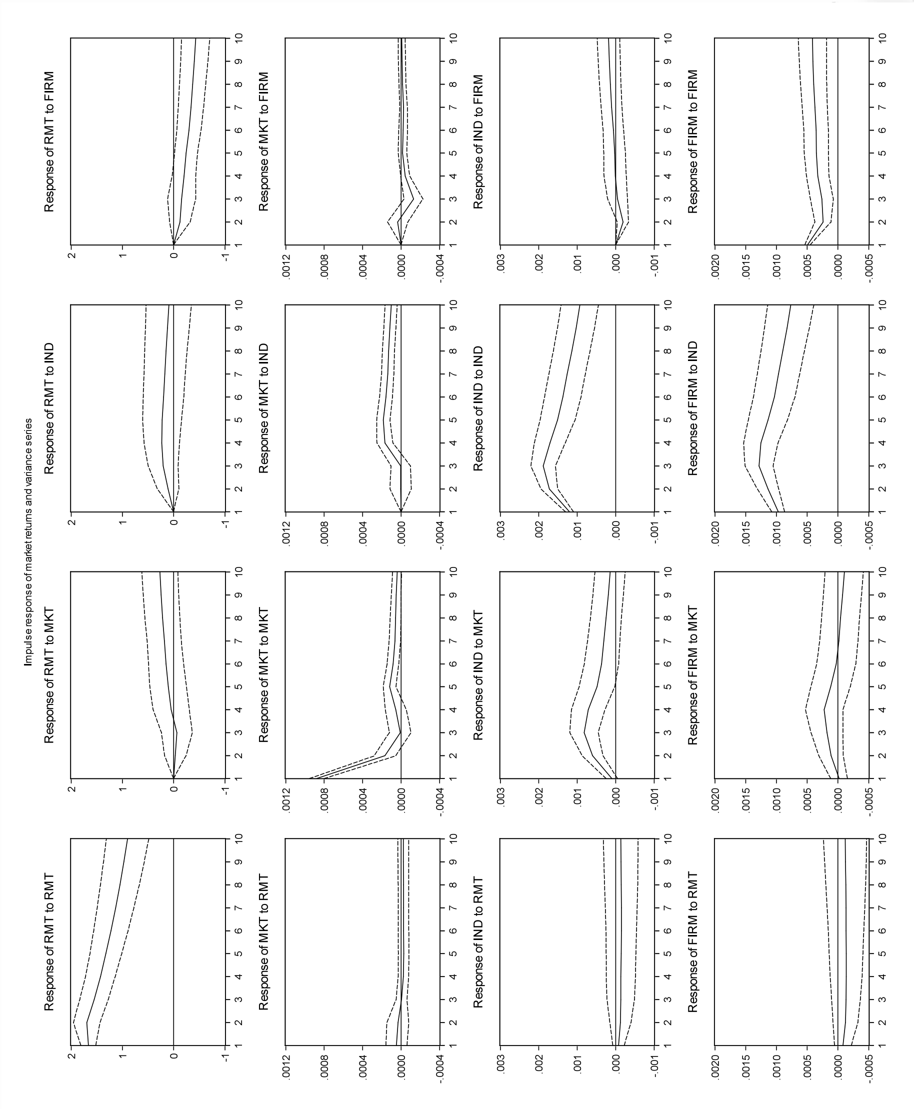


Figure 9. Impulse response of R_{mt}, MKT, IND and FIRM to shocks to each other. The variance series are linearly detrended.

Table 1

Autocorrelation structure			
Autocorrelation	MKT	IND	FIRM
ρ_1	0.374	0.967	0.979
ρ_2	0.228	0.906	0.955
ρ_3	0.256	0.84	0.926
ρ_4	0.414	0.772	0.891
ρ_6	0.226	0.652	0.829
ρ_{12}	0.228	0.358	0.619
	(ρ_{30}) 0,003	(ρ_{33}) 0,005	(ρ_{54}) 0,048

Table 1 reports the autocorrelation structure of monthly volatility series constructed from daily data and are value-weighted variances. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22). ρ_i denotes the *i*th monthly correlation.

Table 2

Unit Root Tests	MKT	IND	FIRM
Constant			
p-value	0,0011	0,0126	0,4488
ADF t-statistic	-4,118405	-3,37877	-1.663.189
Lag order	3	1	0
Constant and trend			
p-value	0,0033	0,0122	0,5368
ADF t-statistic	-4,330315	-3.928.494	-2,110932
Lag order	3	1	0

Table 2 reports unit root tests for monthly volatility series constructed from daily data. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22). All measures are value-weighted variances. The unit root tests are based on regressions that include a constant, or a constant and a time trend. The number of lags is determines by the Schwarz criterion.

Table 3

	MKT	IND	FIRM
Daily			
Mean	0,0455	0,3791	0,4241
Std dev.	0,1019	0,5921	0,5862
Std dev.detrended	0,099	0,5041	0,4237
Linear trend	0,0315	0,41	0,535
F-statistic	15,139	98,682	237,734
(p-value)	0	0	0
Weekly			
Mean * 10^2	0,000216	0,00881	0,0278
Std dev. * 10^2	0,000674	0,00944	0,0504
Std dev.detrended * 10^2	0,000673	0,00854	0,0365
Linear trend * 10^2	0,000047	0,00531	0,0446
F-statistic	0,731	57,718	221,245
(p-value)	0,393	0	0
Monthly			
Mean * 10^2	0,0393	0,0175	0,0184
Std dev. * 10^2	0,1024	0,0282	0,0255
Std dev.detrended * 10^2	0,1002	0,0243	0,0184
Linear trend * 10^2	0,0278	0,019	0,0243
F-statistic	11,337	90,136	239,321
(p-value)	0,0001	0	0
Daily- Large firms			
Mean * 10^2	0,0455	0,3791	0,3833
Std dev. * 10^2	0,1019	0,5921	0,5275
Std dev.detrended * 10^2	0,099	0,5041	0,3786
Linear trend * 10^2	0,0315	0,41	0,485
F-statistic	15,139	98,682	244,663
(p-value)	0	0	0
Daily- EW			
Mean * 10^2	0,0455	0,3915	0,4318
Std dev. * 10^2	0,1019	0,6113	0,6103
Std dev.detrended * 10^2	0,099	0,5194	0,4564
Linear trend * 10^2	0,0315	0,425	0,535
F-statistic	15,139	100,149	204,902
(p-value)	0	0	0

Table 3 reports descriptive statistics and estimates of a linear trend coefficient for monthly volatility series. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22). All measures are value-weighted variances. The top panel uses daily data to construct monthly volatilities, the second panel uses weekly data, and the third panel uses monthly data. The panel denoted large firms uses only the 76 firms with the largest capitalization. The bottom panel, denoted EW, is based on an equal-weighted scheme as opposed to value weighting for other results. Means and standard deviations are multiplied by 100, and the linear trend coefficients are multiplied by 10^4.

Table 4

Industry	Decomposition
Basic Materials	Chemicals
	Basic resources
Consumer Goods	Food and Beverage
	Personal and Household Goods
Consumer Savings	Retail
	Media
	Travel and Leisure
Health	
Financial	Banks
	Insurance
	Real Estate
	Financial Services
Industrial	Construction and Materials
	Industrial Goods and Services
Oil and Gas	
Technology	
Telecommunications	
Utilities	

Table 4 presents the decomposition of each industry

Table 5

Individual Industries							
				IND		F-stat	p-value
	Weight	Beta	Mean	Std. Dev.	Trend	72,172	0
Basic Materials	0,028427	0,064069	0,006721	0,013787	0,0000853	78,22	0
Consumer Goods	0,122801	0,005679	0,006325	0,014271	0,0000911	86,125	0
Consumer Savings	0,111464	0,014715	0.997164	1,612362	0,01067	66,567	0
Financial	0,45981	0,582209	0.004236	0.000776	0,00000465	176,058	0
Health	0,023547	0,349356	0,018814	0,018376	0,000155	75,538	0
Industrial	0,081653	-0,01402	0,745732	1,298032	0,008172	97,164	0
Oil and Gas	0,042949	0,051779	0,004038	0,003989	0,0000276	127,149	0
Technology	0,012566	-0,13554	0,01749	0,022123	0,000168	135,807	0
Telecommunications	0,06154	1,132661	0,022925	0,018677	0,000145	0,555	0,458
Utilities	0,055242	-0,56466	0,013886	0,021199	0,000158		
				FIRM			
	Weight	Beta	Mean	Std. Dev.	Trend	F-stat	p-value
Basic Materials	0,028427	0,064069	0,007643	0,015002	0,000096	79,027	0
Consumer Goods	0,122801	0,005679	0,007081	0,015463	0,000101	83,6	0
Consumer Savings	0,111464	0,014715	1,017466	1,633476	0,010949	89,124	0
Financial	0,45981	0,582209	0,004706	0,001304	0,00000465	115,639	0
Health	0,023547	0,349356	0,018817	0,018381	0,0000096	176,01	0
Industrial	0,081653	-0,01402	0,765711	1,329281	0,0084	76,388	0
Oil and Gas	0,042949	0,051779	0,002444	0,001986	0,0000318	88,935	0
Technology	0,012566	-0,13554	0,018491	0,022124	0,000168	127,166	0
Telecommunications	0,06154	1,132661	0,022929	0,018681	0,000145	135,838	0
Utilities	0,055242	-0,56466	-0,00157	0,001922	3,96E-05	109,219	0

Table 5 reports descriptive statistics for industry and firm volatilities in the industries. Industry volatility IND is constructed using equation (26) and firm volatility FIRM is constructed using equation (27). All volatilities are value-weighted variances, computed monthly from daily data. Weight is computed as the ratio of average market value of firms in an industry to the average total market value of all firms. Beta is computed using a regression of monthly industry returns on the monthly return of the Total Market index of the Thompson Datastream.

Table 6

Unit Root Tests							
IND							
	constant				constant and trend		
	ADF t-statistic	p-value	Lag order		ADF t-statistic	p-value	Lag order
Basic Materials	-3,356054	0,0135	15		-4,298919	0,0037	15
Consumer savings	-3,410541	0,0115	7		-4,143728	0,0062	7
consumer goods	-3,673631	0,005	1		-4,464384	0,0021	1
financial	-2,092727	0,2479	15		-2,255518	0,4563	15
health	-2,674032	0,08	9		-3.927.922	0,0123	13
industrial	-3,204274	0,0209	7		-3,717646	0,0229	7
oil and gas	-3,306905	0,0156	9		-4,129436	0,0006	11
technology	-2,353056	0,1564	14		-3,383997	0,0559	13
telecommunications	-2,279053	0,1796	14		-3,275813	0,0727	13
utilities	-2,523604	0,1111	13		-3,151271	0,097	13
FIRM							
	constant				constant and trend		
	ADF t-statistic	p-value	lag order		ADF t-statistic	p-value	lar order
Basic Materials	-3,067615	0,0304	14		-4,246599	0,0044	15
Consumer savings	-2,72503	0,0712	9		-4,144554	0,0062	7
consumer goods	-3,601281	0,0064	1		-4,416149	0,0024	1
financial	-2,420702	0,1371	14		-2,901148	0,164	14
health	-2,674355	0,0799	9		-3,926258	0,0124	13
industrial	-3,20729	0,0207	7		-3,727304	0,0223	7
oil and gas	1,176515	0,997	5		-0,561616	0,9793	12
technology	-2,352894	0,1564	14		-3,383823	0,0559	13
telecommunications	-2,278862	0,1797	14		-3,275822	0,0727	13
utilities	1,09232	0,9973	8		-0,145669	0,9935	8

Table 6 reports unit root tests on all industry and firm volatility series using the Akaike Information Criterion.

Table 7

Correlation structure					
With Trend			Detrended		
MKT	IND	FIRM	MKT	IND	FIRM
1	0,438	0,355	1	-0,073	-0,103
	1	0,92		1	0,823
		1			1

Table 7 reports the contemporaneous correlation structure of monthly volatility series constructed from daily data. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22). All measures are value-weighted variances. The left panel reports correlations of the series themselves and the right panel reports correlations of the detrended series.

Table 8

Variance decomposition

Series	Step	MKT_t	IND_t	$FIRM_t$
MKT_t	1	100	0	0
	2	99,57	0,21	0,22
	3	97,61	0,21	2,18
IND_t	1	0,01	99,99	0
	2	8,58	84,64	6,78
	3	8,22	81,55	10,22
$FIRM_t$	1	0,82	77,52	21,65
	2	0,98	70,62	28,39
	3	0,97	70,39	28,63

Table 8 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 firsy column explaines by the series reported at the top pf each row. All variables are linearly detrended.

Table 9

Mean and Variance decomposition

	MKT	IND	FIRM
Mean	0,053618	0,446736	0,499764
Variance			
Raw series			
MKT	0,007217	0,036697	0,02933
IND		0,243663	0,442035
FIRM			0,238831
Conditional means			
MKT	0,001815	0,0219	0,017197
IND		0,253139	0,45564
FIRM			0,248417

Table 7 reports the total shares of MKT, IND and FIRM in the total means and variance of the volatility of a typical stock. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22). All measures are value-weighted variances, constructed from daily data. The bottom panel reports a variance decomposition for the conditional expectations of the volatility series.

Table 10

Granger Causality			
Bivariate VAR			
	MKT_t	IND_t	$FIRM_t$
MKT_{t-1}		0,2712 (7)	0,8462 (2)
IND_{t-1}	0,8355 (2)		0 (3)
$FIRM_{t-1}$	0 (7)	0 (3)	
Trivariate VAR (3 lags)			
	MKTt	IND_t	$FIRM_t$
MKT_{t-1}		0,0001	0,0538
IND_{t-1}	0,0111		0
$FIRM_{t-1}$	0,042	0	

Table 8 reports the p-value of Granger-causality VAR tests. The null hypothesis is that lags 1 through *l* of the series indicated in the row do not help to forecast the series indicated in the column, conditional on the other variables in the VAR. In the top panel only the rows and the column series are included in the VAR. In the bottom column all three series are included. For each VAR equation, the lag length *l* is chosen using the Akaike information criterion, and is reported in parentheses. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22). All measures are value-weighted variances, constructed from daily data and are linearly detrended before inclusion in the VAR system.

Table 11

Correlations with GDP Growth								
	Lags	GDP		Lags	GDP		Lags	GDP
MKT	+4	-0,073	IND	+4	-0,116	FIRM	+4	-0,094
	+3	-0,224		+3	-0,019		+3	-0,001
	+2	-0,186		+2	0,012		+2	0,026
	+1	-0,217		+1	0,042		+1	0,049
	0	-0,257		0	0,052		0	0,054
	-1	-0,358		-1	0,003		-1	0,0007
	-2	-0,527		-2	-0,075		-2	-0,09
	-3	-0,582		-3	-0,202		-3	-0,226
	-4	-0,493		-4	-0,347		-4	-0,373

Table 9 reports correlations of MKT, IND and FIRM with GDP growth on lags reported in the table. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22). All measures are value-weighted variances, constructed from daily data, are linearly detrended and time-aggregated to a quarterly frequaency.

Table 12

Cyclical behavior: GDP Growth						
	GDP_{t-1}	Rm_{t-1}	MKT_{t-1}	IND_{t-1}	$FIRM_{t-1}$	R^2(p-value)
Coefficient	0,948	-0,001				0,704
t-statistic	8,583	-0,026				
Coefficient	0,907	0,01	-3,626			0,715
t-statistic	7,715	0,27	-1,035			
Coefficient	0,945	0,018		-0,259		0,705
t-statistic	8,367	0,183		-0,208		
Coefficient	0,944	0,034			-0,345	0,706
t-statistic	9,369	0,339			-0,368	
Coefficient	0,897	0,052	-3,953	-0,546		0,716
t-statistic	7,4	0,499	-1,089	-0,431		0
Coefficient	0,895	0,068	-4,019		-0,546	0,718
t-statistic	7,416	0,632	-1,114		-0,574	
Coefficient	0,949	0,052		7,736	-6,119	0,715
t-statistic	8,4	0,497		0,982	-1,028	0
Coefficient	0,904	0,079	-3,6	6,667	-5,502	0,725
t-statistic	7,424	0,732	-0,983	0,838	-0,918	0

Table 10 reports OLS regressions with GDP growth GDP_t as the dependent variable. All regressors are lagged by one quarter. MKT is market volatility constructed from equation (17), IND is industry-level volatility constructed from equation (18) and (19), and FIRM is firm-level volatility constructed from equations (20)-(22). All measures are value-weighted variances, constructed from daily data, are linearly detrended and time-aggregated to a quarterly frequaency. R_m denotes the quarterly return on the market portfolio. Coefficients are reported with heteroskedasticity-consistent t-statistics in parentheses. The last column reports the regression R^2 and the p-value for a heteroskedasticity-consistent test of joint significance of the volatility measures.