The Structure of Stock Market Volatility *

Burton G. Malkiel
Economics Department
Princeton University

Yexiao Xu †
School of Management
The University of Texas at Dallas
Email: yexiaoxu@utdallas.edu

June 1999

Abstract

This paper uses a disaggregated approach to study the behavior of stock market volatility. While volatility for the market as a whole has been remarkably stable over time, the volatility of individual stocks appears to have increased. We come to this conclusion both from direct testing, motivated by findings from the ARCH literature, and indirect evidence, such as the correlations among securities and the level of diversification needed to produce efficient portfolios. Some factors that may have influenced the apparent increase in the idiosyncratic volatility of individual securities are examined.

*This work was supported by the Princeton University Center for Economic Policy Studies
†We are grateful to John Y. Campbell, Charles Jones, Robin L. Lumsdaine, Jianping Mei, and especially an anonymous referee and René Stultz for extremely helpful comments.

The Structure of Stock Market Volatility

Abstract

This paper uses a disaggregated approach to study the behavior of stock market volatility. While volatility for the market as a whole has been remarkably stable over time, the volatility of individual stocks appears to have increased. We come to this conclusion both from direct testing, motivated by findings from the ARCH literature, and indirect evidence, such as the correlations among securities and the level of diversification needed to produce efficient portfolios. Some factors that may have influenced the apparent increase in the idiosyncratic volatility of individual securities are examined.

Key Words: Market Volatility, Idiosyncratic Volatility, Institutional ownership, Asymmetric Information, Diversification.

Introduction

Ever since the stock-market crash of October 19, 1987 (the largest one-day percentage decline since the Dow Jones stock market average was first published in the 19th century), considerable attention has been paid to overall stock market volatility. Economists such as Shiller (1991) have argued that stock prices are far too volatile to be explained by "fundamentals" such as earnings and dividends. Other analysts have proposed transactions taxes to stabilize prices, and study groups have suggested trading halts, increased margin requirements, and limits on automated trading systems to deal with a perceived problem of increased volatility[1]. The facts suggest, however, that this attention has been misplaced. As shown first by Schwert (1990) and confirmed here with updated figures, the volatility of the market as a whole has not increased.

What has received far less attention is the behavior of the volatility of individual stocks. On theoretical grounds it is possible that the volatility of individual stocks has increased while the volatility of the market as a whole has remained stable. In this study, we show that the volatility of individual stocks has indeed increased over the decades of the 1980s and 1990s. The total volatility for individual stocks and for industry groups is decomposed into systematic volatility (arising from movements in the market as a whole) and idiosyncratic volatility (arising from specific shocks). We find clear evidence that idiosyncratic volatility has trended up. Moreover, we find from cross-sectional regressions that volatility of individual stocks may be related to the amount of institutional ownership.

One might reasonably wonder why idiosyncratic volatility should matter at all. Conventional asset-pricing theory suggests that investors should ignore specific or idiosyncratic risk completely. This is so because idiosyncratic volatility can be eliminated in a well-diversified portfolio. In practice, it is suggested that by the time 20 stocks are held, a portfolio will have achieved essentially "full diversification." But we show that as idiosyncratic volatility has increased, investors need to hold more assets to achieve "full diversification." This can have two effects. On the one hand, this could increase the potential total transactions costs required to achieve adequate diversification. On the other hand, those investors who were insufficiently diversified might feel the risk of their portfolios has increased. Alternatively, even if increased idiosyncratic risk is

[1] See, for example, Summers and Summers (1989) and the Brady Commission Report (1989).

completely washed out in the total portfolio, individual portfolio managers may still feel a need to account for increases in the volatility of the component parts.

Correctly assessing the level and the persistence of volatility is also of great interest to derivative traders. Moreover, interest in understanding time varying volatility has encouraged a large literature based on ARCH and stochastic volatility models (see Ghysels, Harvey, and Renault (1997), Bollerslev, Engle, and Nelson (1994), and Bollerslev, Chou and Kroner (1992)). On the aggregate level, we have learned that conditional volatility seems to be very persistent, i.e., a large volatility shock seems to persist. Our emphasis in this paper is different. We focus on the level of volatility not only at the market level but also at the individual industry and firm level. The ARCH literature has provided us with an efficient way to estimate volatility. Because of computational difficulties in dealing with individual stock returns, and supported by Foster and Nelson's (1996) results, we use a rolling method to estimate volatility instead of the GARCH approach. We will show that any differences with the GARCH approach are small[2].

This paper is organized as follows. In Section 1 we present the basic decomposition of volatility into its systematic and idiosyncratic components. Then we discuss the data and the methodology employed. Section 2 presents our empirical results. First, we update the Schwert (1990) study, confirming that the volatility of the stock market as a whole has not increased over time. We then take a disaggregated look at stock market volatility by examining the volatility of individual stocks and of industry groupings. Here we provide formal tests showing that idiosyncratic volatility has exhibited an upward trend in recent years. In Section 3, we provide alternative indirect evidence of increased idiosyncratic volatility. Here we show that the number of stocks needed to achieve a certain level of diversification has grown over time. Section 4 investigates the relation between the volatility of individual stocks and the proportion of institutional ownership. In Section 5, we examine some factors that may have influenced the apparent increase in idiosyncratic volatility. Section 6 presents concluding comments.

[2]Also related to our work is the article by Braun, Nelson, and Sunier (1995). Although they investigated the volatility issue from both market component and industry specific component, their emphasis is on the predictive asymmetry in both conditional volatilities and conditional beta estimates.

1 The Data and Methodology

Most of the time series data used in this study are constructed from the 1997 version of the CRSP (Center for Research in Security Prices) tape. Data measuring daily returns are available from January 1, 1963 to December 31, 1997, and monthly returns are available from January 1926 to December 1997. As is now common in the literature, we separate our monthly sample into two sub-samples, the pre WWII sub-sample and the post WWII sub-sample. Because of the change in the interest-rate regime following the Accord of the Treasury and Federal Reserve in 1951, our post WWII sub-sample starts in January 1952 (see Campbell (1991)). In our analysis, both exchange traded stocks (New York Stock Exchange (NYSE) and American Stock Exchange (AMEX)) and the NASDAQ data file are used. In principle, we could study the individual securities within the $S\&P$ 500 index, yet we would have to know the composition of the stocks in the $S\&P$ 500 index portfolio each year. Instead, we study a so called simulated "$S\&P$ 500" index series, which is constructed by value weighing the largest 500 stocks in our sample. We also take returns for the actual $S\&P$ 500 index series directly from CRSP data file. There are hardly any differences between these two indices in terms of their composition and their calculated volatility, which is the major concern of this study[3].

1.1 Measuring Idiosyncratic Volatility

In general, the return for each stock $R_{i,t}$ can be written as the sum of its systematic component $R^s_{i,t}$, and its idiosyncratic component $r_{i,t}$. Its corresponding volatility can also be decomposed into two components: systematic volatility and idiosyncratic volatility. Furthermore, we shall define the market portfolio as a value weighted portfolio of N stocks, and its return will be defined as $R^M_t = \sum_{i=1}^N w_i R_{i,t}$, where the w_i represent the weights of each stock in the index, with $\sum_{i=1}^N w_i = 1$. In the case where the systematic element of a security's return, $R^s_{i,t}$, is simply the market return, R^M_t, we have the following relationship,

$$Var(R_{i,t}) = Var(R^M_t) + Var(r_{i,t}) + 2Cov(R^M_t, r_{i,t}), \tag{1}$$

[3]The correlation between the returns of the two series for the postwar period is .983.

and because, by definition $Cov(R_t^M, r_{i,t}) = 0$ obtains, the following cross-sectional weighted sum,

$$\sum_{i=1}^{N} w_i Var(R_{i,t}) = Var(R_t^M) + \sum_{i=1}^{N} w_i Var(r_{i,t}). \tag{2}$$

Equation (2) suggests that the value-weighted aggregate volatility of individual stocks consists of the volatility imparted by movements in the broad market index and aggregate idiosyncratic volatility. While all the volatilities we have used are unconditional volatilities, under the common information assumption the decomposition in equation (2) also holds for conditional variances, namely:

$$\sum_{i=1}^{N} w_i Var_t(R_{i,t}) = Var_t(R_t^M) + \sum_{i=1}^{N} w_i Var_t(r_{i,t}). \tag{3}$$

Here $Var_t(.)$ denotes the variance conditioning on the information available at time t. This equation provides a simple and feasible approach to calculate conditional aggregate idiosyncratic volatility[4]. Based on relationship (3), we can construct an estimator for aggregate idiosyncratic volatility $\hat{v}_{I,t}^2$ as,

$$\hat{v}_{I,t}^2 = \hat{v}_{A,t}^2 - \hat{v}_{M,t}^2, \tag{4}$$

where $\hat{v}_{A,t}^2 = \sum_{i=1}^{N} w_i \hat{Var}_t(R_{i,t})$ is the conditional aggregate volatility calculated from the value weighting of estimates of each individual stock's conditional variance. $\hat{v}_{M,t} = \hat{Var}_t(R_t^M)$ is the estimated conditional volatility of market returns. This estimator will be used throughout the paper. Under the previous assumptions, equation (4) is an exact relationship if $\hat{v}_{A,t}^2$ and $\hat{v}_{M,t}^2$ are unbiased.

The conditional volatility for each underlying security (or a market index) can be estimated using the standard deviation of the stock's periodic returns. However, since volatilities are persistent as we have learned from the ARCH literature, such an estimator of volatility will be biased and inefficient as show by Chou (1988). In principle, one should adopt a GARCH type of volatility estimator. Because of the computational intensity of such an estimator, this strategy was not feasible in our study

[4]Alternatively, we could first estimate the idiosyncratic returns of individual stocks based on some asset pricing model such as the CAPM model. Using these estimated idiosyncratic returns, we could then calculate the idiosyncratic volatility of each security. Finally, by value weighting, we could estimate the aggregate idiosyncratic volatility. This measure is very close to our measure of aggregate idiosyncratic volatility with a correlation coefficient of 96% as shown in Figure 4 below.

where we focus on individual securities. Instead, we use rolling regression estimators with window length τ, namely

$$\hat{Var}_t(R_t^M) = \sum_{k=1}^{\tau} \omega_k (R_{t+1-k}^M - \mu_t^M)^2, \tag{5}$$

$$\hat{Var}_t(R_{i,t}) = \sum_{k=1}^{\tau} \omega_k (R_{i,t+1-k} - \mu_{i,t})^2, \tag{6}$$

where $\mu_t^M = \sum_{k=1}^{\tau} \omega_k R_{t+1-k}^M$ and $\mu_{i,t} = \sum_{k=1}^{\tau} \omega_k R_{i,t+1-k}$. Using these estimators of conditional volatility, equation (3) may not hold if past R^M helps to predict current r_i and vice versa. Fortunately this is not the case here since r_i is an idiosyncratic return. The weights ω_k decline geometrically with $\sum_{k=1}^{\tau} \omega_i = 1$, and τ represents the window length. Although our emphasis is not on the persistence of volatility, we want to estimate volatility as accurately as possible. Obviously both the level and the persistence depend on the weights and the window length, which can be optimally determined using the method proposed by Foster and Nelson (1996). We performed the simulations described below to determine the weights and window length.

1.2 Rolling Methods of Estimating Volatility Compared with GARCH Techniques

Since volatilities are unobservable, all the statistical inferences concerning the characteristics of volatilities have to be based on volatility estimates. As a result, biases may exit as suggested by Ghyseis and Perron (1993). Monte Carlo simulations are needed to assess the efficiency of various volatility estimators. Suppose the data generating process for volatility is a GARCH(1,1) process. In principle, GARCH estimators are infinite rolling regression estimators. In practice, we investigate a finite rolling estimator with geometrically declining weights of ρ^k, which we call the first type of geometric weights. We also study a second type of geometrically declining weights ($e^{-\alpha k}$) proposed by Foster and Nelson (1996)[5]. Foster and Nelson have also suggested that optimal α and τ have a relationship of $\tau/\alpha = \sqrt{3}$.

We have estimated a GARCH(1,1) model of the form $h_t = \kappa + \delta h_{t-1} + \phi(r_{t-1} - \mu)^2$ for the value weighted monthly NYSE/AMEX/NASDAQ index return r_t during the

[5] Two sided rolling regressions maybe optimal in maintaining the persistence of volatility, but they do poorly in detecting a time trend. Therefore, only a one sided rolling regression has been employed.

period of 1952 to 1997. We obtain the following parameter values: $\kappa = 0.9348 \times 10^{-4}$, $\delta = 0.8586$, $\phi = 0.0880$, and $\mu = .0107$, which implies an unconditional monthly standard deviation of 4.18%. Based on these estimates, we generate stock return data over the same time horizon with an added time trend in the volatility, i.e.,

$$R_t = u_t \tag{7}$$

$$u_t = \sqrt{h_t}\nu_t \tag{8}$$

where,

$$\nu_t \quad N(0,1) \tag{9}$$

$$h_t = \kappa + \gamma t + \delta h_{t-1} + \phi u_{t-1}^2. \tag{10}$$

To be comparable with average trend found in our empirical study, we set $\gamma = 2 \times 10^{-6}$. Since equation (10) can be rewritten as,

$$\begin{aligned} h_t &= \kappa + \gamma t + (\delta + \phi)h_{t-1} + \xi_t, \qquad (11) \\ \xi_t &= \phi h_{t-1}(\nu_{t-1}^2 - 1). \end{aligned}$$

An OLS regression will not be efficient because there are heteroscedastic residuals. Therefore, a generalized least squares regression should be employed. Fortunately, the residuals and the regressor are independent. We can use weighted least squares with weights of $\sqrt{h_{t-1}}$. But since Canjels and Watson (1997) have shown that the $t-$ ratio on γ estimator will not have the right size, further investigation on critical values and bias involved in connection with our particular problem is warranted. We have therefore performed simulations with 5000 replications for a sample size of 50%, 100%, 150% 200%, and 400% of 552, which corresponds to the number of months in our empirical study. Furthermore, for each sample size, we set the persistence parameter $\theta = \delta + \phi$ to be 90%, 92.5%, 95% 97.5%, 100%, and 102.5% of that estimated from the composite index returns[6]. Table 1 shows that, on the one hand, when the true persistence is high the slope coefficient on the linear trend γ is biased upward even with a large sample[7]. The bias disappears, however, when persistence is less than .9 with a sample size of over 2000. On the other hand, the persistence estimates are biased downwards and are largely dependent on the sample size. We have also tabulated the t values necessary for rejecting the hypothesis of a zero trend in Table 1. In general, these are larger than the conventional $t-$ratios but they tend to be very close for large samples.

[6] κ is also set so that the unconditional volatility is fixed at 4.18%.

[7] Results are much worse if simple OLS estimators are used.

Insert Table 1

The above simulations suggest that there will be an upward bias in the GLS estimator of $\hat{\gamma}$ even if we know the true volatility. We estimate the unobserved volatilities using rolling regressions. Similar simulations are conducted in order to determine the best structure for the rolling estimator. In particular, we use a sample size of 552 with $\rho = .8, .85, .9, .95$ and with window lengths of 12 and 24 respectively for the first type of geometric weights. We have also tried the second type of geometric weights with window lengths $\tau = 6, 12, 18, 24$. An AR(1) model with trend similar to equation (11) is then fitted to each estimated volatility series using a GLS procedure. We report the distributions for the $\hat{\gamma}$ estimator and the $\hat{\theta}$ estimator in Table 2. Generally speaking the $\hat{\gamma}$ estimator can be biased either upward or downward. At a high persistence level, the first type of weights with window length of 12 seems to induce more upward bias than that of window length 24 which is more conservative at a low persistence level. We thus choose window length of 24 for the first type of weight. Furthermore, we use $\rho = .90$ since it produces almost no bias at a high persistence level and is very conservative at a low persistence level. However, it seems that the persistence estimator $\hat{\theta}$ is biased upwards most of time. Therefore, a second type of geometric weights with and $\tau = 12$ are used. This particular weighting scheme works best in terms of preserving persistency even though it is biased upward when the true volatility is highly persistent. In order to balance the two, both types of weighting schemes are used in our empirical study.

Insert Table 2

Due to the persistence of volatility, the conventional critical value for a $t-$test will not have the right size using GLS. Therefore, for our sample size (T=552), we have computed critical values at different significance for volatility with different persistence. Table 3 reports these critical values using the first type of weights with $\rho = 0.85$ and $\rho = 0.90$ as well as using the second type of weights with $\tau = 12$ and $\tau = 18$. In general, the critical values are larger using the second type of weights with $\tau = 12$ than the conventional level as well as the values under the first type of weights with $\rho = .9$. It is also interesting to note that when volatilities are less persistent, the critical value using first type of weights with $\rho = .9$ is a little smaller than that of the conventional level. This may be due to the fact that this type of estimator is very conservative.

Insert Table 3

1.3 A discussion on the general return structure

The decomposition in equation (4) is not exact for more complex models of systematic return but is a good approximation for the cases considered. For example, in the case where the systematic return $R^s_{i,t}$ is a function of the market return R^M_t, the Capital Asset Pricing Model (CAPM) holds. The systematic return can then be expressed as $\beta_i R^M_t + (1-\beta_i)R^f_t$, where R^f_t is the risk-free rate. Similar to equation (1), we have the following,

$$Var(R_{i,t}) = \beta_i^2 Var(R^M_t) + Var(r_{i,t}) + (1-\beta_i)^2 Var(R^f_t) + 2\beta_i(1-\beta_i)Cov(R^M_t, R^f_t), \quad (12)$$

Taking weighted sums across individual stocks yields:

$$\begin{aligned} \sum_{i=1}^{N} w_i Var(R_{i,t}) &= \hat{\beta}^2 Var(R^M_t) + \sum_{i=1}^{N} w_i Var(r_{i,t}) \\ &\quad +(\hat{\beta}^2 - 1)[Var(R^f_t) - 2Cov(R^M_t, R^f_t)] \end{aligned} \quad (13)$$

because $\sum_{i=1}^{N} w_i\beta_I = 1$ and $\hat{\beta}^2 = \sum_{i=1}^{N} w_i\beta_i^2$. Here again one can replace unconditional second moments by conditional ones if the common information restriction holds. However, as Campbell (1993) has shown, past R^f may help to predict R^M and we do not take such a relationship into account in the computation of conditional variances. Because the predictability is weak, however, the problem of incorrect use of univariate information sets is likely to be small.

Since the risk-free rate, R^f_t, is reasonably stable relative to the market return, R^M_t, the last term in equation (14) is negligible and can be ignored. Therefore, the aggregate conditional volatility can be rewritten as,

$$v^2_{A,t} \approx \hat{\beta}^2 v^2_{M,t} + v^2_{I,t}. \quad (14)$$

When we use equation (3) to estimate aggregate idiosyncratic volatility, $v_{I,t}$, the volatility estimate will be biased by $(\hat{\beta}^2 - 1)v^2_{M,t}$. If, as an approximation, we treat the weights w_i as some probability measure, then $\hat{\beta}^2 - 1$ is the variance of β_i. In this case, the volatility measure will be biased upwards. However, the estimated bias is likely to be small, in the neighborhood of 4% to 5% of the market volatility[8]. Furthermore, if the market volatility is stable, as we shall show it is, the bias will have little effect on the magnitude of the *trend* over time since all the volatility estimates will suffer the same degree of bias. Moreover, the empirical evidence of little correlation between $\hat{v}^2_{I,t}$ and $v^2_{M,t}$ also suggests that the bias is likely to be quite small [9].

Under other models of systematic returns, our estimator of idiosyncratic volatility given by equation (3) is likely to be reasonable. In the framework of APT, for example, with k independent factors, the following relationship can be derived,

$$\begin{aligned}\sum_{i=1}^{N} w_i Var(R_{i,t}) &= \hat{\beta}^2 Var(R_t^M) + \sum_{i=1}^{N} w_i Var(r_{i,t}) \\ &\quad + \sum_{j=1}^{k} V_{\beta_j} Var(R_t^{F_j} - R_t^f)\end{aligned} \tag{15}$$

where $V_{\beta_j} = \sum_{i=1}^{N} w_i(\beta^2_{i,j} - \bar{\beta}_j)$, $\bar{\beta}_j = \sum_{i=1}^{N} w_i \beta_{i,j}$, and $R_t^{F_j}$ is return on factor j. Therefore, the bias depends on both variations in betas and volatilities in excess factor returns. Relatively speaking, it is the first factor that captures most of the variations in returns if factor analysis is used. The variations in betas should be relatively small except for the first factor. Therefore, the same argument we have applied in the case of CAPM can be used in assessing the approximation error.

Although our aggregate idiosyncratic volatility decomposition is an aproximation, it is reasonably insensitive to model specifications. As a practical matter, even if one accepts the CAPM model, it is difficult to estimate an individual stock's beta over a short period of time. Such beta estimates are critical in computing idiosyncratic volatility under the CAPM framework. Our method allows us to avoid specific issues concerning any particular model and it is also computationally efficient.

[8]These bias estimates are based on the construction of 100 portfolios of the type used by Fama and French (1988) over our sample period.

[9]Schwert and Seguin (1990) have shown that the cross-sectional dispersion in betas is correlated with the level of market volatility. This conclusion is reached by comparing an equally weighted group of small stock portfolios with an equally weighted group of large stock portfolios. However, we have used value weighting in this study. Furthermore, by examining their Figure 2, one can see that the large dispersion in betas is much more significant for small stocks than for large stocks.

1.4 Testing volatility trend

In the following section of the study, we will ask three types of questions. First, have *average* volatility levels in different periods differed significantly from each other? In order to answer this question, a simple mean's test will be employed based on conventional volatility estimates[10]. Secondly, when there is a noticeable trend in volatility, especially for the post war period, we will study the characteristics of this trend. This issue will be investigated by fitting an AR(p) model with a time trend. As previous work has suggested, volatility is very persistent and does not behave as a random walk process. If we simply fit a time trend to a finite sample, some of the persistency will translate into the time trend even if there is no time trend under the null hypothesis. Here, we adopt two types of tests. If we believe the volatility is truly generated by a GARCH model, based on the discussion of section 1.2, we can estimate the following model using GLS,[11],

$$v_t = \mu + \rho v_{t-1} + \gamma t + \alpha_1 \Delta v_{t-1} + \cdots + \alpha_p \Delta v_{t-p} + \epsilon_t \ . \tag{16}$$

In this case, the null hypothesis is that $\gamma \geq 0$. Alternatively, under a general structure of volatility, we can examine if trends exist in the framework of unit root tests[12]. As shown in econometrics literature (see Canjels and Watson (1997) and Vogelsang (1998)), one can not use the conventional t statistics for testing the significance of a trend in such framework. Instead, we will apply Vogelsang's (1998) Wald type of tests based on the following model,

$$\begin{aligned} v_t &= \mu + \rho v_{t-1} + u_t \\ u_t &= \alpha u_{t-1} + d(L) e_t, \end{aligned} \tag{17}$$

together with some initial conditions and $d(L) = \sum_{i=0}^{\infty} d_i L^i$. These tests are robust to both I(0) and I(1) errors. However, since we do not believe volatility should follow a random walk (i.e., an I(1)) process as a prior, we use $t - PW^1$ test to preserve the best power[13]. In particular, we construct a corresponding 90% confidence interval

[10]By conventional estimates we mean the sample variance estimates based on monthly data.

[11]This is in the spirit of an augmented Dickey-Fuller regression to allow for the general structure of correlations.

[12]Due to the non-negativity of volatility, we will use a log volatility measure.

[13]Vogelsang's (1998) provided a detailed discussion on the power of the test. We are indebted to Vogelsang for supplying the GAUSS code of the test.

of a linear trend on the logarithm of volatility. Stated in another way, we can say that there is positive growth in volatility if the confidence interval is on the positive orthoaxis. Finally, we will ask if the characteristics of market volatility are different from individual level volatility. Our particular interest is to study the behavior of idiosyncratic volatility over time.

2 The Empirical Results

In this section, we first examine the volatility of stock prices (returns) for the overall market using alternative market indices. Then we will investigate the behavior of volatility with a disaggregated approach. This is accomplished by looking at the volatilities of the most volatile stocks during each period; by examining the volatility characteristics of the individual stocks in the market index portfolio over time; and by studying the volatility characteristics of major industry portfolios.

2.1 The Evidence on Overall Stock Market Volatility

The evidence does not support the popular belief that the market as a whole has become increasingly volatile. The remarkable fact, first documented by Schwert (1991) and updated in the graphs in Figure 1, is that overall stock market volatility has shown no tendency to increase in recent years. To be sure there have been recent episodes of increased volatility, but they have not persisted. Moreover, there is no evident tendency for market volatility to have increased in recent years with the increased institutionalization of the market and with the tremendous growth in derivative markets over the past two decades.

Insert Figure 1

We have plotted in Figure 1 the volatility series for the the value weighted NYSE /AMEX/NASDAQ composite index for the period 1926 through 1997, calculated from monthly return data[14]. The figures show the huge spike in volatility during the late

[14]We have used the conventional measure of volatility here in order to be comparable with previous studies. The volatility plot for the Standard and Poor's 500 Stock Index is almost identical to Figure 1.

1920s and 1930s as well as the higher levels of volatility during the oil and food shocks of the 1970s and the stock market crash of 1987. In general, however, there is no discernable trend in market volatility for either the $S\&P$ 500 series or for the value weighted NYSE/AMEX/NASDAQ composite index. Moreover, the average annual volatility for the 1990-1997 is 11%, which is lower than that for either the 1970s' (14%) or the 1980s' (16%). Similarly, from formal statistical analysis, we can draw two conclusions. First, using a means test, we can state unambiguously that stock market volatility over the past half century (about 13% per year) is lower than it was during the time period of the Great Depression of the 1930s and WWII (about 23%). We can also reject, at a 5% level, the hypothesis of equal means in volatilities for the two periods (1926-1951 vs. 1952-1997), in favor of the alternative hypothesis that the volatility in the early period is larger than that of the later period[15]. Therefore, the interesting question to ask is that if there is any pattern in the volatility series during the postwar period.

Insert Figure 2 and Table 4

The dashed line in the top panel of Figure 2 shows the volatility estimates computed from monthly simulated $S\&P$500 Index returns for the postwar period (1952 through 1997) using the rolling regression method described in the previous section. Here the sharp spike in volatility during the 1987 stock market crash is evident, but we see that volatility quickly receded. Performing a trend test on both the $S\&P$ 500 and NYSE/AMEX/NASDAQ volatility series, we can reject the hypothesis that there are time trends in either volatility series. In fact, Table 4 shows that the trend coefficients γ are not close to being significant using the critical value in Table 3. Furthermore, the robust confidence interval ranges from $-.04\%$ to $.19\%$ for $S\&P$ 500 index volatility. The conclusion that a trend does not exist is therefore very robust whether we use the first type or the second type geometric weights. Without a trend, we can test the unit root hypothesis. Both the augmented Dicky-Fuller test and the augmented Dicky-Fuller t type test strongly reject the hypothesis that the volatility series of $S\&P$500 (and NYSE/AMEX/NASDAQ) returns follow a random walk process, which reconfirms our belief that a unit root process can not be imbedded in the volatility process. The

[15]If we simply split the sample evenly (1926-1961 vs. 1962-1997), the conclusion that market volatility has declined continues to hold.

series is fairly persistent since the autoregressive coefficient θ tends to be large (above .9). Therefore, we conclude that both volatility series appear to be stationary and the original findings of Schwert continue to hold into the 1990s.

2.2 The Volatility of Individual Stocks

The low volatility numbers for the market as a whole seem at odds with both popular perception and casual empiricism. There appear to be obvious patterns of increasing volatility for individual stocks. On any specific day, the most volatile individual stocks move by extremely large percentages. It is not uncommon on a single trading day to find that several stocks have changed in price by 25 percent or more. Indeed, price changes of over 50 percent in a single day for some stocks (excluding new issues) are not at all uncommon. It appears that when earnings of companies are reported that differ slightly from the forecasts of Wall Street analysts, or when companies warn the financial community that earnings may not meet forecasted levels, the market reaction is immediate and usually substantial as institutional investors seem likely to interpret the news in a similar fashion. The question remains whether such impressions from casual empiricism can be documented rigorously and, if so, whether these patterns of volatility for individual stocks are different from those existing in earlier periods.

Figure 3 measures the daily volatility (the standard deviation of daily returns)[16] of the 20 stocks on the CRSP tape each month with the largest percentage price fluctuations for that month during the period of 1963 to 1997. To put the volatility numbers in perspective, we plot at the bottom of the graph five times the daily volatility of the Standard and Poor's 500 Index computed in the same way. Similar pictures are drawn for the 50 most volatile stocks as well as the top 10 and 27 percent of stocks in terms of measured volatility. As shown by Lys and Sabino (1992), the power of certain tests is maximized in comparing the mean values in the extreme-ranked groups when each group contains 27 percent of the sample. Just as one would expect, the most volatile stocks display volatility many times that of the index. But what is striking about the analysis is that when we plot the volatility of different groups of the most volatile stocks over time, there does seem to be an upward drift not seen in the plot

[16] As discussed in the previous section, such a volatility measure is inefficient and underestimates the persistence of volatility. We adopt such a measure here simply because it corresponds to the way stock traders look at volatility and provides a useful summary descriptive statistic.

of volatility for the market as a whole. Furthermore, by using a proportional measure (such as top 10% or top 27%) we can guard against the possibility that our findings showing increasing volatility are simply the result of an increased number of companies in the sample[17].

Insert Figure 3

It does appear that price changes for the most volatile stocks (which are typically displayed in the financial pages of major newspapers) have increased in amplitude, especially during the 1980s and 1990s. The upward trend in volatility for the most volatile stocks is not due to the volatility persistency shown in our trend test, although the autoregressive coefficients θ in Table 5 are all very large[18]. In all the four cases shown, we reject the hypothesis of no deterministic trend in the volatility series at about the 1% significance level using our t-type test based on GLS estimates. The roubst 90% confidence intervals are well above zero. In particular, for the portfolio of 20 most volatile stocks, the standard deviation increases about $0.022\%(= .0048\sqrt{21})$ a month, while the monthly *growth rate* of this volatility is about .3% over the 1963-1997 period. Although these numbers decrease when we include more stocks, as shown in Table 5, they remain statistically significant in both tests.

Insert Table 5

We also looked at the other extreme and tested if there was any tendency for the volatility of the least volatile stocks (measured either in number or in percentage) to have increased over time. We found no trend in these volatility series. There has been no tendency for the most stable stocks to exhibit increasing or decreasing volatility over time.

It is interesting to ask why the most volatile stocks have become more volatile in recent years. In addition to the institutional factors which will be discussed in section 5, an additional factor may be associated with this phenomenon. During the

[17]One might argue that if volatility is drawn from some fixed distribution and we increase the number of draws over time, the upper tail will be more volatile just for this reason.

[18]In addition to AIC and BIC criteria, we use twelve lags in the times series model to account for possible seasonality.

1980s there was a tendency to break up many of the conglomerates that had been put together in earlier decades. Large firms tend to be more stable than smaller firms are. From a statistical point of view, when there are more firms with volatile returns in the sample, the probability that we will observe large deviations from the mean will increase. It might be conjectured, therefore, that our findings are an artifact of the fact that over time our sample is likely to include an increasingly larger number of small companies. The measured volatility of small-company stocks may be larger either because of their small size or because of the larger bid-asked spreads associated with such companies. We tested this hypothesis by examining our sample of most volatile stocks to insure that the size characteristics of such stocks had not changed over time. We found that the size of the "most volatile stocks," however measured, has not decreased over time. Moreover, the relative size of samples of various percentages of the most volatile stocks, compared with the total market capitalization of all stocks, has actually increased during recent periods. Thus, companies of constant absolute or relative size have actually become more volatile over time.

2.3 The Volatility of the Individual Stocks in Major Market Indies

The discussion in section 2.1 reveals that there has been no noticeable or measurable upward drift in the volatility of either the Standard and Poor's 500 Stock Index or the NYSE/AMEX/NASDAQ composite index. Furthermore, on average, markets during the pre war period were more volatile than those of post war period. In the analysis that follows, we concentrate on the post WWII period. Here we look at the volatility of the individual component stocks of both the $S\&P$ index and the NYSE/AMEX/NASDAQ composite index. As was argued in section 2, our simulated $S\&P$ 500, i.e. the value weighted 500 largest exchange traded stocks (in terms of their capitalization), approximates the actual $S\&P$ 500 closely. Thus, we will assume that these 500 stocks, which are rebalanced each year, is representative of the actual $S\&P$ 500 composition. In calculating the aggregate volatility of the individual stocks in the index, we value weight the volatilities of the 500 individual stocks. We call this number AV500. As proposed in section 2, we then subtract the volatility of the calculated values of the index (that is, the $S\&P$ 500 portfolio of stocks) to arrive at a measure of the differential volatility, which we have shown well represents aggregate idiosyncratic volatility. We will do a similar decomposition for the composite NYSE/AMEX/NASDAQ index portfolio.

For illustrative purposes, we have displayed the volatility estimates for both $S\&P$ 500 and AV500 in the first plot of Figure 2 for monthly returns over the period from 1952 to 1997. These estimates are from rolling regressions with the second type geometric weights described in section 2. While there is no observed trend in the $S\&P$ 500 series as discussed before, the AV500 series seems to be increasing over time. A very similar pattern exists for other index portfolios and using other weighting scheme. The trend test results[19] are summarized in Table 4. For $S\&P$ 500 series, none of the tests confirm a deterministic time trend. However, for AV500 series, the GLS based t type of test shows that a deterministic time trend is significant at a 10% level when using either the first type or the second type geometric weights. At the same time, both robust confidence intervals are above zero with a .09% growth rate of volatility. The conclusions are much stronger for the aggregate volatility of the composite index portfolio using both weighting schemes as shown in Table 4 under the "NYSE/AMEX/NASDAQ" column. Furthermore the coefficient θ indicates that the aggregate volatilities are a little more persistent than that of the volatilities computed from indexes. Overall, the evidence indicates some increase over time in the volatility of the individual stocks relative to the indexes.

The explanation for this finding lies in the behavior of idiosyncratic volatility. To see this more clearly, we have plotted the aggregate idiosyncratic volatility estimates for the $S\&P$ 500 index portfolio using the second type geometric weights in the second half of Figure 2. We see visually that the idiosyncratic volatility appears to increase over time. A similar pattern emerges for the composite index portfolio and using different weighting schemes. As Table 4 indicates, the $\hat{\gamma}$ trend estimates are very close being significant at a 5% level with both first type and second type geometric weights. The robust confidence interval is again above zeros with a slightly higher growth rate in aggregate idiosyncratic volatility than that of aggregate volatility. Therefore, a linear time trend is acceptable. Table 4 also shows stronger results for the composite (three exchanges) index portfolio. The corresponding γ estimates are significant at 1% level. It is clear that the idiosyncratic volatility of individual stocks in the index has increased. The idiosyncratic volatility series fluctuates along a rising time trend.

[19] Six lags are used in the time series model according to AIC and BIC criteria.

Insert Figure 4

Certainly, our results depend on the way that idiosyncratic volatilities are constructed. But we have argued in section 1, our method of estimating idiosyncratic volatility is fairly robust with respect to asset pricing models. We have plotted the aggregate idiosyncratic volatility calculated from the CAPM residuals in Figure 4. In particular, we estimate the volatility of the CAPM residuals using current and previous eleven months return data[20] for each of the largest 500 stocks. We then value weight the squared CAPM residuals to construct aggregate idiosyncratic volatility. There is an apparent upward trend in the volatility series. Furthermore, it is more persistent than the one shown in the second half of Figure 2. In addition, we can reject a zero time trend hypothesis at 5% level. The evidence further demonstrates the robustness of our results.

Idiosyncratic volatility is precisely the kind of volatility that is uncorrelated across stocks and thus is completely washed out in a well-diversified index portfolio. According to the capital asset pricing model, such an increase in the idiosyncratic volatility should not command an added risk premium on the market. Thus, while it is possible to argue that the volatility of *individual* stocks has increased, as long as their systematic risk remains unchanged, there should be no consequence for asset pricing, at least according to the CAPM. However, even if the CAPM holds, we will show in section 3 that an increase in idiosyncratic volatility will have an important effect on the number of securities one must hold in a portfolio to achieve full diversification.

2.4 Analysis by Industry Portfolios

In the previous sections we have studied the volatility of stock returns by using data on individual stocks. Here we will study the volatility structure of industry groups. Campbell, Kim, and Lettau (1994), calculated market volatility by using the standard deviation of market excess returns (the difference between the returns from the market and the risk free rate) and volatility across industries by weighting squared residuals from a regression of the excess returns from each industry portfolio on the excess

[20]This corresponds to the time interval used in estimating our measure of idiosyncratic volatility. If two to five years of monthly data are used, the results are similar except the volatility series is smoother.

returns from the market index. Although the emphasis of the Campbell *et. al.* study was on the lead-lag relationships between volatility and a variety of macro variables, they did observe an increasing trend for volatility across industries. Therefore, it is worth investigating the issue using our measures of volatility and performing a trend test for variety of industry aggregates.

We constructed thirteen industry portfolios according to SIC codes for individual stocks. The SIC classification scheme is identical to the one used by Ferson and Harvey (1991) and Campbell (1993). The classified industries are: (1) petroleum, (2) finance and real estate, (3) consumer durables, (4) basic industry, (5) food and tobacco, (6) construction, (7) capital goods, (8) transportation, (9) utilities, (10) textiles, (11) services, (12) leisure, and (13) all remaining industries. This classification captures both diversity across industries in a broad sense and the common features for firms within in each groups.

Insert Figure 5

Figure 5 shows the behavior of volatility for one typical industry portfolio (capital goods) using the second type geometric weights. Three kinds of volatility measures are plotted on Figure 5. Industry volatility (INVOT) is calculated from a value-weighted index of industry portfolio returns; Aggregate volatility of the individual stocks within each industry (AGVOT) is calculated from value weighting the volatilities of each stock; Idiosyncratic industry volatility (IDVOT) is calculated from the difference of the above two volatility series. By examining the plot on the bottom panel of the figure, we observe an apparent upward trend. The same visual conclusion is true for 10 of the 13 industries studied. Such characteristics are identical when using the first type geometric weights. If there is no deterministic trend in a very persistent series, it may still be possible to fit a deterministic trend to the finite sample realized from the process. Therefore, we need to control for persistence when testing a trend. In Table 6 we only show the GLS based t ratios and the robust confidence intervals for the trend coefficient γ. To check for the robustness of our findings, we have listed the results for both weighting schemes.

Insert Table 6

For the industry (INVOT) series, we find no evidence of a deterministic trend except for one or two cases. We reach this conclusion by examining the confidence intervals and the GLS t ratios. Therefore, similar to the overall market volatility, we believe that the volatilities for most of the industry portfolios have been stable. There is, however, a significant time trend for the textiles industry portfolio at 5% level when using the second type geometric weights and at 10% level when using the first type geometric weights, even though it is not the most volatile industry. For the food and tobacco industry, a linear trend also appears to exist using the robust Wald test.

The results change when we examine the aggregate industry volatility (AGVOT) series. Seven volatility series at a 5% significance level and two additional volatility series at a 10% significance level exhibit a deterministic trend from a GLS t test. The same results holds whether the volatilities are estimated using the first type or the second type geometric weights. The results are somewhat weaker when we use the robust Wald type of test. The robust confidence intervals shows there are six industries that exhibit a significant trend for both types of weights. They are consumer durable (the third) industry, basic (the fourth) industry , construction (the sixth) industry, capital goods (the seventh) industry, utilities (the ninth) industry, and textiles (the tenth) industry. Therefore, there is some evidence of increasing volatility for the individual stocks within many of the industry portfolios.

The conclusion can be further supported by examining aggregate industry idiosyncratic volatility (IDVOT). Nine out of thirteen industries have an increasing trend in the IDVOT series at a 5% significance level or smaller under the second type geometric weighting scheme. When using the first type geometric weights, eight exhibit a deterministic trend at a 5% significance level, and one at a 10% level using the GLS t ratios. Among these industries, seven of them also are significant under a Wald type of test. We conclude that idiosyncratic industry volatility is likely to have an upward time trend.

2.5 The Correlation Structure

As discussed in the previous sections, the behavior of volatility for broad indexes, such as the $S\&P$ 500 has been quite stable, while aggregate idiosyncratic volatilities appear to have increased over time. The general conclusions hold even for the thirteen general industry groups. An implication of our finding is that one should be able to observe a decreasing trend in the correlation among the returns for individual stocks over time. This would allow the volatility of the market portfolio to remain the same even if there is an increase in each individual stock's volatility. Computationally, it is prohibitively cumbersome to calculate the pair-wise correlations among each pair of stocks in the NYSE/AMEX/NASDAQ universe[21]. Instead, we have sorted all the stocks on the CRSP tape into ten portfolios by size and computed the pair-wise correlations among stocks within each size portfolio. Such a design not only reduces the computational burden by 90%, but also allows us to examine the correlation structure for each size portfolio.

Insert Figure 6

Correlations among each pair of stocks within each size portfolio are computed using the previous 12 months of returns at any point of time. An equal weighted average is then calculated for each portfolio. The first half of Figure 6 shows the overall average correlation across portfolios through time together with a five year moving average. It does appear that there is a drop in the correlation coefficients from 1950s to 1990s.[22] In order to examine the distribution patterns over time, we have also plotted the 25th percentile, the median, and the 75th percentile of the average correlations in each size portfolio (not shown here). In each plot, the pattern is similar to that of Figure 6. We do observe, however, the decreasing trend is less obvious for large portfolios. It is also the case that the level of correlation is lower for the smallest decile than for the largest decile. The average mean of correlation for stocks in the smallest decile is about .25, while that of the largest decile is about .35.

It is also the case that for the observed patterns in volatilities to hold, the coefficient of determination from a market model has to drop. As an alternative, we have also computed the R^2 for each stock in each size portfolio[23]. The average R^2s are show in the second half of Figure 6 along with the five year moving average. Apparently,

[21]For 6000 stocks over 540 periods, there will be 10 billion correlations.

[22]Since correlations are likely to be constrained between 0 and 1, we are unable to perform a formal test such as those discussed before.

[23]In order to be comparable with the horizon at which we compute volatility, we compute R^2 over twelve months.

there is an even more persistent decreasing trend than was the case for the correlation structure. On average, R^2 is around .3. It is especially low for recent years.

3 Diversification and Idiosyncratic Volatility

Our general conclusion is that while market as a whole has been no more volatile in recent decades, the idiosyncratic volatility of individual stocks has exhibited an upward trend. Although this conclusion is dependent on the particular estimator we have proposed in section 2, supporting evidence from the correlation structure points in the same direction. We turn next to the question of whether there is any economic significance of a rising trend in idiosyncratic volatility. In this section, we will look at the relationship between idiosyncratic volatility and diversification.

Proposition *In order to reach a certain level of diversification, the number of stocks needed in a portfolio grows with an increase in overall idiosyncratic volatility.*

Proof Denote R_i, $R_{S,i}$, and $R_{I,i}$ as the return on stock i, the systematic return on the stock, and the idiosyncratic return respectively. All the variables are stochastic. For an equally weighted portfolio with N stocks, the portfolio return will be $R_p = \frac{1}{N}\sum_{i=1}^{N} R_i = \frac{1}{N}\sum_{i=1}^{N} R_{S,i} + \frac{1}{N}\sum_{i=1}^{N} R_{I,i} = R_{S,p} + \frac{1}{N}\sum_{i=1}^{N} R_{I,i}$. For simplicity, we assume that each stock has the same idiosyncratic volatility σ_I^2. Therefore, the portfolio volatility relative to the systematic portfolio return $R_{S,p}$ can be expressed as the following conditional variance,

$$Var(R_p|R_{s,p}) = Var(R_p - R_{s,p}) = \frac{1}{N}\sigma_I^2.$$

Obviously, in order to achieve a certain level of diversification, that is, to reduce idiosyncratic risk to a certain degree, we need more stocks in the portfolios when idiosyncratic volatility increases. **Q.E.D.**

Intuitively, we are arguing that when idiosyncratic volatility increases, it becomes more difficult to construct a portfolio that will diversify away all idiosyncratic risk and bear only market risk. This conclusion is independent of the behavior of market risk. This proposition has two important implications. First, most individual investors, who face a wealth constraint and incur transaction costs, usually find difficult to hold a large number stocks in their portfolio[24]. Even though they may understand the principle of diversification, they may not be able to eliminate idiosyncratic risk. Therefore, when idiosyncratic volatility increases, the effective level of diversification of their portfolios will decrease.

Second, this proposition provides an alternative approach to test the hypothesis of an upward trend in idiosyncratic volatility over time. We can randomly form portfolios with certain numbers of stocks and study the pattern of portfolio volatility relative to market volatility over time. Specifically, starting 1952, for each year we randomly select n stocks to form an *n-stock portfolio* ($n = 2, \cdots, 30$) using the universe of all NYSE/AMEX/NASDAQ traded stocks. The random selection for each *n-stock portfolio* for any given year will be repeated until all the stocks have been chosen. We can then consider the average volatility from these random samples as the volatility for the *n-stock portfolio.* This process was repeated for all the 46 years ending in 1997 and for forty-nine portfolios with 2, 3, $\cdots$, 50 stocks respectively.

Insert Figure 7

In the top half of Figure 7 we have plotted the idiosyncratic volatilities of portfolios of various sizes over time. As expected, the volatilities of portfolios with fewer stocks are much larger than those with a larger number of stocks. What is more interesting is that for any given portfolio, the idiosyncratic volatility is smallest (and relatively stable) during the first twelve year period (1952- 1963), while a persistently increasing trend is apparent over the later periods. A simple means test among the three equally separated periods confirms our casual empiricism. Once again, we have confirmed that idiosyncratic volatility has increased from time to time.

This phenomenon can be further illustrated using a textbook style portfolio diversification plot, which is shown in the bottom half of Figure 7. For each time period (1952-1966, 1967-1981, and 1982-1997), we have plotted the relationship between the average portfolio volatility and the number of stocks in the portfolio. The graph resembles the conventional diversification diagram, except that there are distinct diversification lines for different time period. The long dashed line represents the diversification

[24]Individuals may, of course, obtain adequate diversification through the purchase of mutual funds, but this strategy also entails significant management fees and often sales charges.

line for the most recent period. It is lies above the diversification lines for both the '50s and early '60s (the first period) and the late '60s and '70s (the second period). The differences are statistically significant[25]. The diversification line for the middle-period also lies significantly above that of the first period.

We conclude that these indirect diversification tests also confirm our finding of increasing idiosyncratic volatility over time. Furthermore, the popular assertion that one needs only about 20 stocks to compose a fully diversified portfolio appears to be somewhat dependent on the time period. With idiosyncratic volatility as high as recent levels, a larger number of stocks will be required to wash away all idiosyncratic risk.

4 Institutional Ownership

As we will argue in the next section, an increase in the proportion of institutional ownership of securities might be expected to contribute to an increase in stock market volatility. It would be desirable to test this hypothesis directly using times series data on institutional holdings. We obtained panel data on institutional ownership for each stock in the $S\&P$ 500 index portfolio during an eight year period from 1989 to 1996. We then examined if the degree of institutional ownership was related to the volatility of individual stocks by testing for a positive cross-sectional relationship during each of the eight years between the volatility of the stocks in the index and the percentage of institutional ownership.

Here idiosyncratic volatility is calculated as the mean of the squared residuals of daily returns over the fourth quarter of the year (which corresponds to the available institutional holding data) from the CAPM model fitted to each stock[26]. Although the logarithmic transformation of volatilities in the OLS regression reduces much of the heteroscedasticity problem, residuals are still apparently positively skewed. Thus, usual statistical inference will be invalid (see McDonald and Newey (1988)). We estimated all the models using a partially adaptive estimator developed in McDonald

[25] If returns are normally distributed, the volatility estimates will have a χ^2 distribution. Therefore, a ratio test between estimates of different periods will have a F distribution.

[26] Since we are interested in the idiosyncratic volatility of individual stocks, this measure is used instead of the one suggested in section 2. Furthermore, in order to obtain stable beta estimates, daily returns over the whole year are used in the estimation of the CAPM.

and Xu (1995)[27]. Such an estimation technique not only nests the OLS method as a special case but also allows skewed and leptokurtic residuals. The first eight equations (Model I) in Table 7 show that, except for 1990, the logarithms of individual stocks' idiosyncratic volatilities are positively and significantly (at 5% level or better) related to the proportion of institutional ownership. The result is strongest for 1995. Malkiel and Xu (1997) found that volatility is also likely to be negatively correlated with the size of the company. When the R^2 is small, the results may just reflect the size effect. Therefore, we have also controlled for the size effect, where size is measured simply as the log of the total capitalized value of each firm. The eight equations of Model II in Table 7 suggest that the institutional ownership is still strongly related to the idiosyncratic volatilities even after controlling for the size effect.

Insert Table 7

In order to provide a summary statistic for our panel data, we have also run a pooling regression, where we pool all eight years of data together. As indicated in Table 7, again we find strong evidence (now with zero $p - values$) that idiosyncratic volatility is positively related to institutional ownership after controlling for the size effect. The conclusion is further supported from evidence on pooled thirteen industry portfolios shown in the last equation in Table 7. The R^2 for the regression is as high as 34%. When the size variable is also included, the R^2 only increase to 38%. In other words, it appears that individual stocks do tend to be more volatile relative to the market, the greater is the percentage of these shares owned by institutions.

The contemporaneous relationship does not reveal causality. Fortunately, we are able to investigate the direction of causality between ownership and idiosyncratic volatility in the sense of Granger causality. In particular, we have estimated the following regression using the pooled industry portfolio data,

$$\begin{aligned} log(V_{idio.,t}) &= -2.767 + .391 log(V_{idio.,t-1}) + .0099 Ownership_{t-1} + \hat{e}_t \qquad R^2 = .481 \\ & \quad\ (0.455) \quad (.0969) \qquad\qquad\qquad (.0026) \end{aligned}$$

We reject the hypothesis that the lagged institutional ownership variable has no explanatory power with an F statistics of 14.08. This means that increases in institutional

[27]Essentially, it is a maximum likelihood estimator based on the exponentially generalized beta distribution of type two (EGB2).

ownership Granger cause increases in the idiosyncratic volatility. Similarly, we can run the following regression,

$$\begin{array}{rcl} Ownership_t & = & \underset{(7.158)}{17.04} + \underset{(.0416)}{.861} Ownership_{t-1} + \underset{(.0152)}{.0261} log(V_{idio.,t-1}) + \hat{e}_t \quad R^2 = .900 \end{array}$$

However, we fail to reject the hypothesis that the lagged volatility variable has no explanatory power (F statistics of 2.93). In other words, Granger causality is not confirmed the other way around. Therefore, the evidence is consistent with our conjecture that the institutionalization of the market may have played some role in increasing the volatility of individual stocks.

5 What Might Explain Increasing Idiosyncratic Volatility?

Over the past two decades, the most significant changes in financial markets have involved changes in information structure and in financial innovation. First, improvements in both the speed and availability of information to stock market investors could have increased the responsiveness of stock prices. Second, the rapid growth in the share of assets held by institutional investors and their virtual domination of trading volume could have an impact on the volatility of stock prices. Third, the growth of derivative markets and other financial innovations may have an influence on stock market volatility. Finally, changes in corporate debt levels may have affected stock market volatility.

5.1 The role of information

The volume of information in the stock market and the speed at which it is disseminated can crucially affect the behavior of stock prices. When almost all investors receive information simultaneously and act on it quickly, individual stock prices may become more quickly responsive. Today, we live in an age where news is transmitted instantly, and where the media tend to produce more news and perhaps even create it. Therefore, news occurs more frequently, giving investors more chances to act. The technology of communications has improved dramatically, and the firm-specific information is more easily and readily available than before. News of changes in an investment firms expectations regarding the future earnings of particular companies are now transmitted electronically to portfolio managers and individuals, who themselves can transmit buy and sell orders electronically to the floors of the exchanges and to a variety of electronic trading networks. Firm-specific information tends to be uncoordinated so that while individual firm volatility may increase, there should be little impact on overall market volatility. The intertemporal dynamic model of Wang (1993) best illustrates the conditions under which more information about the firm can lead to an increase in its volatility.

5.2 The role of institutional trading

The stock market today is no longer a market of millions of individual investors whose buy and sell decisions are often likely to be uncoordinated. Todays market is dominated by institutions who get their news from the same sources, and who are often likely to change their sentiment simultaneously about both individual stocks and the market as a whole[28]. Table 8 presents some indices of growing institutional presence in the stock market. The percentage of total equity held by institutions has increased seven-fold since 1950, and the proportion of block trades (trades of over 10,000 shares, which are almost exclusively executed by institutional investors) has climbed to over half of total volume. Periodic surveys on the composition of traders on the New York Stock Exchange has indicated that on selected days as much as 90 percent of the trading has been generated by institutions (pension funds, mutual funds, etc.).

Turnover on the exchange has more than tripled since 1970. Moreover, when the 500 stocks in the $S\&P$ index were ranked by the percentage of institutional ownership as of December 1997, each of the 50 stocks in the top decile had 80 percent or more of their shares held by institutional investors. Institutional ownership for the median stock in the index was 62.5 percent. Consequently, buying and selling is more likely to be coordinated across institutions, and market prices may be more volatile and more quickly responsive to new information or changes in risk perceptions. While

[28] To the extent that individuals do still participate in trading, they increasingly do so over the internet and they tend to receive the same news simultaneously through electronic channels.

institutional trading can affect both market- and firm-level volatility, we suggest that institutional trading will have far greater impact on individual volatility since the arrival of information on individual stocks is much more frequent. As shown in Section 4, the volatility of individual stocks does tend to be greater, the larger the proportion of institutional ownership[29].

Insert Table 8

5.3 Trading in derivative instruments and stock volatility

There has also been enormous technical change within the financial industry. For example, a variety of derivative products, such as options and futures, are now available that allow portfolio managers to alter the compositions of their portfolios with great speed and at low cost. As argued by Ross (1977) and John (1983), options can complete an otherwise incomplete market and can have a significant impact on the price behavior of the underlying securities. Theoretically, however, the direction of impact is ambiguous. For example, Grossman (1987) has demonstrated that the volatility of stock prices can be substantially lower when real options are traded, since options are not informationally redundant and they can make stocks sell at prices closer to their fundamental values. Alternatively, Stein (1987) argued that introducing more speculators into the market through options trading, for example, can lead to changes in the information content of prices and can result in price destabilization.

Empirically, Nabor and Park (1988) have shown that optioned stocks, on average, experience a statistically significant decline in volatility relative to the market as a whole. Shastri, Sultan, and Tandon (1996) find similar evidence in the foreign exchange market. In fact, they provided evidence that the volatility of exchange rates has decreased following the listing of options for a majority of the currencies. Thus, we should treat the popular argument that the proliferation of derivative instruments will lead to increased volatility with considerable suspicion.

[29]A similar argument concerning coordinated trading may apply to individual investors engaged in "day trading" over the Internet who have tended to focus their trades on Internet-related companies.

5.4 The leverage effect

According to the traditional capital structure theory, changes in corporate financial structure will change the variability of stock returns (see Black (1977)). Since leverage tends to increase an individual stock's Beta, we should find a positive association between volatility and leverage when performing a cross-sectional investigation. Moreover, different patterns of economy-wide leverage during different periods could lead to a positive relationship between volatility and leverage (see Shapiro (1988)). Volatility during the great depression was at least three times higher than that during the 70's and 80's, while leverage was twice as high in the earlier period. Even though the level of leverage is relatively stable (and may have decreased a little) in recent history, such contemporaneous relationship in the market component can still exist, which is the finding of Braun, Nelson, and Sunier (1995). However, it is unclear that leverage will have any impact on the non-market or idiosyncratic component of volatility as shown by Braun, et. al. And we have seen in Section 2 that idiosyncratic volatility appeared to increase during the 1990s, just as U.S. companies were deleveraging.

In conclusion, it would appear that changes in the volume and speed of information dissemination and the increasing role of institutional investors are the most reasonable explanations for the increase in the volatility of individual stocks that we have documented in this paper.

6 Concluding Comments

We have examined several plausible reasons to believe that volatility in the stock market should have increased over recent decades. Improvements in the speed and availability of information, the growth in the proportion of trading done by institutional (and, therefore, informed) investors, and new trading techniques all may have increased the responsiveness of markets to changes in sentiment and to the arrival of new information. The facts, however, at least with respect to the market as a whole, do not suggest that volatility has increased. Except for episodic increases in volatility during Octobers of 1987 and 1989, the volatility of the market portfolio has actually decreased in recent years. In this paper, however, we look not at the market portfolio but rather at individual stocks and industry averages. By taking a disaggregated look at the volatility of stock prices, we reach a very different conclusion that volatility in the stock market has in fact increased considerably during the past quarter century.

We find that the most volatile stocks each month (those with the largest percentage change in total return for the month) display a pattern of increasing volatility over time during the 25-year period from the late 1960s through the 1990s. This finding is not an artifact of some differential character of the most volatile stocks over time, such as a size effect. Moreover, our estimates of the idiosyncratic volatility of the 500 individual stocks in the market index (or all the stocks in our database) show a pattern of increasing volatility. This volatility does not show up in the volatility of returns for broad market indexes since it is diversified away in the market portfolio. Our findings of an upward drift in volatility are confirmed by our trend tests of the volatility series. Moreover, we find that volatility series for 13 industry portfolios generally display an increasing trend as was the case for individual stocks. We also found cross-sectional evidence supporting an association between institutional ownership and the volatility of individual stocks.

In order to study the robustness of our finding of increasing idiosyncratic volatility, we then approached the issue from both a correlation structure and a diversification perspective. A stable market volatility and increasing idiosyncratic volatility is likely to signal a decrease in the correlations among individual stocks. We examine the pair-wise correlations within each of ten portfolios sorted by company size. The results show that these correlations have tended to decrease over time, providing alternative support for our conclusion. Furthermore, increased idiosyncratic volatility implies that it is more difficult to diversify away idiosyncratic risk with a limited number of stocks in a portfolio. We find that the volatility of randomly selected portfolios with fixed numbers of stocks has increased significantly over time strongly suggesting an upward trend in idiosyncratic volatility. If wealth constraints and transactions costs prevent ordinary investors from diversifying fully, these investors will be forced to bear some idiosyncratic risk. This would suggest a positive relationship between idiosyncratic risk and required expected return, confirming the results of Malkiel and Xu (1997 and 1998).

References

[1] Bernake, Ben S., John Y. Campbell, and Toni M. Whited (1990), 'U.S. Corporate Leverage: Developments in 1987 and 1988,' *Brookings Papers on Economic Activity,* No. 1, pp. 255-285.

[2] Black, Fischer (1977), 'Studies of Stock Price Volatility Changes,' *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economic Statistics Section,* pp. 177-181.

[3] Bollerslev, T., R.Y. Chou, and K.F. Kroner (1992), 'ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence,' *Journal of Econometrics,* Vol. 52, pp. 5-59.

[4] Bollerslev, T., R.F. Engle, and D.B. Nelson (1994), 'ARCH Models,' in *Handbook of Econometrics,* Vol. 4 (R.F. Engle and D. McFadden, eds.), Amsterdam: North Holland Press.

[5] Braun, P.A., D.B. Nelson, and A.M. Sunier (1995), 'Good News, Bad News, Volatility, and Beta,' *Journal of Finance,* Vol. 50, pp. 1575-1603.

[6] Campbell, John Y. (1991), 'A Variance Decomposition for Stock Returns,' *The Economic Journal,* Vol. 101, No. 405, pp. 157-79.

[7] ——— (1991), 'Understanding Risk and Return,' *Working Paper,* No. 4554, NBER.

[8] ———, Sangjoon Kim, and Martin Lettau (1994),'Dispersion and Volatility in Stock Returns: An Empirical Investigation,' *Working Paper,* Princeton University.

[9] Canjels, Eugene, and Mark W. Watson (1997), 'Estimating Deterministic Trends in the Presence of Serially Correlated Errors,' *The Review of Economics and Statistics,* Vol. 79, pp. 184-200.

[10] Chou, R.Y. (1988), 'Volatility Persistence and Stock Valuations,' *Journal of Applied Econometrics,* Vol. 3, pp. 279-294.

[11] Conover, W. J. (1980), *Practical Nonparametric Statistics,* Wiley: New York.

[12] Fama, Eugene F. and French, Kenneth R. (1988), 'Permanent and Temporary Components of Stock Prices,' *Journal of Political Economy,* Vol. 96, pp. 246-73, April.

[13] Ferson, W. E. and C. R. Harvey (1991), 'The Variation of Economic Risk Premiums,' *Journal of Political Economy,* Vol. 99, pp. 385-415.

[14] French, Kenneth R., G. William Schwert, and Robert F. Stambaugh (1987), 'Expected Stock Returns and Volatility,' *Journal of Financial Economics,* Vol. 19, pp. 3-29.

[15] Foster, Dean P. and Dan B. Nelson (1996), 'Continuous Record Asymptotics for Rolling Sample Variance Estimators,' *Econometrica,* Vol. 64, No.1, pp. 139-174.

[16] Ghysels, E., A. Harvey, and E. Renault (1997), 'Stochastic Volatility,' in *Handbook of Statistics,* Vol. 14 (G.S. Maddala, eds.), Amsterdam: North Holland Press.

[17] Ghysels, E. and P. Perron (1993), 'The Effect of Seasonal Adjustment Filters on Tests for a Unit Root,' *Journal of Econometrics,* Vol. 55, No.1, pp. 57-98.

[18] Grossman, S. (1989), 'An Analysis of the Implications for Stock and Futures Price Volatility of Program Trading and Dynamic Hedging Strategies,' *The Information Role of Prices,* Wicksell Lectures, Cambridge, Mass. and London: MIT Press, pp. 117-42.

[19] Hansen, Lars Peter (1982), 'Large Sample Properties of Generalized Method of Moments Estimators,' *Econometrica,* Vol. 50, pp. 1029-54, November.

[20] Ibbotson Associates. (1992), *Stocks, Bonds, Bills, and Inflation: 1995 Yearbook,* Chicago.

[21] John, K. (1984), 'Market Resolution and Valuation in Incomplete Markets,' *Journal of Financial and Quantitative Analysis,* Vol. 19, pp. 29-44.

[22] ———, and J. Stiglitz (1980), 'On the Impossibility of Information Efficient Markets,' *American Economic Review,* No. 70, pp. 393-408.

[23] Jagannathan, Ravi, and Zhenyu Wang (1993), 'The CAPM Is Alive and Well,' *Working Paper,* Carlson School of Management, University of Minnesota.

[24] LeRoy, Stephen F. and Richard D. Porter (1981), 'The Present-Value Relation: Tests Based on Implied Variance Bounds,' *Econometrica,* Vol. 49, No. 3, pp. 555-574.

[25] Lys, Thomas and Jowell S. Sabino (1992), 'Research Design Issues in Grouping-Based Tests,' *Journal of Financial Economics,* Vol. 32, pp. 355-387.

[26] Malkiel, Burton G. and Yexiao Xu (1998), 'Idiosyncratic Risk: Theory and Evidence,' *Working Paper,* School of Management, The University of Texas at Dallas.

[27] Malkiel, Burton G. and Yexiao Xu (1997), 'Risk and Return Revisited,' *Journal of Portfolio Management,* Vol. 23, No. 3, pp. 9-14.

[28] McDonald, James B. and Whitney. K. Newey (1988), 'Partially Adaptive Estimation of Regression Models via the Generalized t-distribution,' *Econometric Theory,* Vol. 4, pp. 428-457.

[29] McDonald, James B. and Yexiao Xu (1995), 'A Generalization of the Beta Distribution with Applications,' *Journal of Econometrics,* Vol. 66, pp. 133-152.

[30] Nabar, Prafulla G. (1988), 'Options Trading and Stock Price Volatility,' *Working Paper,* No. 460, New York University.

[31] Pindyck, R.S. (1984), 'Risk, Inflation and the Stock Market,' *The American Economic Review,* Vol. 74, pp. 335-351.

[32] Richardson, Matthew and James H. Stock (1989), 'Drawing Inferences from Statistics based on Multiyear Asset Returns,' *Journal of Financial Economics,* Vol. 25, pp. 323-348.

[33] Ross, S. (1977), 'Options and Efficiency,' *Quarterly Journal of Economics,* Vol. 4, pp. 129-176.

[34] Schwert, G. William (1991), 'Market Volatility: Review,' *Journal of Portfolio Management,* Vol. 17, No. 4, pp. 74-78.

[35] Schwert, G. William, and Paul J. Seguin (1990), 'Heteroskedasticity in Stock Returns,' *Journal of Finance,* Vol.45, pp. 1129-55.

[36] Shapiro, Matthew D. (1988), 'The Stabilization of the U.S. Economy: Evidence from the Stock Market,' *The American Economic Review,* Vol. 78, No. 5, pp. 1067-1079.

[37] Shastri, Kuldeep, Jahangir Sultan, and Kishore Tandon (1996), 'The Impact of the Listing of Options in the Foreign Exchange Market,' *Journal of International Money and Finance,* Vol. 15, No.1 pp. 37-64.

[38] Shiller, Robert J. (1991), *Market Volatility,* Cambridge : MIT.

[39] Stein, Jeremy C. (1987), 'Informational Externalities and Welfare-Reducing Speculation,' *Journal of Political Economy,* Vol. 95, No.6, pp. 1123-45.

[40] Summers, Lawrence H, and Victoria P. Summers (1989), 'Why Financial Markets Work Too Well: A Cautious Case for a Securities Transactions Tax,' *Journal of Financial Services Research,* Vol.3.

[41] Vogelsang, Tim (1998), 'Trend Function Hypothesis Testing in the Presence of Serial Correlation,' *Econometrica,* Vol. 66, pp. 123-148.

[42] Wang, Jiang (1993), 'A Model of Intertemporal Asset Prices Under Asymmetric Information,' *Review of Economic Studies,* Vol. 60, pp. 249-282.