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ESSAYS ON STOCK MARKET VOLATILITY

By

ALESSANDRO CASTALDO

A dissertation submitted to the Graduate Faculty in Business in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

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Abstract

ESSAYS ON STOCK MARKET VOLATILITY

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ALESSANDRO CASTALDO

Adviser: Professor Avner Wolf

This dissertation contains four empirical essays on stock market volatility. The first essay "Volatility Changes, Systemic Risk, and Risk Control Procedures" investigates changes in the volatility of the S&P500 index over time. It shows that the number of volatility changes rose in the 1990's as compared to the 1980's, and this is a reversal of a long term downward trend. It argues that systemic risk and imperfections in the financial system as a whole are behind the increased instability of volatility. It also suggests that risk control methods adopted by financial institutions in the last few years are not always helpful in an environment of changing volatility.

The second essay "Trends in the Volatility of Individual Stocks, A Multiple Measures Approach" examines Volatility, defined in a number of different ways, for a sample of 94 stocks during the period 1993-1999. We study how the behavior of these indicators of volatility differs from that of the standard one, the daily standard deviation of returns. While the standard deviation has increased only slightly, some of the other indicators have increased considerably during this period, showing there have been some changes in how stocks traded during this period.

The third essay "Stock Market Volatility and The On Line Investor" compares the volatility of stocks with a large following among online investors with the volatility of

a control group of stocks. Using high frequency data and two different approaches (a Granger methodology and a measure of market impact) we provide evidence suggesting that retail traders influence the pricing and short-term volatility of such stocks.

The fourth essay "Changes in the Cross-Section of Stock Volatility" provides evidence that the cross-section of stock volatility (that is the distribution of volatility across U.S. stocks at any point in time) has undergone some significant changes over the past 15 years. First, a number stocks with very high volatility have come into prominence, (mainly high-technology, NASDAQ stocks). Second, the origin of volatility has changed, with more coming from idiosyncratic (unsystematic) sources, and less from market-wide (systematic) sources

This work is dedicated
to the memory of
Esra Selcuk
(1959-1998)

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The help and inspiration provided by Prof. Kenneth Mischel deserve prominent mention. His always optimistic and open minded attitude even in the face of obstacles or nay sayers, are to me a model of how academic research should be carried out. In addition he provided several key insights into financial market behavior.

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0. Introduction to volatility research

The volatility of an asset is defined as the standard deviation of returns around the expected return. If the expected return is $\bar{r}$ and the actual return observed in period i is r_i then the volatility per time period is defined as:

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_i - \bar{r})^2}$$

The expected return $\bar{r}$ is difficult to estimate, more difficult in fact than the volatility itself. Already Black (1976) suggested neglecting $\bar{r}$ and computing the volatility in practice as the square root of the average squared return. Figlewski (1998) convincingly argues that assuming $\bar{r} = 0$ is preferable to estimating $\bar{r}$ from the data sample, in that it results in a smaller mean squared error. We have adopted the Black and Figlewski modified definition in our empirical work.

Volatility has been studied by a number of researchers. Simple observation of the course of the stock market over a long period of time shows that volatility is rather large (about 18% per year for the S&P500 during the post World War II period) and characterized by great instability. (See for example Chart 1, page 149).

The Excess Volatility Literature

Starting with Shiller (1979), some researchers have claimed that volatility is excessive compared to fluctuations in the intrinsic economic values of the underlying company cash flows. That is, the value of a company's stock fluctuates more than is justified by fluctuations in corporate profits. This idea remains controversial.

If volatility is excessive, there will be a deviation between stocks' intrinsic value and their current prices. According to some this is not a serious problem since in the long run their intrinsic value emerges. According to others, (e.g. Haugen, 1999) excess stock volatility

alters the process of capital allocation with damaging effects on the economy before in the very long term equilibrium is reestablished. This possibility means that the problem of excess volatility has important policy implications and all by itself would justify a careful analysis of the phenomenon and of its causes and effects.

Volatility determinants

Attempts have been made, in recent years, at relating stock market volatility to other economic variables. According to some of these studies (Schwert, 1989, French Schwert and Stambaugh, 1987), volatility is higher during recessions, and at times of high interest rates. But these results explain only a small part of the differences in volatility that we see in the historical record. According to Shiller (1989) the Schwert paper's contribution lies in documenting carefully "the quite unimportant relation between stock market volatility and the business cycle variables studied". If we accept this view then most volatility changes are not understood at present.

Trading and Volatility

One of the most interesting discoveries about volatility was reported in French and Roll (1986). These authors studied a period when the NYSE was closed each Wednesday. They found that during these days the stock market was less volatile than on days when it was open normally. While this result is based on only a short period and is virtually impossible to replicate on another sample, it has momentous implications. It suggests that some of the volatility we see is created by the process of trading itself. Some have suggested that this extra volatility seen only when the market is open is due to the incorporation of private information into market prices. Others (such as Haugen) see the extra volatility as noise rather than information, in other words as extraneous price movements not justified by the economic fundamentals of listed companies. This is one of the most controversial and interesting open questions in Finance at the present time. Unfortunately no one has been able to devise a way to measure how much extra volatility, if any, is created by traders.

Volatility clustering and mean reversion

Already Mandelbrot (1963) had found that "large price moves tend to be followed by large price moves, though not necessarily in the same direction". While successive ΔP_t are uncorrelated, successive absolute values $| \Delta P_t |$ are positively correlated. In the historical record, there are stretches of time with many large price moves, followed by quieter periods, and then again by periods with large price moves. The name currently given to this phenomenon is "volatility clustering" (Bollerslev, Chou and Kroner (1992)). Put differently, volatility is mean reverting. Although much studied, this phenomenon is not completely understood.

Volatility and Options

The earliest models used for option pricing (Black and Scholes, 1973) assumed that volatility is constant. If volatility is not constant then new models need to be developed. These models necessarily incorporate assumptions about how volatility varies. While theoreticians can develop such models based on any plausible assumption, and indeed have done so, to assess these models requires an understanding of how volatility actually changes. This then is another important reason to study volatility change mechanisms.

Short-term volatility

Several authors (for example Schwartz (1993)) have investigated short-term (intraday) volatility and its link with market mechanisms such as order handling rules, presence of liquidity providers and methods for opening/closing trading (auction/no auction). The objective is the design of improved trading mechanisms that would reduce short-term volatility.

Questions addressed in this thesis

Previous research has shown that stock volatility changes over time. The first chapter empirically investigates month to month changes in volatility and presents evidence of sharp increases in volatility followed by gradual return to normal levels over several months. We argue that some of these volatility explosions are associated with actual or perceived systemic risk in the financial system (rather than say, risks in the real economy). We further argue that adoption of dynamic risk control procedures by financial institutions in recent years has made these financial accidents more likely.

The second chapter looks at the volatility of individual stocks and asks the question: to what extent can we say that their volatility has increased substantially in recent years, as some stock market professionals claim? By examining a variety of volatility measures we are able to give a more complete picture of what has happened than would be possible by using only the traditional definition of volatility presented above.

The third chapter focuses more narrowly on a small subset of individual stocks, those in which online investors have concentrated their trading. Using microstructure data it investigates differences in volatility behavior for these stocks as compared to a control group of stocks.

The fourth chater presents evidence of the appearance in the late 1990's on the U.S. stock market of companies with very high volatilities that have no precedent in the stock market of the mid-1980's. The arrival of these "hyper-vol" stocks is another important new development in stock market volatility.

The fifth chapter summarizes and concludes.

Chapter I. Volatility changes, systemic risk, and risk-control procedures

1.0 Introduction

There is a widely accepted view today that stock market volatility is not constant. What is less clear is why volatility changes and how the theories of Financial Economics that have assumed constant volatility have to be altered to take this new fact into account.

The Black-Scholes (1973) and Merton (1973) theory of option pricing, for example, explicitly assumed a constant volatility. Just three years later Black (1976) provided the first empirical evidence that volatility in fact changes over time. Slowly, other researchers came to similar conclusions; Schwert (1989) in particular, provided a classic study of the question. By then the events of October 1987 had brought the phenomenon of a short term (few weeks) surge in volatility to the attention of the investing public as well. Changing volatility has become an important topic both in and out of academia.

A major stream of research has been the development of GARCH and Stochastic Volatility models, quickly generating a large literature (reviewed in Bollerslev et al. (1992), Ghysels and Harvey (1995)) In these descriptive models the assumption of a constant volatility is replaced by a stochastic volatility that changes randomly over time. A typical example is:

$$d\sigma = k(\sigma - \sigma_0) + g(\sigma)\, dW \qquad (1)$$

This equation describes a volatility that drifts randomly in the neighborhood of a long term equilibrium value σ_0.

To explain volatility changes (as opposed to just describing them mathematically), most researchers focused on the uncertainty of future cash flows and discount rates; for example, during a recession, future corporate cash flows are more uncertain (more difficult to predict) than at other times and therefore stock prices during a recession will be more volatile. Recent research in this line includes Bekaert and Wu (2000), Wu (2001). This approach could be called the mainstream apprach and was endorsed by Schwert (1989b), who nevertheless acknowledged the existence of dissenting views: "There are several theories about the relation between stock volatility and macroeconomic behavior. The most controversial, advocated by Shiller (1981, 1984) and

Summers (1986) is that random or sociological factors have large effects on stock volatility".

This paper argues that descriptions based on "volatility drift models" (such as equation (1)) and explanations based on the stochastic process driving corporate cash flows are incomplete in that they do not account for some of the empirical properties of volatility changes. They provide some insight, but miss aspects that a more careful look at the behavior of investors could help to explain. The behavioral approach in this paper complements Shiller and Summers' work by examining events that occurred after their papers were written; we find that their ideas have merit and were confirmed by these subsequent events. Specifically we provide empirical evidence in support of the following hypotheses:

Hyp1: Volatility changes involve sporadic, explosive rises in volatility over a short time, followed by a more gradual return to a normal level. While the return to normal is well described by an equation such as (1), the spikes themselves cannot be generated by such a Gaussian process. As to the explanation of volatility spikes, we will show that they are often related to systemic risk. Our hypothesis generally is that the origin of these spikes is in the financial system itself, rather than in the cash flows of the corporate sector. Hypothesis 1 can be summarized as "Volatility spikes at time of financial (not macroeconomic) crisis".

Hyp2: During a market crisis reluctance to trade by most investors (due to not-fully-rational but well documented behavioral phenomena such as reluctance to realize losses and uncertainty aversion) clashes with the urgent trading needs of investors who are following mechanical strategies for risk control or other purposes. Enhanced price movements due to this liquidity effect can explain both asymmetric volatility (volatility rises when prices go down) and volatility spikes.

Hyp3: Not only do modern risk control procedures such as ValueAtRisk, henceforth VAR, malfunction when volatility changes. Reliance on such procedures in fact exacerbates the instability of volatility. As evidence of this an

increase in the number of volatility changes in the 1990's coincided with increased adoption of VAR and related risk control methods by financial institutions.

1.1 Plan of the paper

The evidence for our three hypotheses is rather disparate. It comes both from statistical studies of return time series and from a detailed investigation of some specific historical episodes. More specifically:

Section 2 analyzes the behavior of month to month changes in the volatility of daily S&P500 returns using techniques from descriptive statistics: frequency plots and time series decomposition.

Section 3 investigates the "volatility of volatility".

Section 4 investigates the number of statistically significant volatility changes using the methodology of Haugen, Talmor and Torous (1991).

Section 5 contains case studies of two historical episodes of increased volatility: October 1987 and August-September 1998. This section identifies some of the factors at work, factors that Schwert calls random or sociological and finds that they were quite similar in both episodes.

Section 6 summarizes the findings of this paper.

2.0 Properties of month to month volatility changes. Evidence on spikes.

Let us look at some empirical data. First, we computed the volatility of daily S&P500 log-price changes during any calendar month from 1928 to 1999. (The choice of a one-month period was based on the following considerations. There are typically 21 trading days in a month. A simple calculation shows that if daily returns are independently and identically normally distributed, a volatility estimator based on 21 days of data will give results within 30% of the actual volatility 95% of the time. Thus, a calendar month of daily data provides a rough but usable estimate of volatility; a longer measurement

interval would provide a better estimate (ex: 6 months: within 12% of actual 95% of the time), but would reduce the frequency of volatility observations and make it impossible to observe fast changes.)

2.1 Large increases and decreases

Table A Part 1 shows months having the biggest increases or decreases in volatility compared to the previous month.

It is noteworthy that the three largest one month declines occurred in Nov 1989, Nov 1987 and Dec 1963, precisely one month after the three largest volatility increases. In other words there was a large increase in volatility in one month and a large decline the following month.

2.2 Distribution of month to month changes

Chart B is a histogram showing the distribution of month to month changes in log volatility (1962-1998), with a normal distribution plotted for comparison purposes. The visual impression is that the empirical distribution deviates from the normal; it is high near zero, somewhat thin on the sides, and there are a higher number of observations in the tails than would be the case for a normal distribution. This impression is confirmed by two formal statistical tests of normality: the Lilliefors test and the Wilk-Shapiro test. The results are shown in Table BB. By either test vol changes are clearly non-normal. First of all, the skewness is slightly higher than would be expected, but it is only 2 to 3 times the sampling error of SQRT(6/n). Therefore, taking the logarithm of volatility, as we did, has removed much but not all of the skewness. A bigger problem is the very high kurtosis (as was apparent in Chart B); the expected value for a normal distribution is zero (we are using Fisher's definition of kurtosis which involves subtracting 3 in the calculation) with a sampling error of SQRT(24/n). The observed kurtosis is almost 100 times bigger than this.

This shows that a month-to-month geometric random walk model for volatility (such as has been proposed in the stochastic volatility literature) is not a good model. Such a model would generate too few of the large changes in volatility from month to

month that we see in practice. The evidence thus supports Hypothesis 1: the presence of rare but very large (non-normal) excursions in volatility.

2.3 Slow and fast components of volatility

We also analyzed volatility changes using time-series techniques to decompose the volatility into the sum of two components: a slow moving component and a more erratic residual.

The slow component in month t is found by a two step smoothing process. First we take the median of volatilities in months t-5 through t+6, in other words the median volatility in a 12 month rolling period centered on month t. This removes extreme (high or low) observations. As a second step, a 12 month moving average is applied to these numbers, resulting in a somewhat smoother graph. The residual is then found by subtracting the slow component from the actual realized volatility.

The resulting two components are shown in Chart C. The slow component has a fairly sensible interpretation in terms of macroeconomic history: there was an upward bump in 1966, a time of high short term interest rates. The next upward bump in 1970 corresponds both to much higher interest rates (peaking in early 1970) and to the recession of December 1969 to November 1970. A still higher bump centered in the summer of 1974 can be linked to high interest rates (peaking at about that time) as well as the recession of November 1973 to March 1975. A lower, double bump in Summer 1980 and Summer 1982 again corresponds to a period of very high interest rates and two closely spaced recessions: January to July 1980 and July 1981 to November 1982. The bump centered on October 1987, on the other hand is a puzzle in macroeconomic terms; it has no logical explanation. Finally the bump centered in the Fall of 1990 would seem to be linked to the recession of July 1990 to March 1991. The last bump in August 1997 is somewhat hard to interpret and it is still being traced out at the moment; time will tell.

In summary, although the smooth component was constructed using purely statistical techniques, it appears to capture the effect of macroeconomic events (specifically recessions and/or periods of high interest rates that often precede them) on volatility very well. Every recession during this period is accounted for by a bump in the smoothed volatility. Thus we can link economic events to volatility changes.

It remains to explain the residual component. We examinined the behavior of the residual near particularly sharp peaks (these have the most chance of being significant).

Figure D shows that volatility rose sharply in May 1970 and then reverted back to normal in 4 or 5 months.

Figure E shows that volatility rose sharply in August 1982 and then took about 6 months to return to normal. (Although September 1982 was near normal).

Figure F shows an astronomical rise in October 1987, followed by a return to normal in 5 or more months.

Figure G shows a similar pattern: an increase that occurs in a single month (August 1990) followed by an erratic return to normal over 4 or 8 months.

Figure H shows an increase in August 1998, persistence of volatility at a high level for another month and then a two month return to normal.

The important common points of these figures are: a very rapid increase (usually in one month) and a slower (usually multi month) return to normal.

An interesting additional point is that the size of these transient peaks is often large compared to the smooth component of volatility or to the size "bump" that corresponds to a recession. The one month disturbance of October 1997, for example, is larger than the volatility increase that we have tentatively identified with the major 1974-1975 recession.

Finally, it is interesting that these findings offer a partial explanation of Figlewski's conclusions regarding volatility forecasting. Figlewski (1998) tested various simple rules for forecasting volatility. He used the past N months' volatility as the forecast for volatility during the next M months. He tested various values of N to find what works best empirically for each forecast horizon M. Contrary to industry practice of using N=M, he found that using more past data, i.e. N > M usually gave better results. But the most important conclusion for our purposes was: "The accuracy of the forecast of average volatility increased for longer forecasting horizons, so that there were smaller errors in predicting average volatility over the next five years than over the next 6 months". This finding may seem paradoxical in that we normally think of long term forecasting as more difficult than short term. But it is readily explained in view of the occasional, brief, but intense disturbances in volatility we have described. The occurrence of such a disturbance would throw a six month forecast off considerably, while over a

five year horizon the law of averages means the number and effect of such disturbances is more predictable. This is why Figlewski found average volatility over five years easier to forecast than over six months.

3.0 Volatility of Volatility

The coefficient $g(\sigma, t)$ occurring in equation (1) can be interpreted as the "volatility of volatility". The empirical estimation of such a term is not easy, because it requires a large number of observations. As a result empirical research has difficulty discriminating among the many theoretical models that have been proposed in the stochastic volatility literature.

3.1 A simple simulated example

As an illustration of the problems of measuring "volatility of volatility", we will consider a very simple case. Suppose that volatility is constant at 1% per day. We simulated a year's worth of (normally distributed) daily price changes (Fig. I.1), then estimated the volatility, and the volatility of volatility at various frequencies (Fig. I.2-I.6).

When estimated over annual (I.2) or semiannual (I.3) periods, the volatility is quite close to the true value of 0.01 per day. And the volatility of volatility is close to its true value of zero.

With quarterly estimates (Fig. I.4) some discrepancies begin to show up. The volatility appears to be changing even though it is actually constant. The measured "volatility of volatility" is 14% per quarter in this example.

At a monthly frequency the apparent changes are more pronounced. The volatility of volatility is found to be 22% per month using the same sample of simulated data as before. If we estimate volatility weekly our estimate rises to 44% per week. If we attempt to estimate from a single day's observation, the apparent volatility of volatility rises to 150% per day. All this in a situation where the actual volatility of volatility is zero, that is volatility is not changing at all. Simply by not having enough data points for each volatility measurement, we have obtained nonsensical "volatility of volatility" estimates. One to six months of daily data would appear to be a reasonable minimum for volatility estimation.

3.2 "Volatility of volatility", simulation vs reality

We measured volatility of volatility over six month periods, and tested whether it is significantly different from zero. That is, given observed volatilities for six consecutive months, we computed the change in log volatility

$$\text{Volvol} = \text{SQRT}[\ (1/5)\ \sum_{i=2}^{6}\ (\ \log(\sigma_i) - \log(\sigma_{i-1})\ )\text{^}2\ ] \qquad (2)$$

A Monte Carlo simulation was used to calculate the threshold for detecting a non-zero Volvol. Under the null hypothesis the simulation produced a median value of vol of vol of 0.20 and the 95% percent significance level was found to be 0.35. It is interesting to examine just one trajectory produced by the simulation. Figure J shows the simulated vol of vol measured over rolling 6 month intervals for 36 years. As expected the typical value is 0.2; the upper limit of 0.35 was breached 3 times, which is exactly 5% of the 72 six month periods under study.

Next, formula (2) above was applied to SP500 data from 1962 to 1998. The results are shown in Figure K. The significance level was broken 18 times during this period (against an expected 3 times) and often by a large amount. This is an indication that volatility changes significantly during some six month periods.

On the other hand, there are periods when the vol of vol is near the 0.2 reference value corresponding to constant volatility. Only occasionally does it spike above 0.35. Therefore there are 6 month periods when volatility appears to be constant; occasionally there are periods when it is clear that volatility is changing massively.

It seems we can reject both the hypothesis of a constant volatility, and the hypothesis of a constant volatility of volatility, meaning that vol would drift from month to month in a constant fashion. Instead, the graph shows that volatility can be effectively constant for a while, and then jump erratically.

In fact, if we examine all 6-month periods showing high volatility of volatility (i.e.. the peaks in Fig. K) we often find that only one or two of the six months has a volatility markedly different from the others (see Table L). For example a high vol of vol in August 1979 - Jan 1980 seems to be due to one month with high volatility: October 1979 (that, incidentally is the month in which the Fed announced a new monetary policy). Vol

was near normal in September 1979 and Nov 1979, and unusually low in August and December. If we examine individual daily returns during October 1979, we see just three days with substantial price movements (more than 1.5%): October 9, October 19 and October 30. (October 8 was the first trading day after the announcement of the new policy, the return was –1.25%). Although it is difficult to draw conclusions from such sparse data, the impression one gets is that the closer one looks at the data the more concentrated in time the volatility bursts seem to be.

A high "volatility of volatility" does not necessarily mean that volatility itself is high. For example the period 1962 to 1966 was one of historically low volatility on average. However, the volatility during this period was erratic, occasionally swinging up to near normal levels only to drop back. This created some of the spikes visible on the left side of the graph. Conversely there were periods such as 1974-1975 when volatility was high but not particularly volatile during any consecutive 6 month period.

4.0 Detection of statistically significant volatility changes

Next, we applied statistical techniques to detect abrupt volatility changes. Rather than assume that volatility is constantly changing according to some random process (as in Section 3.0), the methods discussed in this section assume that volatility is constant for some time, then abruptly shifts to some new level and remains at that level until the next sudden change. Thus while the models of section 3.0 could be described as "volatility diffusion" models, the techniques in this section are based on a "volatility jump" view. (In reality of course both smooth changes and jumps may occur).

Two techniques for detecting statistically significant volatility changes in a time series are available in the statistics literature: Wichern, Miller and Hsu (1976) and Inclan and Tiao (1994). These techniques have been applied to stock market returns in the U.S. by Haugen, Torous and Talmor (1991) and in emerging markets by Aggarwal et al. (1999).

4.1 Reproducing and extending the Haugen, Torous, Talmor study

The data used in the Haugen, Torous and Talmor (herafter HTT) study is now 10 years old; our study extends it to more recent data to see if volatility changes have become more or less frequent since the HTT study was published.

The HTT study uses daily closing prices for the Dow Jones Industrial Average over the period 1897/01/04 to 1988/07/06. Our study starts at approximately the same date (1896/05/27) and ends on 1999/12/31.

After computing daily logarithmic price returns

$$R_t = \ln (P_t / P_{t-1}) \qquad (3)$$

the technique of Wichern, Miller and Hsu (1976) is applied to these returns. This involves computing a test statistic V for each day and plotting it against upper and lower control limits based on the F-distribution. An example of such a chart is shown in Figure M. The V statistic is the ratio of the realized variance during the 4 weeks that follow a given date to the realized variance during the 4 weeks that precede the given date. That is V is the ratio of the variances for two contiguous 4 week periods. Under the null hypothesis that the returns are independently identically distributed according to a normal distribution with a constant variance, the test statistic V would tend to remain within the control limits. If the V statistic breaks through the upper line shown in Figure M, we conclude that a statistically significant increase in volatility has taken place; conversely when the V curve drops below the lower limit a volatility decrease has occurred. The level of statistical significance can be set as desired; the two lines shown in Figure M are set at the upper and lower one percentile points of the F-distribution.

Because the V curve sometimes crosses the threshold several times in quick succession, it may identify multiple volatility changes where only one occurred. For this reason, HTT suggest a second step in which multiple nearby crossings are examined and only one (the best estimate of where the volatility change occurred) is kept while the others are discarded.

Our findings using this technique are shown in Figure N and O. Figure N is based on a two sided 1% significance level (0.5% in each tail), as suggested by Wichern (1976), while Figure O uses two sided 2.5% significance (1.25% in each tail). The results in Figure O match the HTT results fairly closely, although HTT discuss using 1%

significance in their paper. In any case, the conclusions from the two figures are fairly similar. The number of statistically significant volatility changes in the 1990's was higher than in the 1980's, which in turn was higher than in the 1970's. However, this upturn is rather modest, and the number of volatility changes is nowhere near the very high levels of the 1930's and before.

The 1980's and 1990's saw the introduction of a number of innovations in finance including portfolio insurance, dynamic option replication, and risk control methods based on Value At Risk. We suspect that these innovations may have something to do with the increased instability of volatility. Case studies later in this chapter will explore this idea in more detail. Financial innovation resulted in a financial system with greater complexity and greater coupling between subsystems; these two characteristics, complexity and coupling, increase the frequency and severity of accidents in a variety of settings, according to Perrow (1984).

HTT also researched events reported in the news media at the time of each volatility change. We performed a similar search for the volatility change events detected in the 1990's, and the results are shown in Figure R. As HTT also found, it is difficult to match each volatility change to a specific event. Sometimes no important event seems to have occurred on the given date, and sometimes an event is found which is paradoxical in view of the stock market behavior (for example riots in Los Angeles at the time of a decrease in market volatility). Nevertheless, it is interesting that one volatility increase was associated with the failure of small banks in Rhode Island, while two were tied to sharp one day declines in the Nikkei and Dow Jones indexes.

Finally, all volatility changes that occurred in the 1990's are plotted in Chart S. Each volatility change is represented by a vertical line segment, whose end points represent the volatility before and after the change. These segments were then joined by (horizontal or diagonal) segments so as to form a continuous curve. The non-vertical line segments represent periods in which volatility changed gradually so that the Wichern algorithm did not detect the change (recall that the algorithm is only looking for abrupt changes at a point in time, not gradual changes).

5.0 Volatility increase events and systemic risk

Having shown the existence of volatility spikes, we attempt in this section to link them to the occurrence of systemic risk. By systemic risk is meant the risk of large scale problems in a country's (or the world's) financial system. A chain of bank failures (as occurred for example in the US in 1930) is the most talked about and well recognized case of systemic risk.

To investigate the link between systemic risk and volatility increase events, we compiled a list of events that were viewed at the time as potentially destabilizing for the financial system. They were taken from books about U.S. financial history (Kindleberger(1978,1996), White(1990)) and from recent events. We then checked what happened to stock volatility in each case. This exercise was conducted before the detailed study of historical volatility described in Section 4.0. Twelve events were identified and are listed below.

1. June 21, 1970 – failure of Penn Central corporation, large issuer of commercial paper
2. May 17, 1982 Drysdale Securities failure, worries about strength of financial system
3. July 5, 1982 Penn Square Bank failure
4. August 13, 1982 Mexico crisis, bailout by Federal Reserve/U.S. treasury, loosening of monetary policy
5. May 8, 1984 Bank run on Continental Illinois
6. October 19, 1987 Stock Market crash
7. December 20, 1994 Devaluation of Mexican peso, "tequila crisis"
8. February 23, 1995 Collapse of Barings bank
9. July 2, 1997 Devaluation of Thailand Bhat, start of "Asia crisis"
10. July 24, 1997 Depreciation of several East Asian currencies
11. August 17, 1998 Russian devaluation
12. September 23, 1998 The hedge fund LTCM reached an agreement with lenders

In the case of events 1, 4, 6, 11 and 12 there was a rise in stock market volatility at the time of the event and a return to lower levels thereafter. For the other seven out of twelve events there was no evidence of such a rise.

In retrospect the long-term repercussions of each of the twelve events on the U.S. economy was relatively limited (although several of them affected foreign economies

drastically). Arguably only event #1 had some long-term effects in the form of tightened credit standards for large corporations. It is hard to argue that any of them generated significant new information about the economy. None was a signal of a structural break that would require models of the U.S. economy to be re-estimated or drastically changed. It is true that these events were accompanied by major news coverage as epoch-making events and this generated concern at the time, but they later faded in significance. And yet in 5 out of 12 cases U.S. stock market volatility increased, if only temporarily.

In summary, we have had mixed success in finding high volatility during crises of systemic confidence. Several crises did in fact lead to higher volatility, others did not. Systemic risk appears to be one factor, but not the only one.

5.1 In depth analysis of two episodes (Summer 1998, Fall 1987)

We will use a case study approach to analyze two historical episodes of volatility increase: August-September 1998 and October 1987, in detail, then try to draw some general conclusions.

5.1.1 A recent example: August-September 1998

From a level of 15.6% in July, the volatility of the S&P 500 average rose to 34.2% in August and again was 34.2% in September. It declined to 24.2% in October.

According to contemporary accounts two events played a role in the volatility increase: the devaluation of the ruble in August and the near-collapse of the hedge fund LTCM in September. The return of volatility to more normal levels is usually attributed to the subsequent easing of monetary policy by the Federal Reserve. However it is not clear why these events would strongly affect U.S. stock market volatility. As the IMF (1998) states there is "an apparent disproportionality between the extraordinarily high degree of turbulence seen recently in both emerging and mature financial markets and the seemingly more limited scale of the triggering events". After a detailed review of developments during this period, the IMF report presented its explanation; for our purposes the key elements are the following.

5.1.1.1 Key points raised by the International Monetary Fund

- The Russian default caused the markets to drastically revise their understanding of the world economic situation. Previous assumptions that the Asian crisis was easing and that the IMF would help Russia muddle through were overturned. A different and more pessimistic set of scenarios came into view.
- Technical issues such as margin requirements, leverage and risk control procedures of market participants played an important role. Markets may have become illiquid for a time when there was a rush by large players to adjust positions quickly while market makers were reluctant to take risks. Risk control procedures adopted by individual institutions had an effect on market behavior.
- Once increases in spreads had brought LTCM to the brink of collapse, systemic risk became an issue. The perception was that other financial institutions might experience similar problems. The financial system was seen to be extremely vulnerable. A new, internally generated element of risk (systemic risk) was added to the picture.
- Volatility increased in many different markets, not just the stock market. Interestingly, hedge funds and the global investment banks were active in all these markets. Their responses to events in one market may have brought volatility to other markets. The direct linkages between the Russian economy and the U.S. economy were relatively small, but additional indirect linkages existed between them because of financing, risk control strategies, and generally the involvement of the same institutions in both financial markets.
- An increase in "risk or risk aversion" is said to have taken place. The increase in risk clearly came from the interpretation given to events in Russia and from the appearance of systemic risk. Increased risk aversion is more puzzling when one recalls that in economic theory risk aversion is a fairly stable characteristic of each investor; it becomes more plausible if one adopts the Behavioral Finance view that investors are more sensitive to losses than gains.

5.1.1.2 Alan Greenspan's view of the 1998 crisis

Federal Reserve Board Chairman Alan Greenspan's discussion of these events also began by noting the disproportionality between causes (the Russian debt moratorium) and effects: "Clearly the size of the Russian economy, either in real terms or in financial terms, can scarcely [engender] the types of consequences that have occurred subsequent to that moratorium." "So what we're looking at is really a far more fundamental shift in attitudes for which the Russian episode was essentially the triggering mechanism." (Greenspan, 1998b). He continued:

[What] "the Russian experience has created is a major shift towards risk-aversion pretty much throughout the world, as exhibited mainly in the financial markets."

"[O]ne of the other aspects of this post-Russian adventure has been a fairly dramatic shift towards pure liquidity-protection desires, as distinguished from risk aversion".

"Risk aversion is a positive, conscious calculated adjustment that the risks of security A have risen or fallen relative to the risks of security B. Liquidity protection, however, results not from a judgement, some conceptual insight, but rather a loss of knowledge; that is a destruction of what one perceived that they knew about".

"As a consequence, what is occurring is a broad area of uncertainty or fear. And when human beings are confronted with uncertainty, meaning they do not understand the rules or the terms of particular types of engagement they're having in the real world, they disengage. When you're crossing the street and you are uncertain as to whether a car is coming, you stop. You disengage from that particular process. And when you are uncertain about commitments in the marketplace, you disengage. And since most of our markets are net long in the sense that they are not a zero sum game, disengagement, of necessity, means that prices fall."

"A major shift towards liquidity protection is not really a market phenomenon - it's a fear-induced psychological response. And markets cannot efficiently function in an efficient manner in that environment".

Summarizing, he stated "a marked shift in investor psychology away from risk and towards liquidity and safety has exacerbated the problems in foreign markets [...] and has spread to the financial markets in the United States".

In another speech on September 4, Mr. Greenspan (1998a) had made some similar comments. "Human actions are always rooted in a forecast of the consequences of those actions. When the future becomes clouded, people eschew actions and disengage from previous commitments."

For our purposes the key points of Mr. Greenspan's explanations are the following:

- A broad loss of confidence in the functioning of markets may have occurred. Investors began to doubt their own ability to understand and forecast the future when their previous forecasts and models proved to be wrong. The "general state of confidence of consumers and investors" was adversely affected.
- Events in August led to a "loss of knowledge" rather than piling one more new fact onto a long list of already known facts. This process is very different from the Bayesian updating usually assumed in economic theory. Mental models that investors had constructed collapsed (just like a scientific theory may collapse when contrary evidence is discovered) and required rebuilding rather than modification.
- Mr. Greenspan makes a distinction between "risk-aversion" and "liquidity-protection" which recalls the distinction made by Frank Knight (1921) between "risk" and "uncertainty". Risk occurs when probabilities of various events can be estimated; uncertainty when they cannot. "Risk-aversion" behavior consists in adjusting one's portfolio based on changes in one's estimates of the probabilities involved. "Liquidity-protection" or as we might call it "uncertainty aversion" is the desire to disengage because one simply does not understand what is going on and cannot list possible outcomes and estimate their probabilities. The distinction between risk and uncertainty is usually not made in financial economics, where only risk is assumed,

but is required in Mr. Greenspan's world view. (Basili (2000) reviews attempts by various theorists to introduce Knightian uncertainty into formal financial economics models; these attempts do not appear to have been very successful so far).

- By its very nature a loss of confidence will be very difficult to forecast. It is an occasional, out-of the-blue phenomenon rather than an ongoing process. It can be thought of as a breakdown or near breakdown of the financial system, caused by a "fear-induced psychological response" to an outside event. Curiously enough the financial system usually manages to start working again after a short time (although the wealth of some individuals or organizations may be permanently affected).

5.1.1.3 The role played by VAR control limits: Dunbar's view of Aug/Sep 1998 events

In his book, Dunbar (2000) reconstructs the same events through interviews with market participants. He adds some interesting details about the role of risk management in transmitting the volatility increase from one market to another.

"[...] on the week of 17 August, the Russian losses began to filter through. [...] the Russian contribution to VAR rose rapidly. The effect was to cause many trading desks to breach their VAR limits. According to Basle committee rules [(set up for banks in 1996)], once such a breach took place so many times, more capital would have to be allocated or positions had to be cut".

"All the big investment banks are leveraged to some degree, and capital is a precious commodity. Cutting positions was the route taken. [...]"

"A similar story was happening at dozens of hedge funds, many of which used VAR to manage their risk. [...] many had to reduce exposure across the board, as capital was eaten away by the Russian debacle. Many banks instructed their hedge fund clients to put more capital against their trades – which had the same effect. Where did the hedge funds and prop[rietary trading] desks find the money to do this? They had to raid their other, still profitable positions. The result was that capital began flowing out of those swap and government bond markets which LTCM, other hedge funds and the world's biggest proprietary desks had been specializing in."

"Bob Litzenberger, a highly experienced quant at Goldman Sachs who would later become chief risk manager for the firm, describes what happened: <<Consider a situation where volatilities rise and there are some trading losses; VARs would be higher and tolerances for risk would likely be lower. For an individual firm, it would appear reasonable to reduce trading positions; however if everybody were to act similarly it would put [downward] pressure on their common trading positions>>."

"It was the same issue which had been overlooked all those years before, in October 1987: liquidity. Although VAR isn't the same as option theory [...], both are built on the same assumption: that markets are liquid and continuous".

"As we saw with Black Monday, the result [of overestimating liquidity] is inevitable [..]: there are huge jumps downward in the price. [...] everything started moving in the same direction, except for on-the-run Treasury's which moved the other way. Suddenly [correlations rose and] risk seemed a lot higher, and this made the epidemic even worse. Bob Litzenberger: <<The very fact that the positions were held in common created the correlation>>".

5.1.1.4 Volatility increase, systemic risk and disengagement: our proposed explanation

We take the Russia-LTCM crisis of August-September 1998 as an example of a sudden increase in volatility that has occurred many times in the past. Other examples could be the Mexican default of August 1982 or the introduction of a new Federal Reserve policy in October 1979.

In each of these cases, an outside event served as an initial trigger. The event was seen as somehow overturning previous assumptions and raising questions about he future. Investors asked "What will happen next?". The stability of the financial system, that is the viability of major financial institutions and the smooth operation of the markets was called into question.

When the prevailing model was found wanting, investors could not immediately replace it with a new economic model. Instead there was for a time the absence of a model, that is a situation of Knightian uncertainty. Some investors sought to "disengage", that is temporarily reduce their positions in financial markets; liquidity

became scarcer and markets more volatile. This lasted for as long as there was a loss of confidence in the system. In some cases (such as the fall of 1998 or the summer of 1982) a loosening of monetary policy was deliberately used by the Fed to restore confidence. This use of monetary policy, which has a long central banking tradition behind it, is rather different from the one more commonly mentioned in economics: to control bank lending and money growth.

The idea that financial crises lead to volatility increases has been advanced before. Schwert (1989) found a correlation between banking crises or financial panics and U.S. stock volatility. The financial crises he considers involve bank runs and failures in the period before deposit insurance. As a result his sample does not include any events after World War II. The example of August-September 1998 shows that financial panics of a sort still can happen today, although in a different form, and still led to volatility increases.

These financial crises are described as systemic because they are not restricted to one particular type of security or one financial market. The financial system itself is endangered. Ironically having financial institutions that are involved in a variety of markets at home and abroad is no defense against this type of crisis. On the contrary multinational finance tends to spread the crisis more widely.

5.1.2 The second case study: October 1987

From 17% in September 1987, volatility rose to 96% in October, then fell back to 29% in November. By May 1988 it was again at the 17% level.

The events of October 1987 are sufficiently well known. Steep declines occurred on October 14, 15 and 16. These were –2.9%, -2.3% and –5.2% respectively. When the market reopened on Monday October 19, there was a record decline, with the S&P500 falling 20.5%. The rest of the month continued to be volatile, with 7 movements of more than 1% in absolute value in the remaining 9 days.

An important feature of the October 19 decline was that it was reflected in other stock markets around the world, that is it was not purely a U.S. phenomenon.

Another aspect much commented about was the lack of any major new information that would explain the decline. Nor were there any subsequent economic events (such as a recession) that the market could retrospectively have said to have forecast.

The Presidential Commission set up to investigate the market break concluded that "the precipitous market decline of mid-October was triggered by specific events: an unexpectedly high merchandise trade deficit which pushed interest rates to new high levels, and proposed tax legislation which led to the collapse of the stock of a number of takeover candidates. This initial decline ignited mechanical, price insensitive selling by a number of institutions employing portfolio insurance strategies and a small number of mutual fund groups reacting to redemptions. The selling by these investors, and the prospect of further selling by them, encouraged a number of aggressive trading-oriented institutions to sell in anticipation of further market declines. These institutions included, in addition to hedge funds, a small number of pension and endowment funds, money management firms and investment banking houses. This selling in turn stimulated further reactive selling by portfolio insurers and mutual funds". [...]

"While no default occurred, the possibility that a clearing house or a major investment banking firm might default, or that the banking system would deny required liquidity to the market participants, resulted in certain market makers curtailing their activities and increased investor uncertainty. Timely intervention by the Federal Reserve System provided confidence and liquidity to the markets and financial system".

It should be noted that the merchandise trade deficit and the change in takeover legislation were both announced on Wednesday October 14. When the Brady Commision refers to these events as the triggers they are using the language a bit loosely. As previously mentioned, on October 19 there was relatively little news, and the deficit and takeover stories were stale by then.

A phrase made famous by the commission was "the illusion of liquidity": "The liquidity apparent during periods of normal volume provided by the activities of market makers and active traders on both sides of the market is something of an illusion. Liquidity sufficient to absorb the selling demands of a limited number of investors becomes an illusion of liquidity when confronted by massive selling, as everyone shows up on the same side of the market at once. [...] Ironically, it was this illusion of liquidity

which led some similarly motivated investors, such as portfolio insurers, to adopt strategies which call for liquidity far in excess of what the market could supply".

In conclusion, the explanation of the events of October 19 remains somewhat obscure. A modest decline may have been made worse by market practices such as portfolio insurance. Once the decline occurred, it created its own financial crisis in the sense that default risk became a concern and the possibility of systemic damage surfaced.

5.1.2.1 Haugen's view of October 1987

One point made by Haugen (1999) is that investors use recent realized volatility as a guide to what is likely or possible in the future. In this view, during the three large declines of October 14, 15 and 16 the market was in the process of "scaring itself to death", that is learning that a large decline was possible. The process of protecting oneself against such a large decline would then help to bring it about.

Haugen also brings up the issue of volatility feedback. If the market expects stocks to be more volatile in the future, then it would use a higher discount rate to value them. Haugen claims that the October 19 event is of a size consistent with this explanation. The idea of volatility feedback was first suggested by Pyndick (1986). However it was criticized by Poterba & Summers (1986). Much depends, they point out, on how long the higher volatility is expected to last; if it only lasts a few months then it should not affect the prices of long lived assets very much.

5.1.2.2 October 1987: our proposed explanation

October 1987 is our second example of volatility increase. When the price of an asset drops for any reason, there is a possibility of continued high volatility. In extreme cases the drop can be so severe that it raises concern about systemic stability (as occurred in October 1987). There are similarities between our two examples, although in 1998 there was a clear outside triggering event (the Russian devaluation) but none in 1987.

When the price drops sharply, there is increased uncertainty as investors wonder what everybody else knows that they do not. There is a dangerous period as investors try

to discover whether there is significant new information and what it is. There may also be concern about systemic risks from bankruptcies of other participants.

The capacity of market-makers to handle the demands of investors comes under strain as the liquidity of the market is shown to be finite rather than infinite (the famous "illusion of liquidity"). Large price movements are the result.

The adoption of new techniques by investors played a role both in 1987 and 1998. In 1987 the new technique was portfolio insurance (Brady Report, 1988); in 1998 fixed income arbitrage methods developed by LTCM and copied by a number of imitators (BIS, 1999). These techniques generated correlated trading to an extent which may have surprised the advocates of the techniques themselves. The sociological rather than economic phenomenon of imitation may have played a role in both cases. After 1987 a consensus developed that the October crash had been due to a peculiar set of circumstances which made it a one time event; the reappearance of some of the same causes in 1998 (correlated trading arising out of a widely imitated financial innovation) casts doubts on the "one-time event" interpretation.

5.1.3 Implications for volatility theories

The above reconstructions of specific historical episodes suggest the following observations. First of all, volatility disruptions lasting for weeks or months are part and parcel of the way markets work. I have suggested that at least some of them (including outstanding recent examples) are related to financial market developments that can be broadly described as crises of confidence. Not all disruptive events in the financial system trigger a volatility increase, for example the Mexican crisis of late 1994 did not. Nevertheless they have the potential of doing so; from a social point of view the benefits of sophisticated financial intermediation have to be traded off against the cost of occasional malfunctions in financial institutions and markets. The financial system, rather than simply reflecting volatility in the rest of the economy, may also occasionally be a source of volatility in its own right. Central bankers, including Mr. Greenspan, appear to be comfortable with this view. Market participants, who swap information with

each other about the state of the market or the doings of other players, also take it for granted that there can be internally generated volatility. Confidence in the market, and in the solvency of other participants, is an important prerequisite for their trading. As this confidence varies, so does volatility.

Second, the volatility may not be tied to a specific event, but rather to its interpretation. The Russian default of August 1998 is an example of an event that caried relatively little information per se ("Russia has defaulted on its debt") but had a much more substantial interpretation ("The international financial crisis is not over, more countries may well default"). It is the interpretation (that it is implications for future events) that determines the market impact, rather than the event itself. This explains the size of the initial market reaction, but perhaps not the persistence of the volatility itself.

Third, specific risk control strategies adopted by financial institutions come into play. For example under a Value At Risk methodology, empirically derived 95% confidence limits for price fluctuations are used to set acceptable risk levels. The risk control methods adopted affect the behavior of the market, at least in the short run, because these methods often require automatic action to be taken in response to market events. Examples include dynamic hedging, stop-loss rules or requirements that Value At Risk be kept below a pre-specified figure. These automatic actions place demands on market liquidity. As two economists from Deutsche Bank have put it (Financial Times Jan-6-1999): "Modern risk control methods are liquidity-hungry". They will not affect the market as long as there is ample liquidity, but since liquidity in any market is limited, there is the possibility that risk control procedures will on occasion exhaust the available liquidity and increase volatility. This phenomenon will correct itself within a short time, consistent with what we see: brief rises in volatility followed by return to more normal levels.

Fourth, in addition to risk control methods, limited market participation also plays a role in keeping volatility high after an initial shock. Unlike a fish market auction, where the entirety of the day's catch of fish is sold off, the stock market involves the buying and selling every day of only a small fraction of the available securities by a small percentage of the available buyers and sellers. Furthermore this liquid fraction fluctuates from day to day. This may be important in understanding why volatility changes so much over the

short run. Volatility spikes correspond to disruptions in liquidity. If a group of stock holders wish to sell their stock, the potential buyers are not all investors in the economy, but only a fraction that are active at that time. These consist mostly of professional traders and others willing to hold stock over a relatively short time, as well as a smaller number of long term investors. If the capacity of the liquidity providers is temporarily exceeded, unusually large price movements may occur until additional participants are brought to the marketplace. At least one possible cause of these temporary liquidity droughts has already been mentioned: correlated sales by investors following similar risk control rules, but other cases are possible whenever investors follow fairly similar policies (for example similar technical trading rules).

Fifth, participation, in addition to being limited, also varies over time. A decrease in confidence, due to an increase in systemic risk, or simply as a reaction to events that prove difficult to understand leads to what Mr. Greenspan called "disengaging" and heightens volatility for those who are still "engaged". Theoretical models in which participation is inversely related to volatility have been presented by Allen and Gale (1994) and Pagano (1989).

Sixth, in addition to the traditional channels that explain why events in one market affect another (for ex: a recession in Russia will affect the profits of U.S. corporations that export to Russia), the events described above suggest that other channels may also operate. The operation of financial institutions across markets is one such channel. There is evidence, to cite one example, that international stock markets have become somewhat more correlated in recent decades (Longin and Solnik (1995)), just as international investing has become more popular among institutional investors. As another example: A decision by an institution to decrease leverage may lead to sales in widely separated markets, as seems to have occurred in August-September 1998.

6.0 Volatility increase: a proposed mechanism

Two key ideas drawn from the recently developed field of Behavioral Finance can go far in explaining temporary volatility increases like the ones described in the previous section: Reluctance to Realize Losses and Uncertainty Avoidance.

6.1 Reluctance to Realize Losses

Reluctance to Realize Losses, also known as the Disposition Effect, refers to the tendency of investors to prefer to sell shares that show a profit rather than those that show a loss (Shefrin and Statman, 1985). From the classical economic point of view a $1 loss and a $1 gain have an equal effect on Utility (that is the utility function is differentiable in the neighborhood of the current wealth level). Furthermore the rational investor recognizes a loss as soon as it occurs (mark to market accounting) rather than when the shares are sold. For such an investor the gain or loss should not be a factor in the decision to sell; when we consider the tax advantage of realizing short term losses, there would actually be an argument on favor of realizing losses rather than gains. Yet researchers in Behavioral Finance have shown empirically that investors are reluctant to realize losses (Odean 1998). The origin of this behavior lies in psychological phenomena such as Loss Aversion (a $1 loss is subjectively more serious than a $1 gain), Mental Accounting that does not use mark to market, and Self Attribution (the tendency to see a sale at a profit as a reflection of one's own ability).

Empirical work by Lakonishok and Smidt (1986) and Haugen has shown that this quirk of investor behavior can have an effect on the market as a whole. They found that volume was higher after a price run up than after a price decline. After a price decline fewer investors have gains and more of them have losses, and the result is a reduction in aggregate trading.

6.2 Uncertainty avoidance

The observation that in practice people seem to make a distinction between Risk and Uncertainty has its roots in experiments reported by Ellsberg (1961) and is sometimes called the Ellsberg Paradox. This is a controversial area as most economists do not accept such a distinction or do not find it useful, almost a century after it was introduced by Frank Knight. In his terminology, risk refers to situations where the outcome is random but subject to probabilistic analysis, for example an urn containing

roughly equal numbers of white and black balls. Uncertainty refers to situations where people are unable or unwilling to make such an analysis. Alan Greenspan described what people do when they are faced with uncertainty: they disengage from their current activity ("When you are crossing the street and you become uncertain you stop", cited above). This is what we call Uncertainty Avoidance. It is a psychological, not a rational response. (It is not particularly rational to stop in the middle of the street). In a market situation disengaging takes the form of refraining from trading, neither buying nor selling until one feels that rational probability calculations are possible once again. A systemic risk scenario is but one example of a situation where uncertainty avoidance manifests itself, and in this paper it serves as a proxy for uncertainty avoidance, but there may be other conditions where this behavior manifests itself.

6.3 Proposed explanation

The increases in volatility discussed in this paper are essentially an illiquidity phenomenon. In a bull market, trading is very active and liquidity is therefore plentiful. It is easy to take large positions, and the situation resembles the perfect markets assumed by economic theory.

If a price decline occurs for any reason, the reluctance to realize losses will begin to have an effect. Trading volume and liquidity will go down.

If the situation is perceived to be murky and not subject to rational analysis then Uncertainty Avoidance would kick in with similar effect: a reluctance on the part of many investors to trade and a further reduction in liquidity. For the remaining investors trading becomes more difficult and attempts to add to or reduce positions have a larger effect on price. The observable result is an increase in volatility. Theoretical models in which lower liquidity leads to higher volatility, such as those of Pagano (1989) and Allen and Gale (1994) support this notion.

One technique that traders have long used to overcome their reluctance to realize losses is to decide ahead of time at what price level a sale is to be made. Either a stop-loss order is entered at that price or an informal decision is made to sell should the predetermined level be reached (sometimes called a "mental stop-loss"). This precaution is unnecessary for a rational investor, but is helpful to an investor who fears that he may

act irrationally later on. In recent years techniques for loss limitation have been greatly extended and generalized. Investment banks and hedge funds have created Risk Management departments that monitor risk closely (using such measures as Value At Risk and Historical Volatility) and are ready to act to reduce positions if predetermined risk levels are reached. The flaw in this whole risk management philosophy is that sales must be made at the worst possible time, when other investors are reluctant to buy and when other institutions using broadly similar risk measurement methods are also trying to sell. The effect has been to make the volatility increase at such times even worse. A rule of thumb that is helpful to individual traders (decide ahead of time when you will get out) has proven counterproductive when applied on a large scale by institutions to systematically reduce their positions as the price drops. Similar analyses of the limitations of risk management techniques have recently appeared elsewhere, for example Persaud (2001), Capon (2001) and the book by Dunbar (2000).

6.4 Some consequences of the theory

This theory explains a number of facts about the observed behavior of volatility:

We have seen that large volatility increases are short term. Often the volatility will increase in one calendar month only to come back down the following month; at other times the high level may last 2 or 3 months. These periods are too short to be related to structural changes in the economy. On the other hand uncertainty avoidance can dissipate very quickly: measures by the Central Bank to deal with systemic risk, or simply the realization that the feared wave of financial institution bankruptcies is not taking place, can restore market participants' willingness to trade in a few days. Reluctance to realize losses lasts a bit longer, but eventually is overcome as more and more investors buy stocks at near-current price levels and therefore do not have a locked-in loss. In any case even if reduced liquidity lasts for some time, the distressed sales required by formal or informal risk management rules soon cease as positions are gradually adjusted to desired levels.

Many years ago Fischer Black (1976) noted that market volatility increases after the market drops. He attributed it to the leverage effect, that is to the fact that at lower market levels the debt to equity ratio of corporations increase. However the increase

occurs even for companies that have little or no debt and is generally too large to be explained this way (Christie, 1982). Behavioral factors like those mentioned provide a more powerful explanation. The abruptness of the price drop seems to influence the volatility increase, so that for example a 5% price drop in a day seems to have a larger effect on volatility than a 5% drop in a month. Formal econometric tests should therefore be able to distinguish between the leverage and behavioral explanation. The Fischer Black effect applies to implied volatility as well as actual volatility; for example from 1998 to 2001.6 the correlation between the VIX index of implied volatility and the previous 4 week S&P500 return was an impressive –0.47.

Finally the fact that volatility spikes have increased in frequency since the introduction of dynamic hedging and dynamic risk control is another consequence that could have been predicted from our theory.

7.0 Conclusions

We have seen that volatility is neither constant nor subject to random drift, but rather experiences occasional sharp increases followed by returns to more normal levels. This paper argued that some of these volatility surges may be the consequence of systemic risk events, that is fears regarding the solvency of financial institutions. After allowing for these surges the normal level of volatility varies in a slow fashion over a number of years, but these changes are relatively mild. Our empirical work showed that the sharp disruptions were slightly more frequent in the 1990's than in the 1980's. Correlated trading by financial institutions following similar risk control rules may have been behind the sharp volatility increase of August-September 1998. This episode has similarities to October 1987, when correlated trading was caused by portfolio insurance strategies.

Both episodes support the Shiller-Summers view of volatility as partly influenced by investor confidence and investor fashions.

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Tables and Figures

See following pages.

Table A Part 1. Large volatility increases or drops from previous month

This table shows the largest increases or decreases in calendar-month volatility of the S&P500 during the period 1962 to 1998.

Date	Increase	Month's vol (annual basis)	Accompanying event
Oct 1987	+171%	96.5%	Stock crash of 87
Oct 1989	+114%	26%	Stock mini crash of 89
Nov 1963	+103%	20.7%	President Kennedy shot
Aug 1982	+91%	26.7%	Mexico default and bailout
Jul 1996	+85%	16.5%	
May 1966	+83%	15.3%	
May 1970	+82%	31.1%	Credit stringency, corp. failures
Jun 1965	+80%	14.5%	
Aug 1998	+78%	34.2%	Russian default
Aug 1971	+74%	16.6%	Nixon closes gold window
Aug 1990	+71%	25.4%	Kuwait invasion
Apr 1992	+65%	14%	
[...]			
May 1968	-75%	6.6%	
Oct 1986	-79%	10.3%	
Feb 1988	-79%	15.6%	Cont. recovery from 87 crash
Aug 1965	-81%	3.5%	
Nov 1989	-94%	10%	Aftermath of crash of 89
Nov 1987	-119%	29%	Aftermath of crash of 87
Dec 1963	-128%	5.7%	Aftermath of Nov 1963 increase

Table A Part 2. High or low vol months

Oct 1987	96.5%
Jan 1988	34.4%
Sep 1998	34.2%
Aug 1998	34.2%
Oct 1974	32.8%
Oct 1997	32.3%
Sep 1974	31.4%
May 1970	31.1%
Nov 1987	29.4%
[...]	
Mar 1964	3.7%
Aug 1965	3.5%
Feb 1964	3.1%

Chart B. Histogram of month to month changes in log volatility of S&P500 for all calendar months 1962-1998.10 [light color]. Normal distribution with same mean and variance for comparison [dark color]

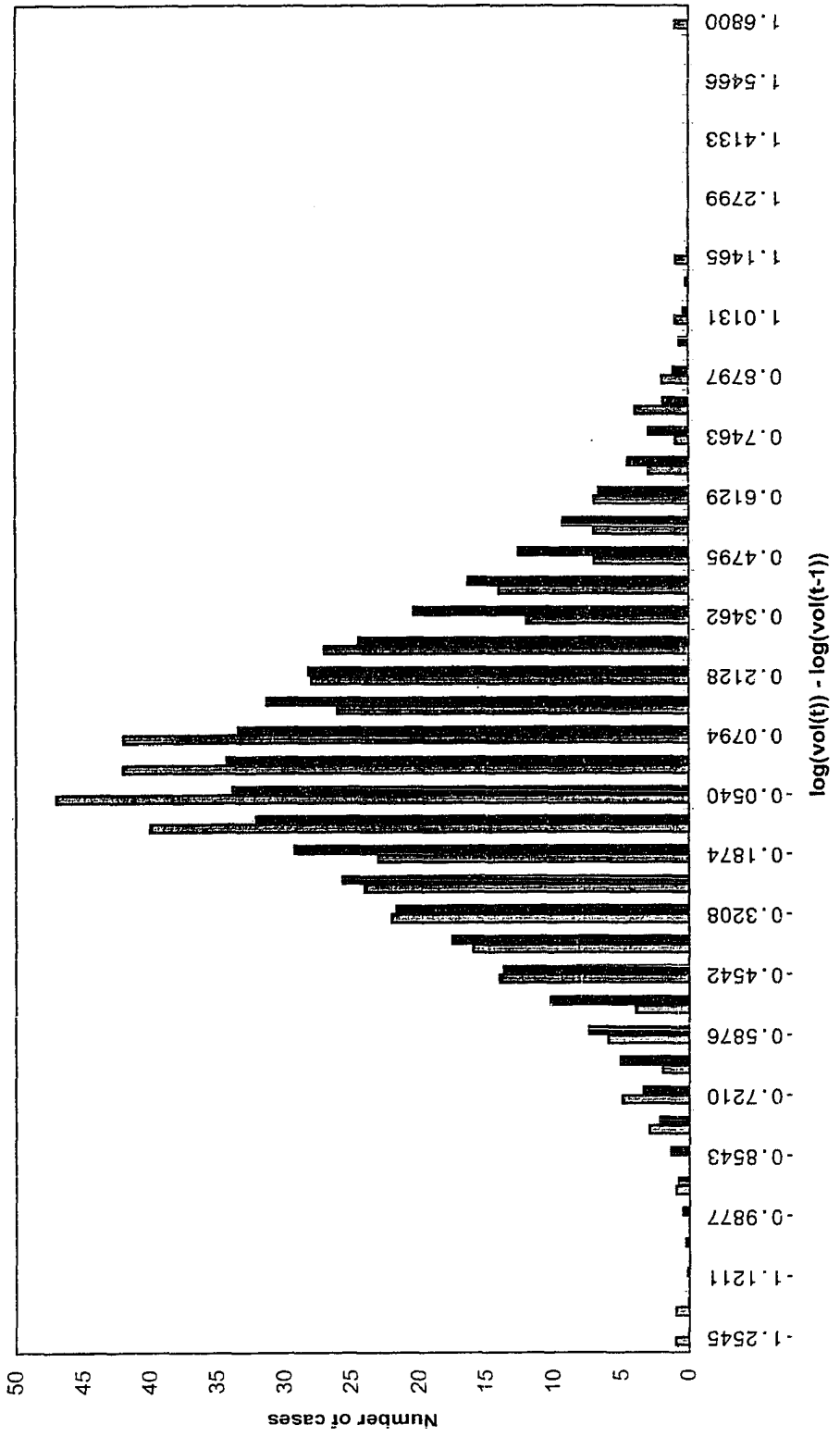


Table BB - Tests of Normality for Month to Month Vol Changes

Statistical tests of normality for the data shown in Chart B. The volatility of the S&P500 was computed for all calendar months from 1962 to 1999. The changes in the logarithm of volatility from one month to the next are tested, that is log(vol(month_t)) – log(vol(month_t-1)) or equivalently log(vol(month_t)/vol(month_t-1)). The logarithmic transformation was introduced to reduce skewness. The tests rejected the hypothesis of a Normal Distribution. The period 1928 to 1999 was also tested with similar results.

S&P 500 1962-1999

LILLIEFORS TEST FOR NORMALITY
n=456
mean=0.00118685 stdev=0.340323 skew=0.294098 kurt=2.16298
Kolmogorov-Smirnov statistic d=0.0545620
Lilliefors prob=0.00244365 [Highly significant rejection]

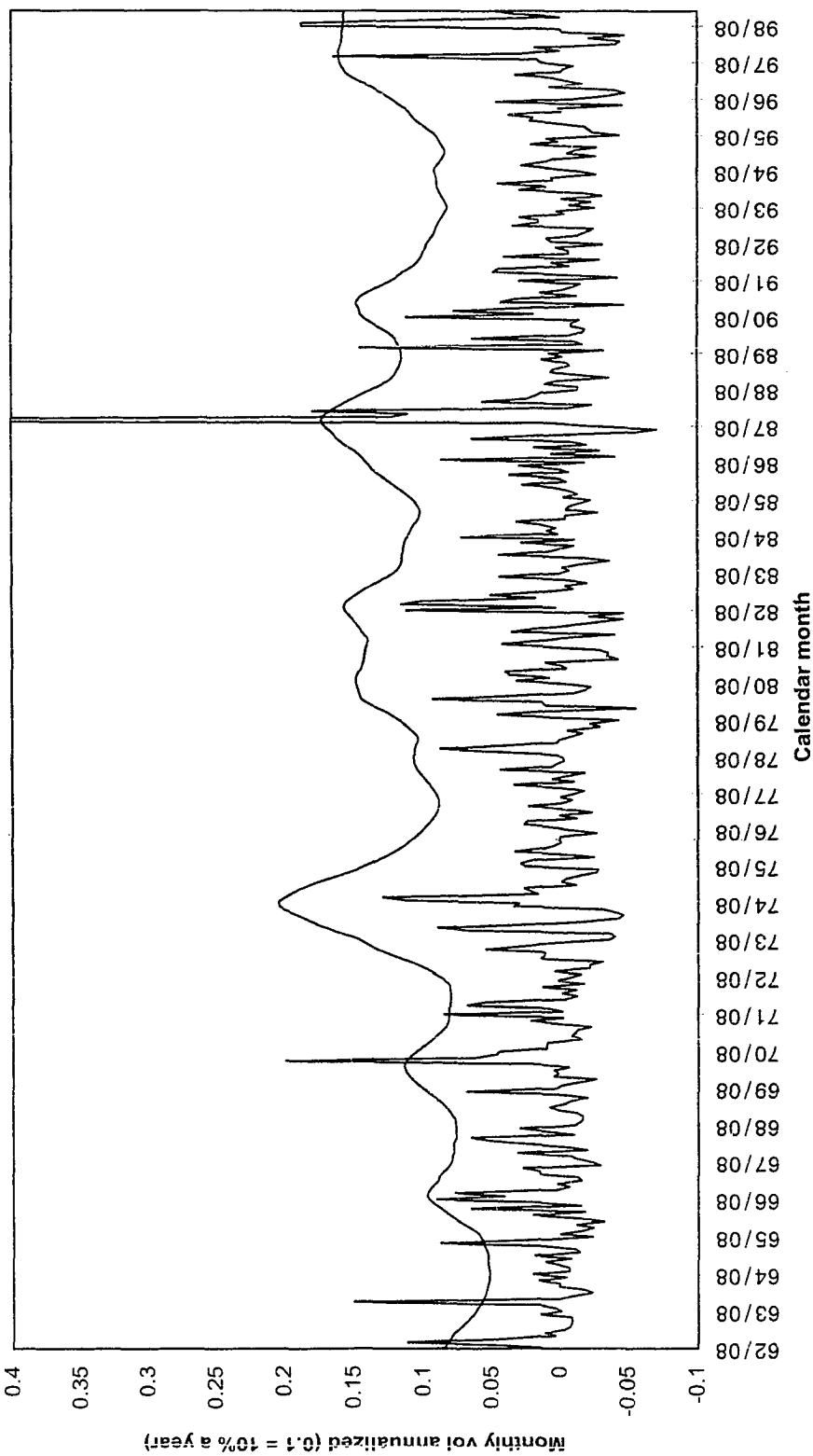
SHAPIRO-WILK TEST FOR NORMALITY
n = 456 w = 0.978422 prob = 0.00000273 [Highly significant rejection]

S&P 500 1928-1999

LILLIEFORS TEST FOR NORMALITY
n=862
mean=0.248408E-03 stdev=0.354514 skew=0.241525 kurt=1.67361
Kolmogorov-Smirnov statistic d=0.0347505
Lilliefors prob=0.0155859 [Significant rejection]

SHAPIRO-WILK TEST FOR NORMALITY
n = 862 w = 0.984158 pw = 0.000000048 [Highly significant rejection]

Chart C. Vol decomposition into fast and slow components. The time series of S&P500 calendar month volatilities was smoothed by taking the median of rolling 12-month periods and then a 12-month moving average (upper), leaving a residual (lower)



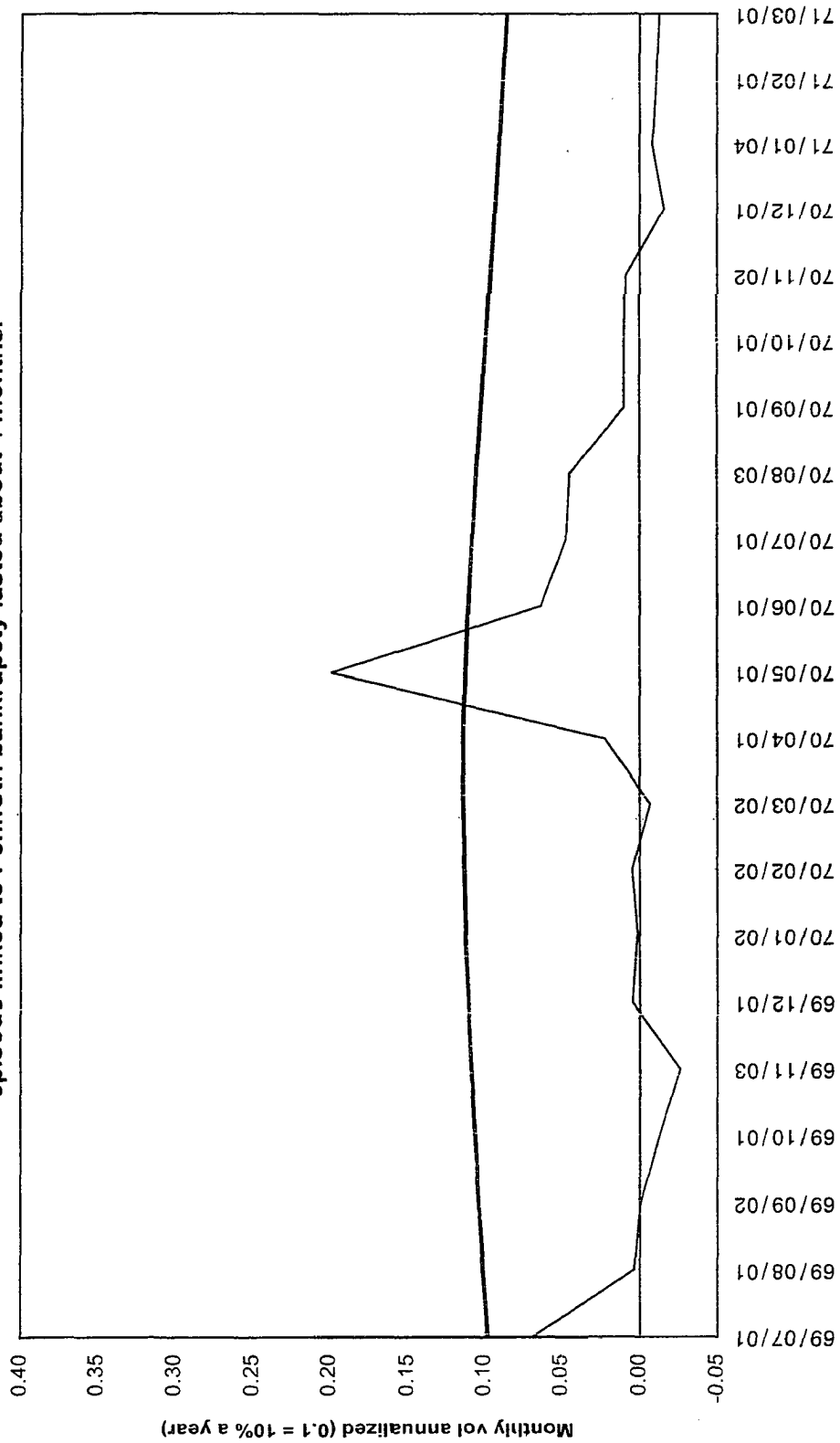
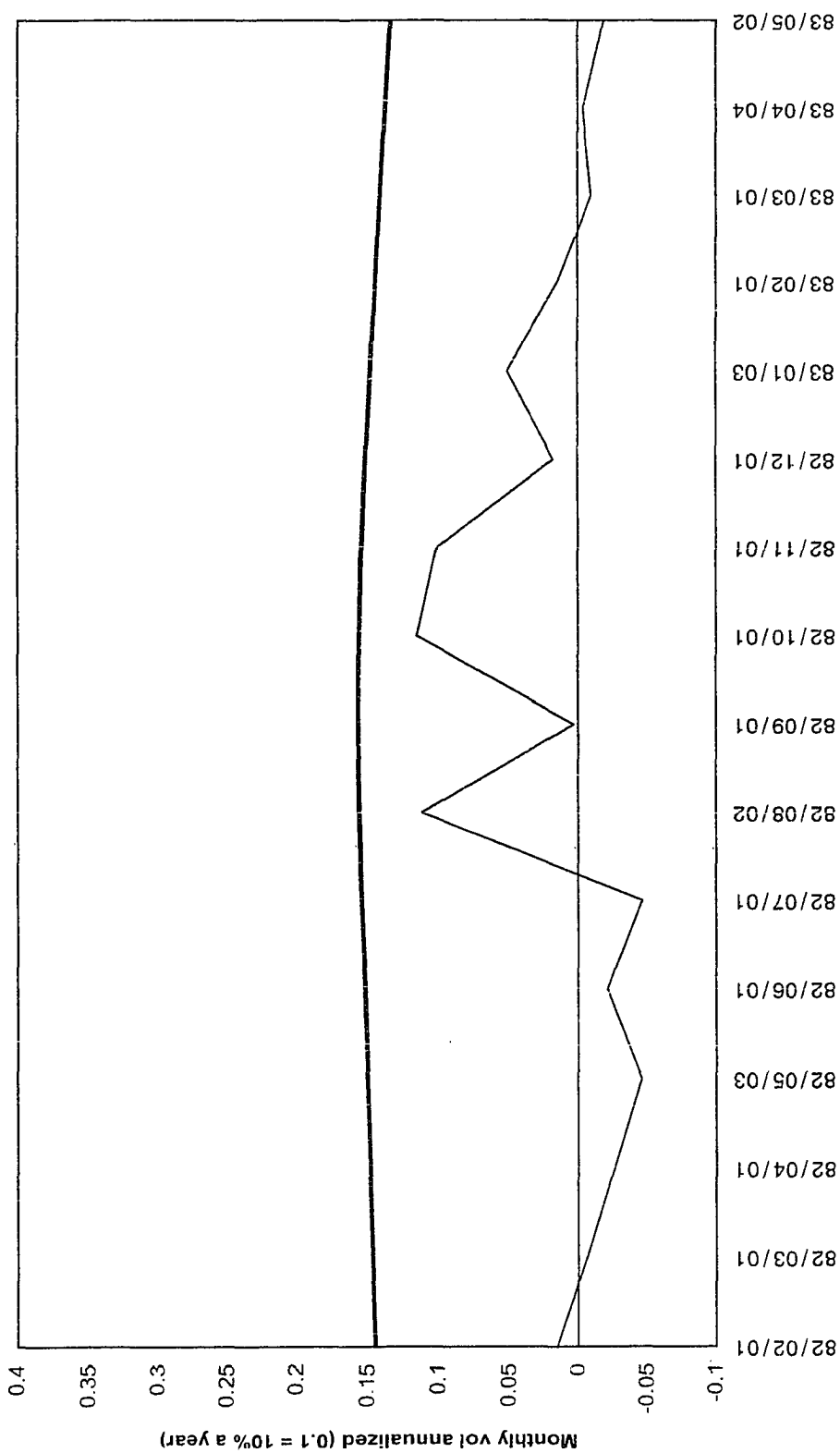


Chart D. Vol decomposition into fast and slow components: closeup near May 1970. Smoothed vol (upper curve), residual (lower curve), x-axis (straight line). This high vol episode linked to PennCtrl bankrupcty lasted about 4 months.

Chart E. Vol decomposition - fast and slow components: closeup near August 1982. U.S. Mexico bailout; duration of high vol 4 to 6 months. The excess volatility (lower curve) was about three quarters of the steady level (upper)



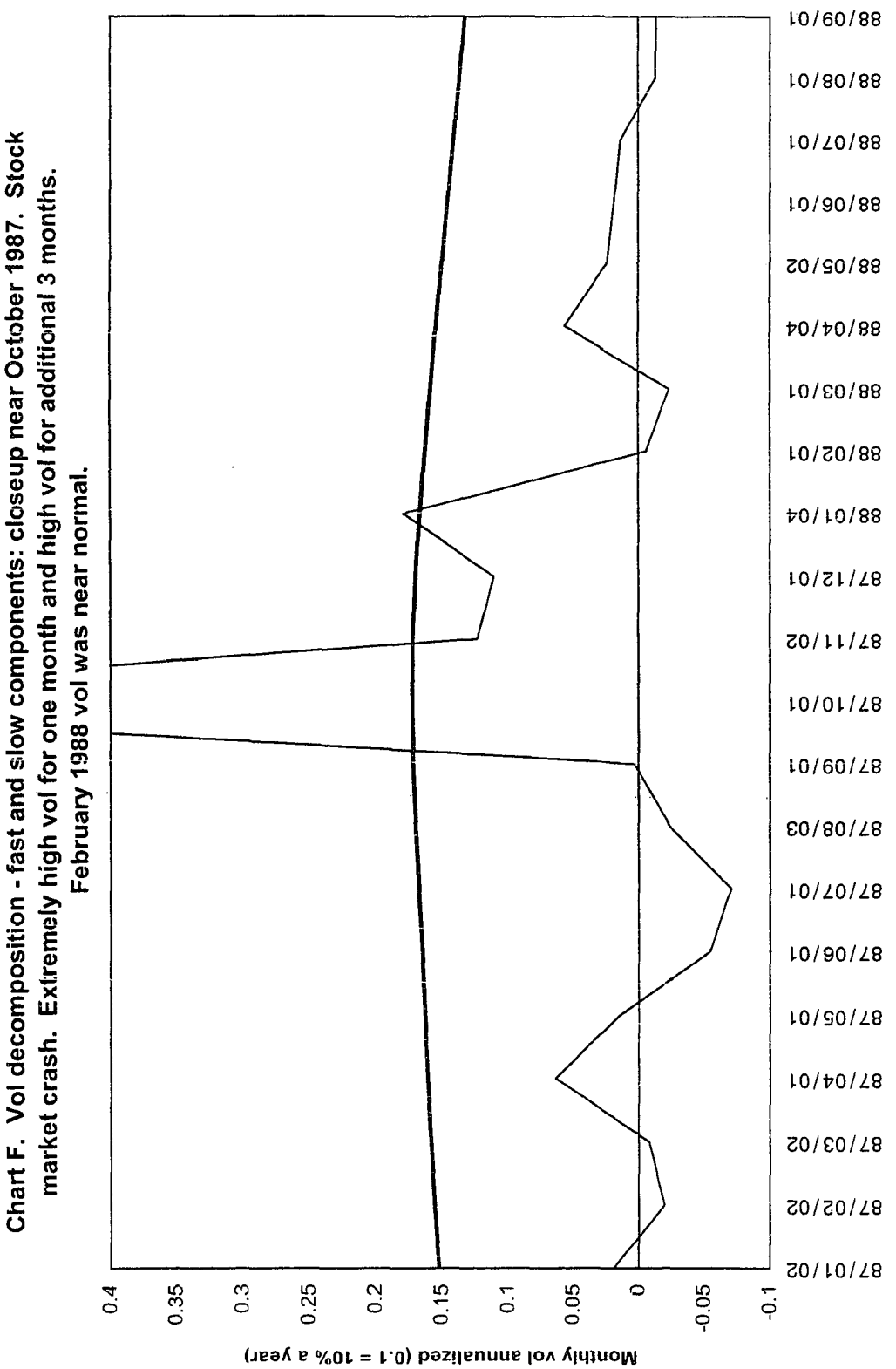


Chart F. Vol decomposition - fast and slow components: closeup near October 1987. Stock market crash. Extremely high vol for one month and high vol for additional 3 months. February 1988 vol was near normal.

Chart G. Vol decomposition into fast and slow components: closeup near August 1990. Invasion of Kuwait and start of U.S. recession. Residual volatility (lower curve) was highest in August and October

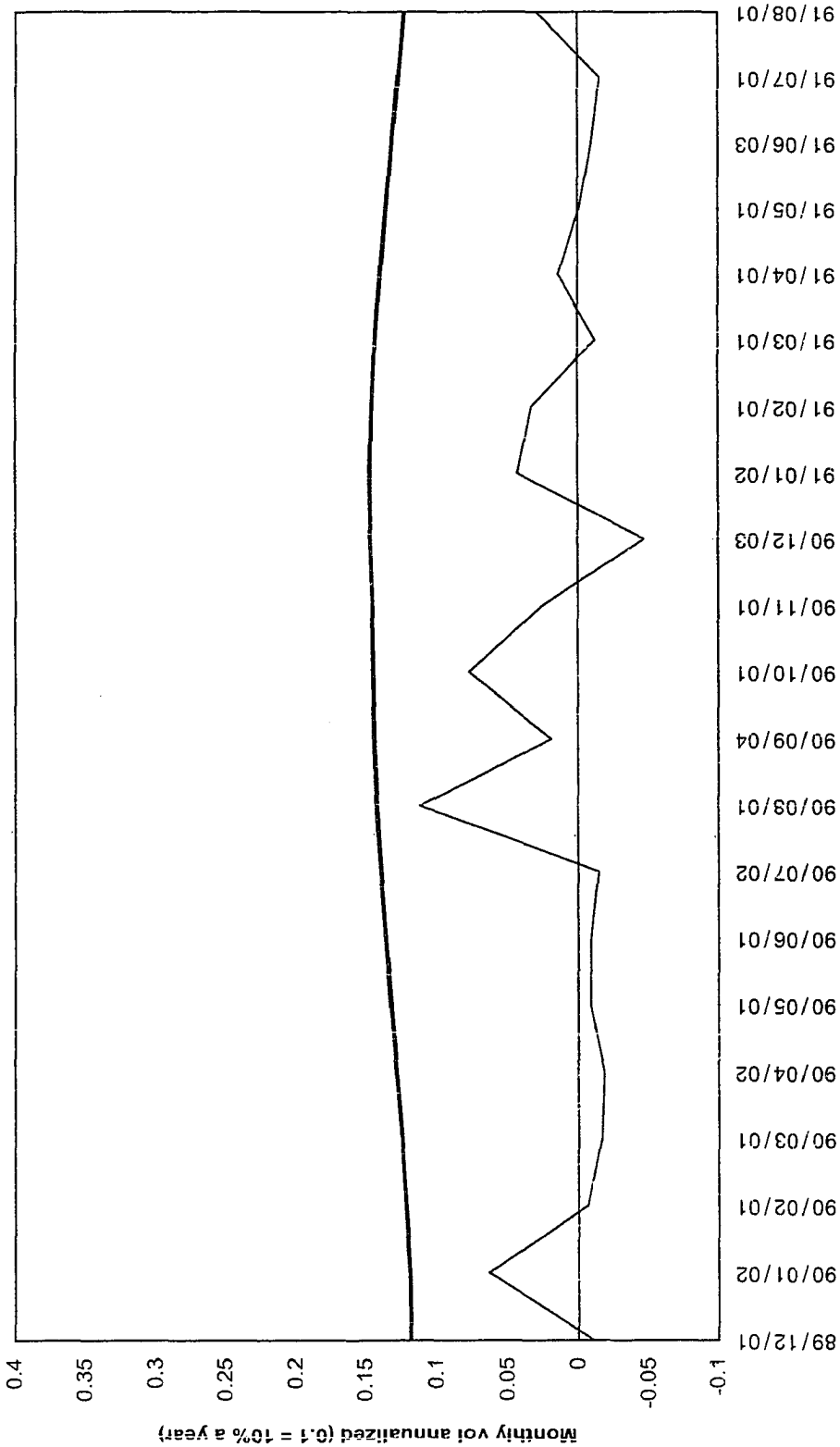


Chart H. Vol decomposition - fast and slow components: closeup near August 1998. Russia default (August) and LTCM rescue (Sept): residual vol bigger than normal vol for 2 months (i.e. total vol more than double normal), then somewhat high for 1 month

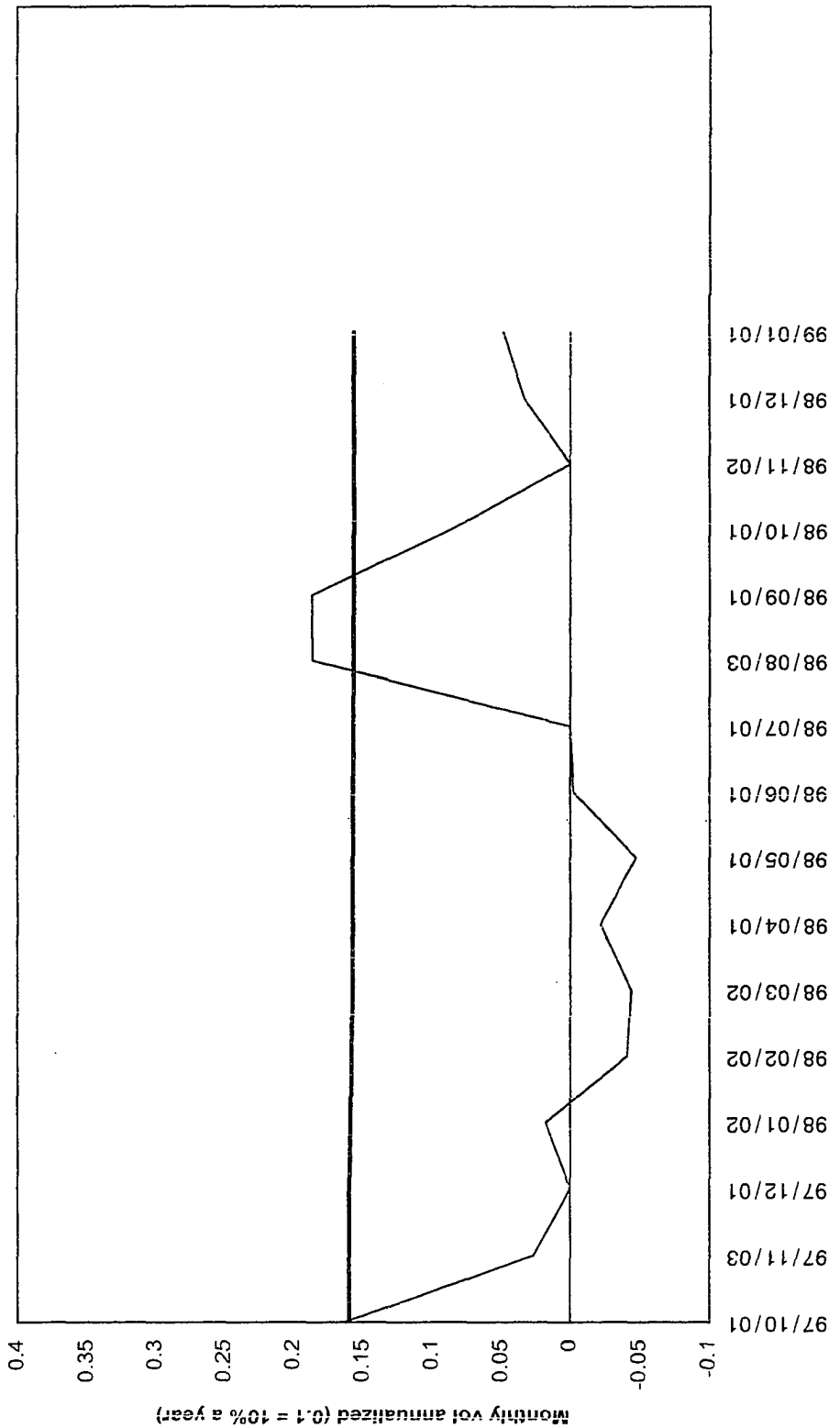


Chart I – Volatility measured every N days

These charts show the result of measuring volatility over non-overlapping N-day periods where N=126, 84, 42, 21, 5 and 1. The y-axis shows volatility converted to percent per day. The underlying random price data is the same for all six charts; it consists of 250 simulated trading days with a volatility of 1% per day. For small values of N the measured volatility differs considerably from the expected 0.01 value. Source: Monte Carlo simulation by the author.

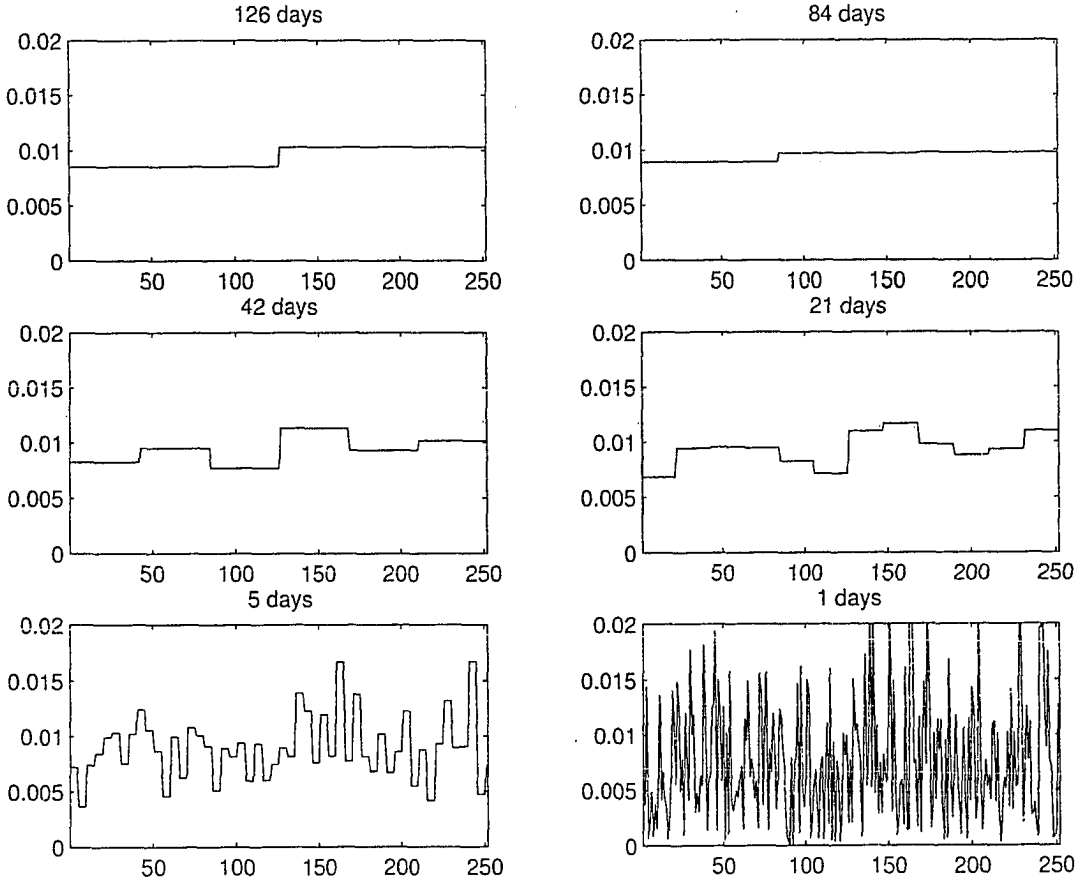
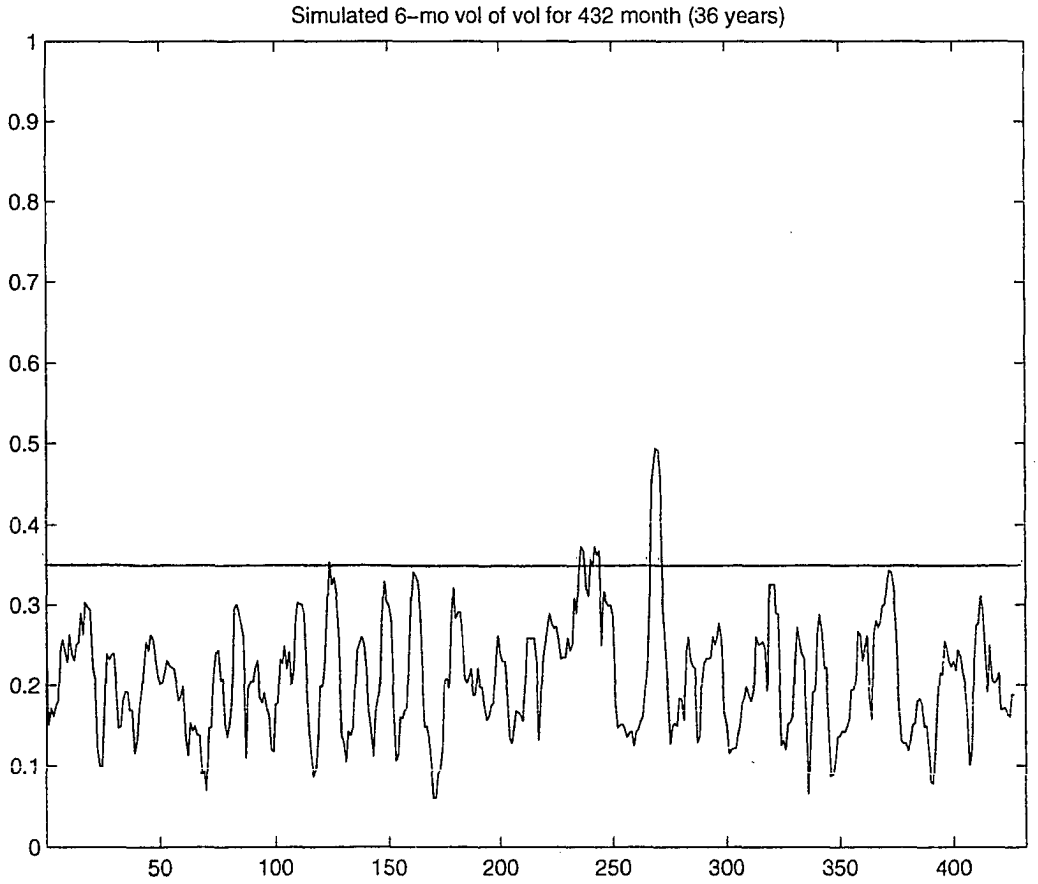


Chart J – Simulated Volatility of Volatility

36 years of daily stock market returns were simulated using a normal distribution and a constant volatility of 20% per year. The rolling 6 month Volatility of Volatility was computed and plotted (lower line). It is defined as SQRT [(1/5) SUM_I=1 to 5 (Log(Vol(I)) – Log(Vol(I-1)))^2] where Vol(I) is the volatility observed in calendar month(I). (Essentially this assumes that Log(Vol(I)) receives random shocks from month to month and measures the standard deviation of these shocks). Repeated simulations showed that Vol of Vol would be below 0.35 for 95% of the time; this reference level is plotted as the horizontal line and is used elsewhere for significance tests. Source: Monte Carlo simulation by author.



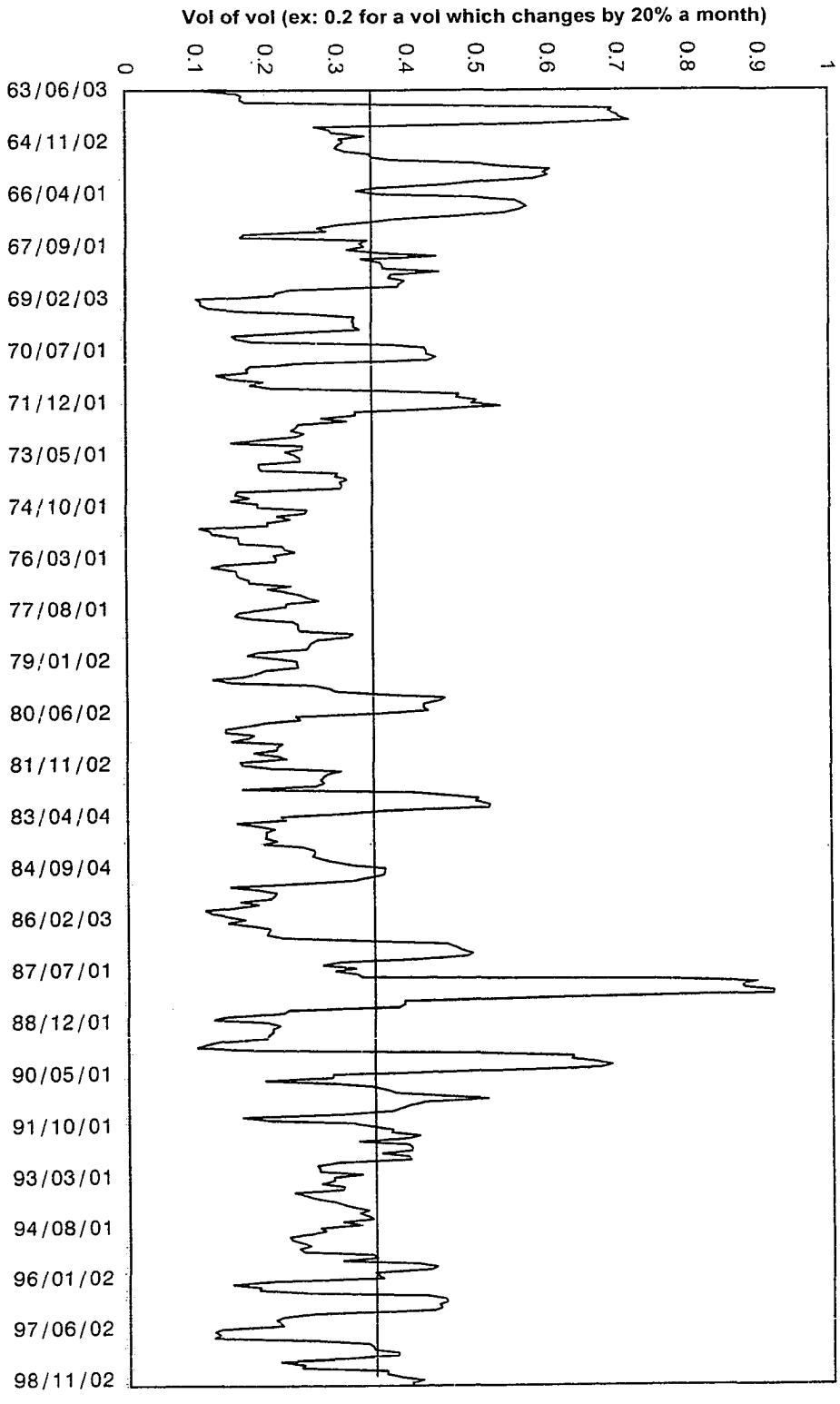


Chart K. Six month rolling Volatility of volatility for S&P500 from 1962 to 1999
Horizontal line: 5% significance level for rejecting constant volatility asumption

Table L: Six month periods showing elevated Volatility of Volatility

The rolling 6 month Volatility of Volatility for the S&P500 was computed from 1962 to 1999.1 and is plotted in Chart K. This table lists the periods during which the Vol of Vol exceeded the reference value of 0.35 also shown in Chart K. It adds some comments on the behavior of the Vol itself during these periods of high Vol of Vol.

From	To	Comments
Nov 1963	Apr 1964	Vol rose in Nov, fell sharply in Dec/Jan/Feb/Mar, picked up from all time low level in Apr. A "vol collapse"
Mar 1965	Aug 1965	Mainly a one month surge in vol in Jun 65 during a period of low vol
Mar 1966	Aug 1966	An erratic pattern of vol changes
Jun 1967	Oct 1968	Lasted for 18 months, erratic
Feb 1970	Jul 1970	One month vol surge in May 1970
Aug 1971	Jan 1972	One month vol surge in Nov 1971
Aug 1979	Jan 1980	High vol in Oct 1979
Aug 1982	Jan 1983	High vol in August, fell a bit picked up again in Oct, Nov 1982
Apr 1984	Sep 1984	Surges in Jun and Aug 1984 against a low background
Aug 1986	Jan 1987	Up in Sep, down a lot in Oct, up again in Nov, down Dec, up Jan 1987. See saw pattern.
Oct 1987	Mar 1988	Astronomical rise in Oct 1987, fell back afterwards
Sep 1989	Feb 1990	Mainly a surge in Oct 1989 from a low level in Sep
Aug 1990	Jan 1991	Vol high in Aug 1990, low in Dec 1990
Aug 1991	Jan 1992	Unusually low vol in Sep 1991 and Jan 1992
Apr 1995	Sep 1995	Vol low but erratic
Apr 1996	Sep 1996	Vol rose in Jul 1996
Oct 1997	Mar 1998	Big vol rise in Oct 1997
May 1998	Oct 1998	Very high vol in Aug and September 1998

Chart M – Wichern test statistic V

The Wichern, Miller, Hsu (1976) test statistic V was computed for 101 years of daily Dow Jones returns. When V rises above the upper control limit it indicates that a statistically significant volatility increase has taken place and conversely a penetration of the lower control limit indicates a decrease in volatility. This chart shows the period 1968 to 1972 and gives the dates of volatility increases (above the chart) and decreases (below the chart).

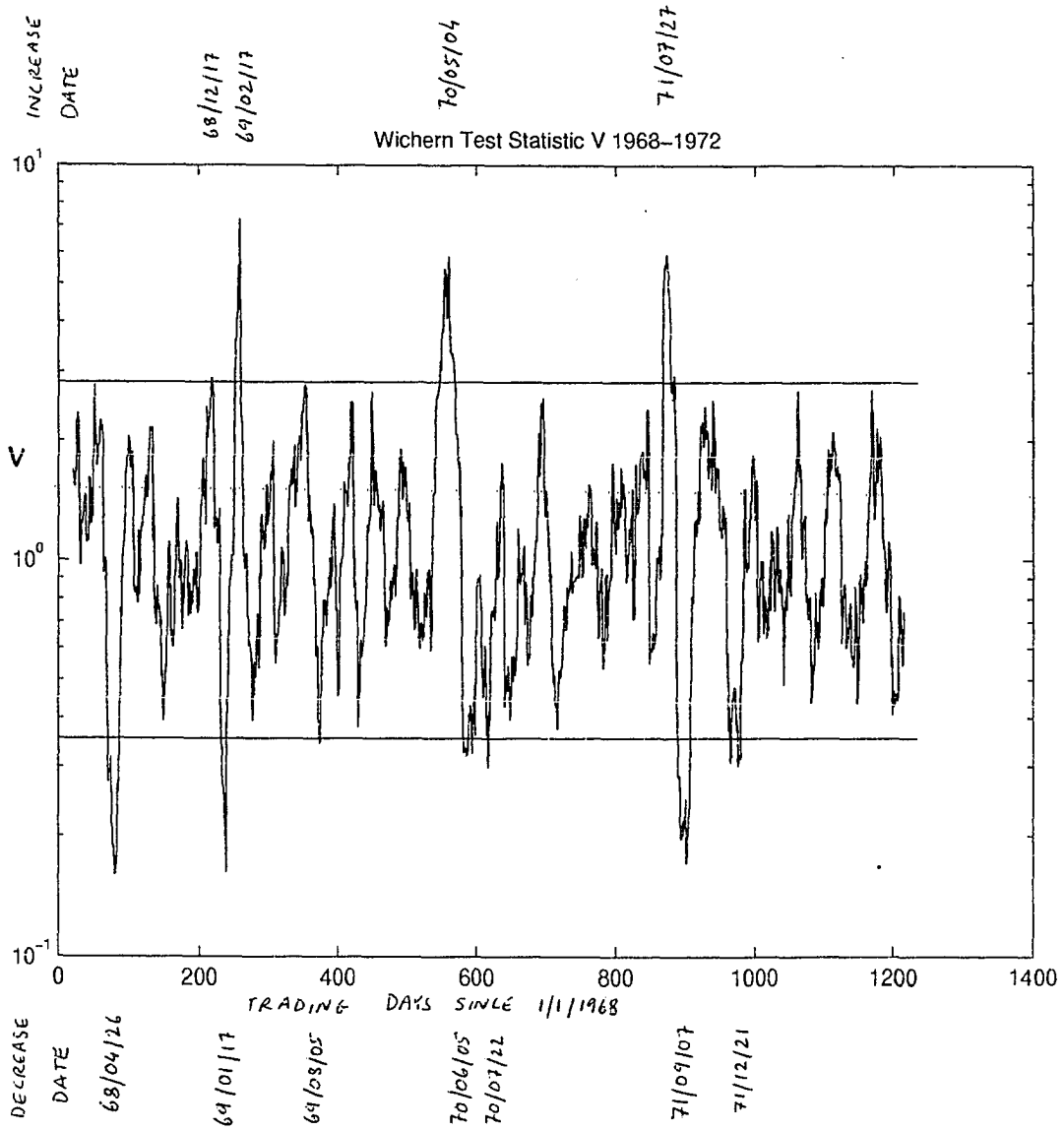


Table N - Extending the Haugen, Talmor, Torous (1991) study of vol changes (Part 1)
Panel A shows the number of volatility increases detected in the Dow Jones average in each decade from 1897 to 1999 using a 1% significance level, and the number reported in the original study by H, T and T.
Panel B shows the number of volatility decreases for the same periods.

A: Volatility Increases (alpha=1%)

Period	Number of Events	Avg Prior Volatility	Avg Subsq Volatility	Events reported by HTT
1897-1988	*151*	*0.1034*	*0.2506*	*205*
1897-1899	6	0.1324	0.3104	6
1900-1909	22	0.1077	0.2604	28
1910-1919	22	0.1037	0.2652	28
1920-1929	19	0.1166	0.2565	23
1930-1939	19	0.1629	0.3919	24
1940-1949	22	0.0752	0.1832	27
1950-1959	13	0.0625	0.1516	23
1960-1969	12	0.0634	0.1469	20
1970-1979	6	0.1035	0.2326	10
1980-1989	12	0.0984	0.2856	16 (To 1988)
1990-1999	14	0.0930	0.2043	

B: Volatility Decreases (alpha=1%)

Period	Number of Events	Avg Prior Volatility	Avg Subsq Volatility	Events reported by HTT
1897-1988	151	0.2477	0.1115	197
1897-1899	4	0.2831	0.1335	5
1900-1909	26	0.2406	0.1030	32
1910-1919	21	0.2774	0.1094	24
1920-1929	20	0.2644	0.1244	21
1930-1939	20	0.3925	0.1974	32
1940-1949	22	0.1720	0.0798	28
1950-1959	13	0.1553	0.0711	18
1960-1969	14	0.1428	0.0637	18
1970-1979	4	0.1616	0.0779	9
1980-1989	9	0.3395	0.1310	10 (To 1988)
1990-1999	12	0.1987	0.0964	

Table O - Extending the Haugen, Talmor, Torous (1991) study of vol changes (Part 2)
Panel A shows the number of volatility increases detected in the Dow Jones average in each decade from 1897 to 1999 using a 2.5% significance level, and the number reported in the original study by H, T and T.
Panel B shows the number of volatility decreases for the same periods.
This Table differs from Table N in the use of a different level of statistical significance; note that the values are very close to those reported by H, T and T in 1991.

A: Volatility Increases (alpha=2.5%)

Period	Number of Events	Avg Prior Volatility	Avg Subsq Volatility	Events reported by HTT
1897-1988	207	0.1076	0.2368	205
1897-1899	6	0.1324	0.3104	6
1900-1909	28	0.1070	0.2413	28
1910-1919	29	0.1093	0.2523	28
1920-1929	25	0.1188	0.2446	23
1930-1939	26	0.1916	0.4073	24
1940-1949	29	0.0754	0.1696	27
1950-1959	23	0.0687	0.1429	23
1960-1969	15	0.0612	0.1358	20
1970-1979	10	0.0964	0.1990	10
1980-1989	18	0.1043	0.2574	16 (To 1988)
1990-1999	19	0.0908	0.1896	

B: Volatility Decreases (alpha=2.5%)

Period	Number of Events	Avg Prior Volatility	Avg Subsq Volatility	Events reported by HTT
1897-1988	210	0.2383	0.1173	197
1897-1899	6	0.2525	0.1273	5
1900-1909	34	0.2368	0.1108	32
1910-1919	26	0.2655	0.1136	24
1920-1929	21	0.2545	0.1330	21
1930-1939	33	0.3805	0.2050	32
1940-1949	29	0.1605	0.0785	28
1950-1959	19	0.1414	0.0693	18
1960-1969	17	0.1422	0.0667	18
1970-1979	11	0.1926	0.1056	9
1980-1989	16	0.2655	0.1168	10 (To 1988)
1990-1999	18	0.1852	0.0944	

Table R Part 1

Extraordinary 2nd Block Events Associated with Volatility Increases

This table reports each volatility increase detected using the Haugen et al (1991) methodology and the event if any in Facts-On-File that approximately matched each vol increase date. ("2d Block" is the term used by Haugen to indicate the period of and immediately following a vol change).

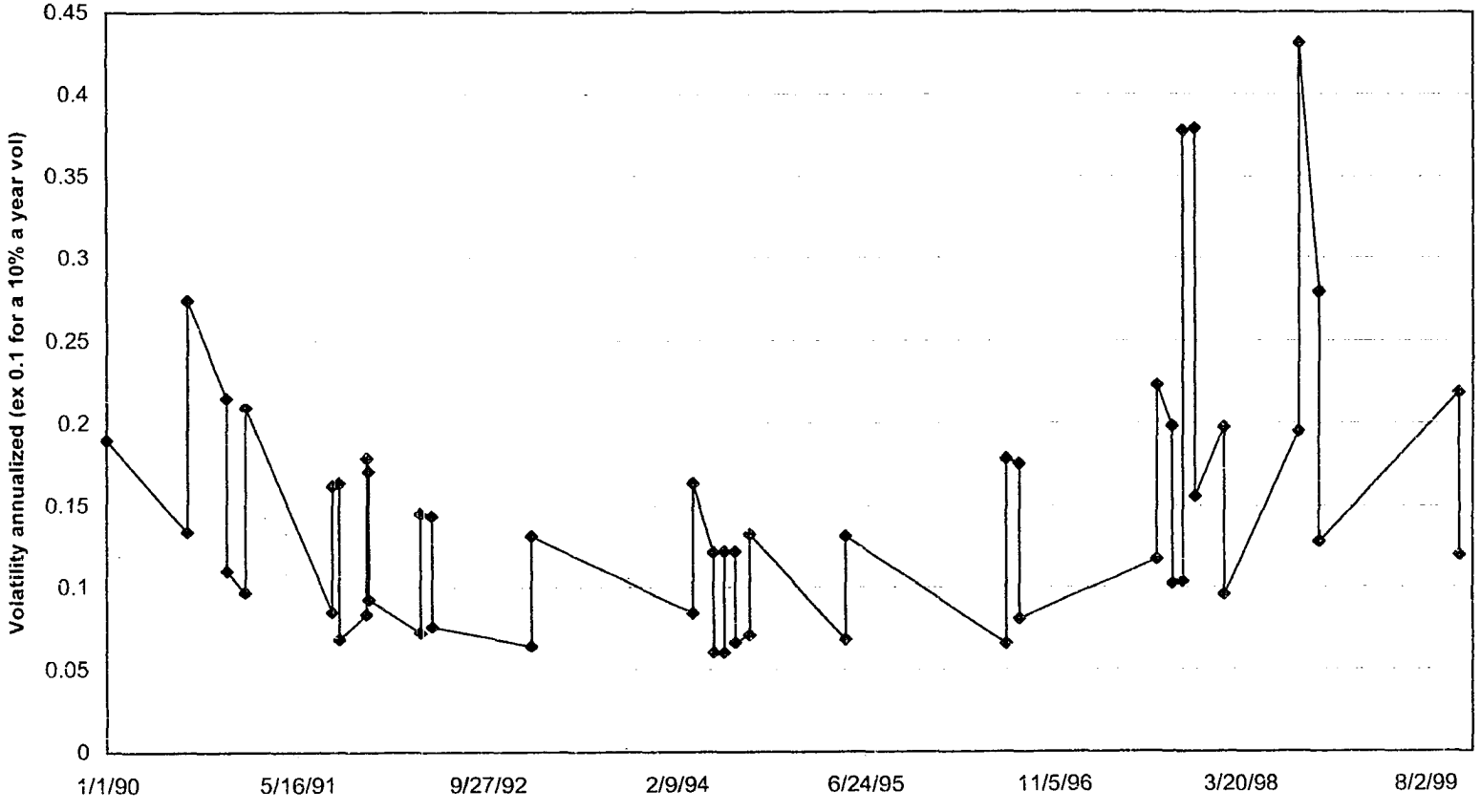
Volatility Shift Date	Matched Date(s)	Description of Matching Event (from Facts-On-File)
1989/09/25		(No event found)
1989/12/29		(No event found)
1990/08/02	Same	Invasion of Kuwait by Iraq
1991/01/02	Same	Rhode Island shuts 45 credit unions and small banks
	01/09	US-Iraq talks (Baker-Aziz) fail to reach agreement that would forestall war. Stocks plunge 1/9, then rebound 1/10.
1991/08/16	08/19	Soviet hard liners attempt coup against Gorbachev
1991/11/15		(No event found)
1992/04/06	04/07	Sharp decline in Nikkei April 7-9 possibly began to affect other markets. Bank stocks lead Nikkei plunge. DJIA April 7-8 lost a combined 94 points (-2.87%).
1993/01/20		(No event found)
1994/03/24		(No event found)
	03/22	Fed pushed up Federal Funds rate
	03/23	Mexico's leading presidential candidate assassinated
1994/06/16		(No event found)
1994/08/23		(No event found)
1995/05/03	Same	The index of leading economic indicators dropped 0.5%, the Commerce Dept reported 05/03, the decline was the largest in two years
1996/07/01		(No event found)
1997/08/07	08/06	The Fed said 08/06 that the economy had taken a modest upward turn (paradoxical)
1997/10/16		(No event found)
	10/27	Massive one day sell off on Monday October 27, down 7.18% or 554.26 points. Market had declined in previous two days also. Rebounded on Tuesday 10/28.
1998/08/26	8/27	Russian Central Bank ceases to support Ruble, currency plunges

Table R Part 2
Extraordinary 2nd Block Events Associated with Volatility Decreases

This table reports each volatility decrease detected using the Haugen et al (1991) methodology and the event if any in Facts-On-File that approximately matched each vol decrease date. ("2d Block" is the term used by Haugen to indicate the period of and immediately following a vol change).

Volatility Shift Date	Matched Date(s)	Description of Matching Event (from Facts-On-File)
1988/09/07	09/05	Unemployment rose, fears of impending interest rate hike eased
	09/05	FSLIC rescued American Savings and Loan w/ $2B package
1989/08/25		(No event found)
1989/11/10		(No event found)
1990/11/13	11/16	Fed loosened monetary policy for the second time in three weeks.
	11/28	Greenspan said the US economy had entered a "meaningful downturn". [Note that the S&P rallied by 8% from Oct 11, 1990 to November 12]
1991/09/04	09/05	Soviet Congress cedes power to the republics
	09/06	Soviet Union grants independence to Baltic States
	09/11	Gorbachev announced negotiations to remove Soviet troops from Cuba
1991/11/20		(No event found)
1992/05/06	Same	Prices on the LSE hit record highs May 6
		Riots in Los Angeles (paradoxical)
1994/05/18	05/17	Fed raised interest rates May 17, it was taken to be the last increase for some time. Stocks and bonds soared in trading May 17 (1.3%).
1994/07/15		(No event found)
1996/08/05		(No event found)
1997/09/17		(No event found)
1997/11/18	11/21	(South Korea seeks $20 billion from IMF) (paradoxical)
	11/24	(Yamaichi Securities closed) (paradoxical)
1998/02/04	02/03	President Clinton proposes a balanced Federal budget, first in 30 years
1998/10/19		"Stock prices moved higher again, the sixth advance in the last seven sessions, as investors remained optimistic ..."
1999/11/01		(No event found)

Chart S - Dow Jones Volatility shifts in the 1990s (based on Wichern, Miller, Hsu's statistical test). Vertical lines are abrupt transitions detected by the test, diagonal lines are gradual transitions. The picture is U shaped, with low vol in mid-decade



Chapter II: Trends in the Volatility of Individual Stocks, A Multiple Measures Approach

1.0 Introduction

Recently, doubts have been expressed about indicators of volatility that have been widely accepted in the academic community. Leslie Rahl, a well known consultant on Risk Management said "I do not think that volatility as Black and Scholes defined it, or as embodied in Value-At-Risk, is at all helpful in understanding what is happening in markets today. We need to rethink what "volatility" really means" [1]. This rethinking began in the business community after the near failure of the hedge fund LTCM in 1998 and the wide swings in some Nasdaq stocks in 1999-2000. However, up until now, academic researchers have not done much work on alternative measures of volatility. This paper represents a step in this direction.

After briefly reviewing the definitions for several alternative measures of stock volatility, we empirically study how these measures have evolved during the period 1993 to April 1999 for a sample of 94 U.S. stocks. The data includes all transactions occurring during these 6.3 years on the main market (NYSE, or NASDAQ) on which each stock trades. Therefore, our study combines a long time frame with trade by trade data and multiple volatility measures. The classic studies of stock volatility (such as Beckers (1981) and Christie (1982) used daily data and the standard deviation definition. Some other studies proposed alternative formulas for computing volatility, such as the extreme value estimators of Parkinson (1980), Garman and Klass (1980) and Beckers (1983). Finally, in recent years the availability of trade by trade data has led to studies of volatility at a very short time frame, for example Andersen, Bollerslev, Diebold and Labys' (1998) study of foreign exchange. The present study follows the Andersen et al. approach of using of large amounts of high frequency data to study volatility in a model-free manner but applies it to stocks rather than to foreign exchange[2]. As could perhaps have been expected, different volatility measures yield somewhat different conclusions about recent trends in volatility.

2.0 Sample Selection

The objective was to select a set of stocks that could be considered representative of stocks that are of interest to institutional investors. In particular the sample should

include both NYSE and NASDAQ stocks, and both Large Cap and Medium Cap stocks that meet certain minimum liquidity conditions. The liquidity requirement, and the exclusion of Small Cap stocks, mirror institutional investor practice and are in any case necessary if some of the short term volatility measures we use (such as half-hour variance) are to be meaningful.

Stocks were selected based on information available on December 31, 1992 i.e. at the start of the period we study. "Large Cap" stocks were defined to be those with a Market Capitalization of $1.5 Billion or more on this date. "Medium Cap" were those with a market capitalization between $500 Million and $1.5 Billion. A search of the CRSP tape showed that there were 500 Large Cap stocks and slightly more than 500 Medium Cap stocks available to choose from. A stock was defined as liquid if at least 7,500,000 shares traded in 1992. This corresponds to about 30,000 shares per day.

The sample selection started with 30 Large Cap NYSE stocks. In addition 20 Medium Cap NYSE stocks were added, as well as 20 Large Cap NASDAQ and 20 Medium Cap NASDAQ. These were chosen at random, subject to the condition on 1992 annual volume, and to the requirement that CRSP contains data for each stock for the complete 1993-1998 period (i.e. no delisting). After 3 stocks were dropped due to miscellaneous problems, the sample contained 87 stocks. Their names and other basic information are shown in Table 1.

TABLE I
Description of Stocks Included in Sample

Company	Tkr	Exch	Cap	Sector
Alcoa Inc	AA	NYSE	Big	Bas Mat
Apple Computer	AAPL	Nasdaq	Big	Tech
Adc Telecomm	ADCT	Nasdaq	Med	Tech
Allied Signal	ALD	NYSE	Big	Cap Goods
Alex & Baldwin	ALEX	Nasdaq	Med	Misc
Amgen Inc	AMGN	Nasdaq	Big	Medical
Asa Holdings	ASAI	Nasdaq	Med	Cons Cycl
Amer Express Co	AXP	NYSE	Big	Financial
Boeing Co	BA	NYSE	Big	Cap Goods
Bed Bath&Beyond	BBBY	Nasdaq	Med	Cons Cycl
Boise Cascd Cp	BCC	NYSE	Med	Bas Mat
Briggs & Stratt	BGG	NYSE	Med	Cap Goods
Ball Corp	BLL	NYSE	Med	Cons Stpl
Bmc Software	BMCS	Nasdaq	Big	Tech
Biomet	BMET	Nasdaq	Big	Medical
Pac Century Fin	BOH	NYSE	Med	Financial
Caterpillar Inc	CAT	NYSE	Big	Cap Goods
Cabot Corp	CBT	NYSE	Med	Bas Mat
Citicorp	CCI	NYSE	Big	Financial
Ceridian Corp	CEN	NYSE	Med	Tech
Chiron Corp	CHIR	Nasdaq	Big	Medical
Chevron Inc	CHV	NYSE	Big	Energy
Cincinnati Finl	CINF	Nasdaq	Big	Financial
Cisco Systems	CSCO	Nasdaq	Big	Tech
Cintas Corp	CTAS	Nasdaq	Med	Misc
Du Pont (Ei) De	DD	NYSE	Big	Bas Mat
Dell Computer	DELL	Nasdaq	Big	Tech
Disney Walt	DIS	NYSE	Big	Cons Cycl
Eastman Kodak	EK	NYSE	Big	Cons Cycl
Focal Comm Corp	FCOM	Nasdaq	Med	Tech
Fiserv Inc	FISV	Nasdaq	Med	Tech
Fifth Third Bk	FITB	Nasdaq	Big	Financial
Meyer(Fred) Inc	FMY	NYSE	Med	Cons Cycl
First Sec-De	FSCO	Nasdaq	Med	Financial
Genl Electric	GE	NYSE	Big	Misc
Genl Motors	GM	NYSE	Big	Cons Cycl
Goodyear Tire	GT	NYSE	Big	Cons Cycl
Harsco Corp	HSC	NYSE	Med	Cap Goods
Hewlett Packard	HWP	NYSE	Big	Tech
Intl Bus Mach	IBM	NYSE	Big	Tech
Intel Corp	INTC	Nasdaq	Big	Tech
Intl Paper	IP	NYSE	Big	Bas Mat
Ipalco Entrps	IPL	NYSE	Med	Utilities
Johnson & Johns	JNJ	NYSE	Big	Medical
Jones Apparel	JNY	NYSE	Med	Cons Cycl
Morgan (Jp) &Co	JPM	NYSE	Big	Financial
EOT				

Company	Tkr	Exch	Cap	Sector
Kelly Svcs A	KELYA	Nasdaq	Med	Cons Cycl
Coca Cola Co	KO	NYSE	Big	Cons Stpl
Lancaster Colon	LANC	Nasdaq	Med	Misc
Leggett & Platt	LEG	NYSE	Med	Cons Cycl
Manpower Inc Wi	MAN	NYSE	Med	Cons Cycl
Mcdonalds Corp	MCD	NYSE	Big	Cons Cycl
Min Mining&Mfg	MMM	NYSE	Big	Misc
Philip Morris	MO	NYSE	Big	Cons Stpl
Molex Inc	MOLX	Nasdaq	Med	Tech
Merck & Co Inc	MRK	NYSE	Big	Medical
Microsoft Corp	MSFT	Nasdaq	Big	Tech
Noble Affiliate	NBL	NYSE	Med	Energy
Novell Inc	NOVL	Nasdaq	Big	Tech
Northern Trust	NTRS	Nasdaq	Big	Financial
Nevada Pwr Co	NVP	NYSE	Med	Utilities
Ohio Cas Corp	OCAS	Nasdaq	Med	Financial
Oracle Corp	ORCL	Nasdaq	Big	Tech
Paychex Inc	PAYX	Nasdaq	Med	Tech
Paccar Inc	PCAR	Nasdaq	Big	Cap Goods
Procter & Gambl	PG	NYSE	Big	Cons Stpl
Pacificare-Cl A	PHSYA	Nasdaq	Med	Medical
Rowan Cos Inc	RDC	NYSE	Med	Energy
Sears Roebuck	S	NYSE	Big	Cons Cycl
Safeco Corp	SAFC	Nasdaq	Big	Financial
Sigma Aldrich	SIAL	Nasdaq	Big	Bas Mat
Southtrust Corp	SOTR	Nasdaq	Med	Financial
Questar	STR	NYSE	Med	Energy
Sun Microsys	SUNW	Nasdaq	Big	Tech
AT&T Corp	T	NYSE	Big	Utilities
Tci Group-A	TCOMA	Nasdaq	Big	Tech
Tektronix Inc	TEK	NYSE	Med	Tech
Thomas & Betts	TNB	NYSE	Med	Tech
T Rowe Price	TROW	Nasdaq	Med	Financial
Utilicorp Utd	UCU	NYSE	Med	Utilities
Union Carbide	UK	NYSE	Big	Bas Mat
Utd Techs Corp	UTX	NYSE	Big	Cap Goods
Wash Fedl Inc	WFSL	Nasdaq	Med	Financial
Wal-Mart Stores	WMT	NYSE	Big	Cons Cycl
Wausau P Mills	WSAU	Nasdaq	Med	Financial
Worthington Ind	WTHG	Nasdaq	Med	Bas Mat
Exxon	XON	NYSE	Big	Bas Mat

2.1 Database creation and cleanup

The TAQ (Trades and Quotes) database provided by the New York Stock Exchange was used as the main data source. TAQ comes in the form of CD-ROMs, with one CD-ROM containing between 1 month and 1 week's worth of trades (depending on market volume). The earliest available CD is for January 1993. A total of 146 CD's were read in and data for the selected stocks was transferred to disk.

To guard against data errors, transactions at a price above or below the previous price (on the same day) by a factor of 2 or more were flagged and removed. All cases appeared to be keying errors (such as a stock priced at 51, suddenly trading at 541 and then immediately back to 51).

2.2 Classification of trades, estimation of bid-ask spread

As is well known from previous research (such as Roll (1984)), stock price volatility is affected by the bid-ask spread. The term "bid-ask bounce" refers to the tendency of the transaction price to oscillate between the bid price (price at which the public sells stock to the market maker) and the ask price (the price at which the public buys stock from the market maker). This oscillation causes the transaction price to be more volatile than it otherwise would be. (Chart 1).

There are several ways to cope with the bid-ask spread. One is to do nothing, the other is to remove the effect of the spread. If we have available bid and ask data, we could compute the bid-ask midpoint and use it, rather than the transaction price, in our calculations. Alternatively, if we have available trade by trade data, we can use rules to classify each trade as a buy or a sell and estimate the spread, then adjust the transaction price accordingly. For example we can use the Lee and Ready (1990) tick-tests to classify the trade: a trade is considered a buy if it occurs on an uptick or a zero-uptick, otherwise it is considered a sell; the amplitude of the small oscillations yields an estimate

of the spread. The buy price minus half the spread, or the sell price plus half the spread gives us an estimate of the mid-price that is input to the volatility calculation. This method will be used in the empirical work described in the next section. As an example Figure 1 shows the result of applying the method to some transaction data. While this method is only approximate compared to the bid-ask method, it was judged adequate for the purpose of volatility calculation.

Each of the volatility measures described below was computed in two different ways: using raw transaction data (in which case we are measuring the volatility of the observed transaction prices) and using data adjusted for bid-ask bounce by the Lee and Ready heuristic as described above (in which case we are measuring the volatility of the "mid-price" or "buyer-seller compromise value" of the security). Where necessary we will refer to these two measurements as the "transaction volatility" and the "mid-price volatility" respectively. Our main interest will be in the "mid-price volatility".

3.0 Description of Volatility Measures

The methods of volatility measurement used in this paper will now be described.

3.1 Close-to-close volatility

This is the most commonly used method of measuring daily volatility and therefore serves as a benchmark for all others.

$$\sigma_{CC} = SQRT[\ (1/N)\ \Sigma_t\ (\ln(P_t)-\ln(P_{t-1}))\text{^}2\ ]$$

where P_t is the daily closing price and N the number of days.

3.2 Open-to-open volatility

This uses opening prices rather than closing prices. Previous research (Stoll and Whaley 1990) has suggested that this is higher than close to close volatility for NYSE stocks. We will test this hypothesis using our data.

3.3 Close-to-open and open-to-close

This allows us to split the volatility into nighttime volatility (close-to-open) and daytime volatility (open-to-close). Open-to-close is the natural benchmark for methods of volatility measurement that use intraday data.

3.4 Half-hour volatility

By breaking up the trading day into 13 intervals lasting half an hour each, we are able to compute half-hourly volatility. A half hour interval is sufficiently long that, for the highly liquid stocks we will consider, there are likely to be many trades during the interval. At the same time it is sufficiently short to qualify as a short-term interval, i.e. it is about an order of magnitude shorter than a day.

By considering the next overnight (close-to-open) period as a 14^{th} period, we can calculate a "generalized half-hour volatility" that incorporates a whole day's market action (from open to open). This method was used by Hasbrouck and Schwartz (1988).

3.5 Parkinson's extreme value estimator

This method is based on the highest and lowest prices for the day. The estimator of daily variance used is

$$\sigma_P\text{^}2 = (\text{high} - \text{low})\text{^}2 / (4 \ln 2)$$

high is the log of today's highest price, low is the log of today's lowest price. The factor 4 ln 2 in the denominator is derived under the assumption that price changes are normally distributed (Parkinson(1980)).

An attractive property of this estimator is that it is based on all trades observed during the day, not just on prices measured at half-hour (or some other) interval. It therefore belongs to the class of continuous monitoring estimators, those which use all of the available data.

The Parkinson estimator is used by some option traders. Academic studies, such as Beckers (1983), have found it to work well in predicting future volatility. However, the Parkinson estimator might be biased low if there are factors that tend to make the price trajectory smoother than the assumed Brownian motion. One such factor is that trades occur at discrete time intervals [Garman & Klass (1980)], another that the price itself can only take on certain values (multiples of 1/8 or 1/16) [Gottlieb and Kalay (1985), Harris(1990)]. Based on these published results we therefore expect that Parkinson volatility will be smaller than close-to-close volatility in our sample.

A question we will investigate is whether the relationship between Parkinson volatility and close-to-close volatility is changing over time. Some people believe that although close-to-close volatility has not changed much, the market in recent years has been a "roller-coaster" market in which large intraday movements occur, only to be reversed before the close. Some stock brokers interviewed as part of the NYSE Volatility Report (NYSE, 1990) expressed this concern. Newspapers cited April 4, 2000 as an example of the phenomenon: the NASDAQ at one point was down about 12% from the previous close, but recovered to close down only 0.5%, which would qualify as a dull day if one overlooked the intraday movement. If such occurrences (large intraday reversals) really are becoming more common, we would expect the ratio of Parkinson volatility to close-to-close volatility to have increased.

3.6 Intraday Dispersion

A possible problem with Parkinson's method is that it is very sensitive to data errors. If a trade at a very high price appears in the data (due to the price being incorrectly keyed in), that price becomes the high price of the day and enters into the calculation of Parkinson's estimator, giving a biased result. Similarly for the low.

This suggests using a measure of price spread other than the price range, one less sensitive to two specific trades. An obvious alternative is the standard deviation of the day's prices.

In this study, dispersion was defined to be the standard deviation of the logarithms of the prices of all trades that occurred during the day. Dispersion is an intuitively

reasonable measure of volatility. If two traders bought the stock at two different random times during the day, dispersion measures how far apart their prices were likely to be. A simple description of a volatile stock would be: one such that postponing or moving up the time of purchase by a small time interval is likely to result in a large difference in price. Dispersion is a way to make this concept operational by taking the time interval to be one day.

Dispersion does not consider the order in which trades occurred, only the location of the transactions in the price dimension. The intraday time dimension is completely ignored. This provides an interesting contrast to some of the other methods described here, which are sensitive to the order of trades (for ex. Path, described below).

3.7 VWAP volatility

This is similar to close-to-close, except instead of using closing prices we use the VWAP (Value Weighted Average Price) as the representative price for the day.

3.8 VW Intraday Dispersion As a Percent

This is similar to dispersion, except instead of measuring the standard deviation of log prices, we measure the value-weighted standard deviation of price around the VWAP, then state this as a percentage of the VWAP. The ordinary Dispersion measure gives equal weight to every trade, while the VW Dispersion gives greater emphasis to large trades.

Traders already use the VWAP for a particular day as a benchmark for execution quality. They may find using the value weighted standard deviation of prices around the VWAP just as natural as an intraday volatility measure. VWAP volatility (how VWAP changes from day to day) and VW Intraday Dispersion are complementary, just like close-to-close and dispersion are. VW Intraday Dispersion is a measure of the difficulty a trader has in achieving the VWAP price.

3.9 Path

Path is a measure of volatility defined by Prof. Robert A. Wood of the University of Tennessee at Memphis. It takes its name from the fact that it tries to measure the distance traveled by the price during the course of a trading day. Path is computed by adding up the absolute values of successive changes in the log of price.

Since Path is new, a brief discussion of its properties may be helpful. It is provided in Appendix A.

3.10 Number of Price Changes

In looking at the price trajectory of a highly traded stock, after the bid-ask bounce has been removed, one usually sees several trades at a given price, after which the price will jump to a new level, then several more trades at the new price, and so on. We will be interested in the number of price changes that occur in the course of the day. We will also be interested in the ratio of the number of trades to the number of price changes, which measures how many trades occur at a given price level before the price jumps.

Although number of price changes can be considered a measure of volatility in its own right, we will also be interested in it as a companion to Path. It turns out that Path and Number of Price Changes, when used together tell us more than either could alone (this finding is described in Section 5.1.3).

3.12 French-Roll 1984

This method is discussed and given its name by Harris (1990). It starts with half-hour volatility and embodies a correction for 1st order serial correlation. Although serial correlation caused by the bid-ask spread has been removed from our data, there is still some serial correlation of unknown origin, so this formula may be appropriate for our data.

$$\sigma_{FR84}\text{^}2 = \text{Var}(\Delta P) + 2\ \text{Covar}(\Delta P)$$

The general procedure is similar to that for the generalized half-hour volatility described earlier. We will measure logarithmic price changes during 13 half hour intervals and

during the following overnight interval. The average square of these price changes is denoted Var(Δ P)

$$\text{Var}(\Delta P) = (1/14)\ \Sigma_{i=1 \text{ to } 14}\ (\Delta P_i)^2$$

while the average of successive product terms is denoted Covar(Δ P)

$$\text{Covar}(\Delta P) = (1/14)\ \Sigma_{i=1 \text{ to } 14}\ (\Delta P_i)\ (\Delta P_{i-1})$$

where ΔP_0 is the overnight return that preceded the trading session and ΔP_{14} the one that followed.

Note that the term Var(Δ P) is identical to what was called in 3.4 the generalized half-hour variance. σ_{FR84}^2 is therefore a modification of generalized variance that accounts for serial correlation.

3.13 Market Efficiency Coefficient (MEC)

Although MEC is a measure of market quality rather than a measure of volatility, MEC was included in this study because it is related to volatility, in fact it is the ratio of two volatilities.

The definition used here is the one given by Hasbrouck and Schwartz (1988), with a minor change because the markets now open a half-hour earlier. The input data consists of the raw transaction prices; the adjustment described earlier to remove the bid-ask spread was not performed since it would defeat the purpose of computing the MEC.

$$\text{MEC} = \text{two\_day\_variance} / (28 * \text{half\_hourly\_variance})$$

Two_day_variance is the variance of return from the close of day t to the close of day t+2. Return is defined as the logarithmic return, with allowance for splits and dividends. Half_hourly variance is measured over 28 intervals that occur between the close of day t and the close of day t+2. The first period is actually the overnight period that begins at the close of day t and ends at the open on day t+1, next come 13 half-hourly periods on day t+1, another overnight period, and 13 half-hourly periods on day t+2. Normally we expect MEC < 1, because the half_hourly_variance in the denominator is inflated compared to the longer term variance in the numerator.

In Schwartz (1993) a slightly different definition of MEC was used. The open was skipped, so that the first period goes from the close to a time a half-hour after the start of trading the next day. In this paper the original 1988 definition is being used.

3.14 Implied Volatility

Most stocks in our sample have options traded on them. It thus becomes possible to calculate the volatility that option market participants are forecasting for each stock, based on the Black-Scholes formula.

The option prices available to us (from the data vendor Prophet Data) only cover the period November 1995 to present. Furthermore experience has shown that this data is not as clean as the other data we are using, i.e. it contains more errors. Manual checking and filtering of the data was required.

To avoid possible biases caused by the volatility smile, options that are nearly At The Money were used. Specifically the strike price chosen is close to $S_0 \exp(rT)$ that is to the forward price of the stock.

The implied volatility was estimated from the sum of the closing market prices of a Put and a Call of the same strike and maturity (that is the price of a straddle). The desired implied volatility is the one which, when plugged into the Black Scholes formulas for a European Call and a European Put matches the observed price of the straddle as closely as possible. Dividends are assumed to have been correctly forecasted in advance, that is the actual values of dividends over the options' life are used.

4.0 Empirical findings: Time trends

For each volatility measure and each stock, we computed a value in each of the calendar years from 1993 to 1999 (only the first 4 months of 1999 are used). By fitting a least squares trend line through these seven points we are able to estimate the behavior of each volatility measure over this period (falling, constant or rising) for each stock in our sample.

In a second step, we regress the slope of this trend line on dummy variables that describe the characteristics of each stock (for example NYSE listed versus traded on NASDAQ). This allows us to determine how different groups of stocks have behaved. The specific variables used in these regressions are:

Exch (0=NYSE, 1=NASDAQ)

MktCap (0=medium, 1=big)

HighVol (0=low volume, i.e. volume below median, or less than 0.279% of shares *trade on an average day*

1=high volume, more than 0.279%)

Tech (0= company sector is other than Technology or Medical

1= company sector is Technology or Medical)

4.1 Overall results

Results are presented in Table II. The main results that emerge from this table are the following:

The classic measure of volatility, close-to-close standard deviation, shows a modest increase during this period. The increase amounts to 2.7 percentage points per year, which is not very large, but is common to most stocks in the sample (85% show an upward trend). Volatility in 1994 was unusually low, while volatility in 1998 and 1999 was quite high.

The most striking result in the table is the large and persistent increase throughout this period in the Number of Changes in Mid-Price Per Day. Its median value in the sample rose from 18 per day in 1993 to 163 per day in early 1999. This increase cannot be explained solely by the rise in the number of trades. Although it is true that the number of trades per day rose greatly, the number of price changes rose even more. This can be seen from the fact that the ratio of the number of trades to the number of price changes shows a (statistically significant) declining trend. This ratio can be thought of as the number of trades that occur during any price plateau, i.e. before the mid-price changes, and is therefore a measure of price stability (the opposite of price volatility).

The contrast between these two measures is marked. The close-to-close volatility showed little increase until the crucial year 1998, which was characterized by stock market turmoil related to the Asia and Russia crises. The number of price changes, on the other hand, was increasing steadily throughout this period. This increase would have been missed by those who only observe closing prices, since it is based on intraday data. It may be that when stock market professionals report enormous increases in volatility in recent years (as many do), they have in mind something like the number of price changes, rather than the classical measures that economists use, such as close-to-close volatility. Stock market professionals are aware of intraday price changes since they have on their desks computer terminals that display real-time prices; these usually blink or change color when the price changes. It is plausible that one could have detected an increased number of price changes simply by observing the displayed prices every day over some period of time.

An important observation from Table II is that the average trade size began to drop in 1997. This could be evidence either of increased participation by small investors, or of fragmentation of large trades into smaller trades due to lack of liquidity. The fact that the reduction in trade size is so pervasive across stocks (affecting 84% of the stocks in our sample) and not just restricted to stocks of retail interest argues in favor of the fragmentation explanation. Fragmentation due to illiquidity is also a partial explanation for the increased number of price changes: a large trade that would previously have gone through at a single price is now broken up into several smaller trades at different prices.

The Path measure also shows an upward trend. The behavior of the median Path for our sample is fairly similar to the behavior of close-to-close volatility: relatively constant in the early years, with a notable increase in 1998 and 1999. The average Path is much higher than the median Path, showing that the sample contains a small number of stocks with very high Path, which push the average up. The upward trend in Path is very consistent, occurring for 95% of the stocks in our sample.

An interesting conclusion emerges when half-hour generalized variance (that is half-hour variance where the overnight period is treated like just another half-hour period) is compared to close-to-close variance. Under simple theoretical assumptions

(i.e. a random walk) the ratio of daily to half-hourly variance should be 14, since there are 14 sub-periods in the interval between successive closing prices. The presence of a bid-ask spread would suggest a ratio smaller than 14, but recall that the effect of the bid-ask spread has been removed from our data. The half-hour generalized variance we are working with is the variance of the mid-price (midway between bid and ask) and therefore we expect the ratio to be 14. The empirical findings differ from this: the ratio is less than 14 in the early years (by a statistically significant margin) but gradually increases until, in 1999, it is not statistically different from 14.

The behavior of VWAP-to-VWAP Standard Deviation is fairly similar to that of close-to-close standard deviation. The intraday value-weighted dispersion as a percentage of VWAP shows a gradual and pervasive upward trend. We can better evaluate the behavior of VW intraday dispersion by comparing it to the day to day standard deviation. The ratio of these two measures shows a slight drop (statistically significant across our sample). The intraday dispersion has therefore increased less than one might expect given the increase in day to day volatility. This leads us to reject the hypothesis of spurious intraday volatility (at least from a value-weighted perspective).

The figures for Parkinson's measure of volatility (based on the daily high and low) are very similar to those for close-to-close standard deviation. As found in previous published studies (Beckers (1983) and many others), Parkinson's measure somewhat underestimates the close-to-close volatility. However, the ratio Parkinson/close-to-close is less than one to a statistically significant extent for only two of the years we examined (1996 and 1999). In any case, it is apparent that the ratio does not have a trend (there is a slight decrease, but it is not statistically significant). The hypothesis of "roller coaster" markets (Krugman, 2000), that is daily highs and lows that are getting farther and farther apart in proportion to the close to close volatility, can therefore be rejected.

TABLE II

Behavior of Volatility Measures for 87 Stocks 1993-1999

(All measures were computed using transaction data adjusted for the bid-ask spread, except for MEC which was computed using raw transaction data)

Close-to-close standard deviation (annualized)

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	.337	.303	.310	.356	.359	.448	.473	.027
Median	.275	.256	.244	.267	.311	.394	.402	.024
t-Stat								8.05
% > 0								85%

Number of changes in equilibrum price (per day)

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	52	60	93	130	243	348	631	86
Median	18	19	22	28	69	109	163	20
t-Stat								3.35
% > 0								97%

Number of trades (per day)

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	301	319	473	621	1066	1565	2565	346
Median	122	147	163	219	308	436	656	75
t-Stat								3.34
% > 0								99%

Ratio of Num Trades to Num Chgs in Equil Price

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	9.7	9.5	9.9	9.1	5.6	4.5	4.7	-1.06
Median	5.6	5.0	6.1	6.0	4.6	4.1	4.1	-0.21
t-Stat								-5.63
% > 0								31%

Average trade size

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	2165	2312	2239	2024	1833	1689	1602	-121
Median	1966	1943	1800	1753	1595	1444	1443	-92
t-Stat								-6.18
% > 0								16%

Path (per day)

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	.182	.188	.225	.291	.440	.447	.783	.089
Median	.061	.056	.053	.062	.109	.172	.200	.025
t-Stat								3.39
% > 0								95%

Ratio of Close-to-Close Variance to Gen Half-Hour Variance

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	12.4	11.8	12.3	12.4	13.1	13.5	13.9	0.31
Median	13.1	12.4	13.3	12.8	13.3	14.0	14.0	0.23
t-Stat(1)	-3.5	-5.10	-3.91	-4.49	-2.96	-1.53	-0.14	3.96
% > 0								

(1) Test that the yearly avg. differs from the theoretical value of 14

TABLE II (continued)

VW Dispersion as a % of VWAP

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	.604	.580	.571	.599	.646	.764	.854	.04
Median	.565	.539	.539	.544	.608	.734	.805	.04
t-Stat								12.9
% > 0								92%

VWAP Std Deviation (annualized)

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	.305	.273	.279	.322	.318	.400	.443	.025
Median	.239	.230	.213	.240	.272	.332	.359	.021
t-Stat								7.29
% > 0								84%

Ratio of VW Disp as a % of VWAP to VWAP Std Dev

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	.350	.371	.370	.348	.350	.335	.346	-.0038
Median	.357	.372	.371	.372	.367	.351	.350	-.0022
t-Stat								-2.47
% > 0								35%

Parkinson Std deviation (annualized)

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	.317	.283	.309	.289	.398	.420	.368	.021
Median	.227	.208	.217	.211	.253	.332	.337	.024
t-Stat								3.19
% > 0								84%

Ratio of Parkinson Std deviation to Close-to-Close Std Dev

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	1.05	1.03	1.03	.85	1.00	.95	.87	-.02
Median	.79	.82	.81	.81	.84	.84	.87	.01
t-Stat(2)	-.3	-.2	-.3	-3.0	-0.1	-.70	-6.0	-1.0
% < 1	85%	79%	77%	89%	85%	85%	86%	
% > 0								70%

Ratio of Open-Open Variance to Close-Close Variance

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	1.06	1.11	1.09	1.06	1.11	1.02	1.11	0.00
Median	1.04	1.08	1.07	1.06	1.06	1.01	1.02	0.00
t-Stat(2)	3.9	6.9	5.4	4.2	4.2	1.4	1.45	0.00
% < 1	32%	23%	33%	33%	28%	47%	44%	

MEC (Market Efficiency Coefficient)

Year	1993	1994	1995	1996	1997	1998	1999	Slope
Average	.780	.709	.754	.766	.814	.928	.880	.028
Median	.826	.741	.833	.814	.844	.956	.877	.022
t-Stat(2)	-6.1	-8.8	-6.9	-7.7	-7.9	-2.9	-3.5	5.2
% < 1	71%	83%	73%	77%	83%	59%	62%	
% > 0								67%

(2) Test that the yearly average differs from 1

TABLE III
Trend in volatility measures for various sub-groups of stocks

Trend in Close-to-Close Volatility

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	.0143	.0020	.0163	.0016	.0051
t-Stat	2.3	0.3	2.4	0.2	0.6

Trend in Number of Changes in Mid-Price

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-80.0	101.7	123.0	10.0	159.3
t-Stat	-1.9	2.0	2.6	0.2	2.6

Trend in Number of Trades

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-321	93	506	44	632
t-Stat	-1.9	1.9	2.7	0.2	2.6

Trend in Ratio: Num Trades to Num Chgs in Equil Price

	Intercept	ASDAQ	BigCap	HiVolume	Tech&Med
Value	-1.30	1.75	-1.3	0.73	-0.51
t-Stat	-4.8	5.5	-4.4	2.2	-1.3

Trend in Average Trade Size

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-87.3	-12.4	-25.8	-53.3	41.7
t-Stat	-2.3	-0.3	-0.6	-1.1	0.8

Trend in Path

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-0.074	0.113	0.112	0.011	0.151
t-Stat	-1.7	2.2	2.3	0.2	2.4

Trend in Ratio: Close-to-Close Variance to Gen Half-Hour Variance

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-.020	.789	.050	.015	-0.163
t-Stat	-.2	5.1	0.3	0.1	-0.9

TABLE III (continued)
Trend in volatility measures for various sub-groups of stocks

Trend in VW Dispersion as a % of VWAP

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	.0437%	-.0170%	.0125%	-.0028	.0007
t-Stat	7.5	-2.5	2.0	-0.4	0.1

Ratio of VW Disp as a % of VWAP to VWAP Std Dev

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-3.98	5.49	5.01	1.64	6.67
t-Stat	-1.8	2.1	2.1	0.6	2.1

Trend in Parkinson Std Deviation

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-0.007	0.030	-.002	0.020	0.021
t-Stat	-0.6	2.2	-0.2	1.4	1.3

Trend in Market Efficiency Coefficient (MEC)

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	.027	.031	-.024	.004	-.005
t-Stat	2.9	2.7	-2.2	0.3	-0.4

TABLE IV
Volatility measures in 1999:1..4 for various sub-groups of stocks

Close-to-Close Volatility

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	0.268	0.104	0.098	0.114	0.178
t-Stat	5.9	1.9	2.0	2.0	2.8

Number of mid-price changes

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-582	745	872	79	1138
t-Stat	-2.0	2.2	2.8	0.2	2.8

Path

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	-0.62	1.01	0.91	0.12	1.25
t-Stat	-2.0	2.7	2.7	0.3	2.8

Ratio of Open-Open Variance to Close-Close Var

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	1.2	.16	-.11	-.13	-.15
t-Stat	8.3	.9	-.6	-.7	-.7

Market Efficiency Coefficient (MEC)

	Intercept	NASDAQ	BigCap	HiVolume	Tech&Med
Value	0.864	-0.307	0.054	0.113	0.202
t-Stat	16.1	-4.8	0.9	1.7	2.7

The ratio of open-to-open to close-to-close variance can be considered a measure of "excess volatility at the open". (Stoll and Whaley, 1990). This ratio is above 1 throughout the period under study. When we examine stock groupings, we find that none of our variables have any explanatory power. In particular excess volatility at the open appears to be a phenomenon of NASDAQ stocks just as much as NYSE stocks. The original research on this phenomenon focused on NYSE only and attributed it to the special procedures used to open stocks for trading on the NYSE. Our finding is that it occurs for NASDAQ also.

The final measure in Table II is the Market Efficiency Coefficient. As expected average MEC's are below one (statistically significant), showing that trading costs are positive. Interestingly the MEC's steadily increase during this period, showing greater efficiency (lower trading costs).

4.2 Disaggregated results based on stock characteristics

The previous section showed that the measures of volatility we examined have an upward trend during the period under study. In this section we will examine whether this trend is more or less pronounced for various sub-groups of stocks that make up our sample. To do this each stock's trend over the period 1993-1999 was regressed on dummy variables that describe the characteristics of the stocks in our sample.

The results are reported in Table III and summarized as follows:

The upward trend in close-to-close volatility is most pronounced among Big Cap stocks, and this result is statistically significant. The other three variables are not statistically significant. In particular Technology stocks have not increased in volatility more than other stocks (this result applies of course to Technology stocks that have existed throughout the 1993-1999 period. New issues (IPOs) are excluded from our sample).

The upward trend in number of changes in mid-price has affected Big Cap, Nasdaq and Technology stocks more than others. These variables are also significant in the equation for trend in number of trades. That these two are different phenomena,

however, is shown in the next regression. The ratio of the number of trades to number of price changes has dropped for Big Cap stocks while it has increased for Nasdaq. It is only Nasdaq stocks, not NYSE stocks, that have experienced the puzzling phenomenon of price changes increasing faster than the number of trades.

The decline in average trade size is a pervasive phenomenon that has affected all stocks. Distinctions among stocks (including NYSE vs Nasdaq) had no statistical significance in explaining this phenomenon.

The next regression shows that the upward trend in Path is also concentrated among Big Cap, Nasdaq and Technology stocks. These are the same variables that were significant in the first two regressions.

The next regression shows that the convergence of the close-to-close variance towards the theoretically predicted value of 14 times the half-hour variance is a phenomenon of Nasdaq stocks. In 1993 there was some excess half-hourly volatility (over and above that caused by the bid-ask spread) for Nasdaq stocks which caused the ratio to be below 14, but this excess volatility disappeared and half-hour returns for Nasdaq stocks came closer to the statistical independence assumed in theoretical models.

Table IV examines volatility measures for our stocks in early 1999. The goal is to examine the characteristics of volatile stocks during this period (the focus is now on volatility level itself, rather than the long term trend in volatility, as in Table III).

Three variables: NASDAQ, BigCap and Tech&Med are statistically significant contributors to volatility, whether measured by close-to-close, number of mid-price changes or path. High relative volume is not significant.

No group of stocks showed higher (or lower) excess volatility at the open. In particular NYSE and NASDAQ stocks were statistically indistinguishable; this is somewhat surprising since the literature that described and explained this phenomenon focused on NYSE stocks. The procedures for opening trading on NYSE and Nasdaq are different and yet the same increase in Open-to-Open volatility is seen in both cases.

The final result from this table is that NASDAQ stocks have a lower Market Efficiency Coefficient (that is higher trading costs) by a statistically significant margin.

5.0 Empirical findings: interrelationships among measures

5.1 Relationship between Path and Conventional Measures of Volatility

Since Close-to-Close is the conventionally accepted measure of stock volatility and Path is a newly proposed measure, it is important to study the empirical relationship between them.

The hypothesis to be tested is that Path provides a superior measure of volatility over periods of a day or longer. This is plausible in that Path uses intraday information and this added information could result in a better reading than just using closing prices. The opposite is also possible, however, since intraday information could introduce noise and microstructure biases into the measurement, resulting in a less informative measure than Close-to-Close. We will attempt to settle the question with a series of empirical tests.

5.1.1 Cross-sectional test

This test is intended to show that Path identifies volatile stocks correctly. That is: stocks that are volatile based on the close-to-close measure are also volatile based on Path. This is a basic test to see that Path makes sense as a volatility measure. If there is no relationship at all between close-to-close and Path, we would conclude that path is simply not doing the job it is supposed to do. Conversely if Path appears to have some validity we will proceed with more elaborate comparisons.

We will compare the 1996 volatility of stocks in our sample computed in two different ways: as close-to-close standard deviation and as Total Path (that is night path plus trading session path). A scatter diagram (Chart 2) shows that ranking stocks based on standard deviation gives fairly similar results to ranking them based on Path; the rank correlation coefficient is 65%. The results look reasonable.

A closer look at the relationship between standard deviation and path reveals a problem, however (Chart 3). For a given level of standard deviation Nasdaq stocks systematically exhibit higher Path values than NYSE stocks. For example IBM and Amgen have nearly identical daily standard deviations (2.23% and 2.05%) but IBM's path is 11.9% while Amgen's is 79%.

In addition, the Path values are more skewed than the standard deviation values. Although most Path values are in a reasonable range, there are a few that are very, very high (and all of these concern Nasdaq stocks).

5.1.2 Cross-sectional test, two time samples

This test is designed to show that Path measures stock volatility more consistently. The consistency of a scientific instrument is tested by measuring the same object on two separate occasions; the closer the two results, the more consistent the instrument is said to be. The approach here will be similar.

We take one year's worth of data and divide it into two equal sub-samples. The first sub-sample consists of the odd days (the first, third, fifth, etc.); the second sub-sample contains the even days (second, fourth, etc.).

Because the samples contain only half a year's data each, the volatility estimates derived from them will be less precise than the ones based on a full year of data that were used in the previous test. The percentage difference between the estimates from the two samples is a measure of this imprecision. The ratio of the imprecision for Std Deviation to the imprecision for Path measures which of the two measures is more consistent.

An example may make this clearer. Here are the volatility estimates for GM:

	Even Sample	Odd Sample	Imprecision
Std Deviation	0.01629	0.01665	2.1867%
Path	0.05408	0.05423	0.2590%

In this case the Path is about 8 times more precise.

The results for the full sample of stocks and for the year 1996 are as follows:

	Ratio
Full sample (Geom. Average)	3.6
Full sample (Median)	2.9

This test conclusively shows that the use of intra-day information by Path results in a more precise measure of volatility than close-to-close standard deviation (by a factor of approximately three on average.)

5.1.3 Converting between Path and conventional volatility measures

5.1.3.1 A simple theoretical equivalence

Suppose that the price of a stock follows a Geometric Brownian motion with constant volatility σ, and that the prices P_i observed in the market place during a trading session are the values of this Brownian motion sampled at NS equally spaced times during the day (that is there are NS-1 price changes ΔP_i during the day). Then it follows that the expected value of Path will be equal to

$$E(Path) = sqrt(NS)\ \sigma_T\ \ sqrt(2/\pi)$$

Where σ_T is the per trading session standard deviation. Conversely we can recover σ_T if we know E(Path):

$$\sigma_T = E(Path)\ sqrt(\pi/2)\ 1/sqrt(NS)$$

5.1.3.2 Testing the simple equivalence

Since we know the number of mid-price changes for each stock each day (NEPC), we can use NS = NEPC+1 in the above formula, together with our estimate of Path to derive an equivalent σ_T for each stock. We can then compare this to the conventional open-to-close estimator.

Chart 4 shows the result. The fit between the predicted and the actual standard deviation is fairly good. The correlation coefficient is 0.745, an improvement over the 0.526 correlation in Chart 3. Clearly taking into account both Path, and Number of Changes improves our ability to predict Standard Deviation over just using Path.

On the other hand, Nasdaq stocks continue to have their volatility overestimated. The Nasdaq stocks cluster separately from the NYSE stocks and on a line with a slope clearly different from 1.

Clearly the above formula is only partially successful in predicting standard volatility from Path. The different intraday behavior of Nasdaq stocks is apparently responsible.

5.1.3.3 An empirical conversion formula

We will use the same equation form for all stocks:

$$Ln(\sigma_T) = K + Alpha * ln(Path) + Beta * ln(NEPC + 1)$$

But we will estimate the coefficients K, \alpha, \beta separately for NYSE and Nasdaq stocks. OLS estimation gave the following results:

NYSE stocks

	K	Alpha	Beta
Value	0.72895	1.0845	-0.5454
t-Stat	1.6	11	-9

NASDAQ stocks

	K	Alpha	Beta
Value	-1.9507	0.5858	-0.2958
t-Stat	-3	5	-3

Source: mayKv3sa.xls

The result of applying these equations in sample to predict the standard deviation is shown in Chart 5. The correlation coefficient between predicted and actual is now 0.83. The fit is good. Perhaps not surprisingly, high volatilities are more difficult to predict than low volatilities.

5.1.4 Time-series prediction test

This section considers the value of intraday volatility measures in forecasting future volatility. Specifically we consider whether knowledge of today's Path and Number of Price Changes can be used to improve upon a volatility forecast based on past daily data. This is an empirical issue, since two opposing effects are at work: On the one hand intraday data gives us more up to date information about current volatility than is available using daily data only, possibly leading to a more accurate forecast. On the other hand intraday data picks up instability, noise and microstructure effects that may be counterproductive for long term forecasting.

Suppose we have to forecast the volatility of a stock at a one month horizon. Specifically, on the third Friday of each month, after the market closes, we will forecast volatility until the third Friday of the next month.

A simple forecasting method uses an average of volatilities during past months. To fix ideas, we can take as our forecast the average of the last 24 months' volatilities, where each monthly volatility is computed from third Friday to third Friday using daily close-to-close returns. This straightforward procedure will serve as a benchmark.

We will attempt to improve on this forecast by using intraday data for the day on which the forecast is to be made. Specifically we use the Path and Number of Price Changes for the day in question to compute a volatility estimate V_{PE} using the "simple equivalence" formula of section 5.1.3.1. We would expect that when V_{PE} is high our forecast should be higher than the average of the last 24 months would indicate, and vice versa. To make this precise, we can use a regression to estimate how the V_{PE} and the subsequent volatility were related in the past 24 months:

$$VOLP_{t+1} = \text{alpha} + \text{beta} * (V_{PE})_t \qquad (1)$$

and then use this equation to forecast next month's volatility. The question to be answered is whether such forecasts are more accurate than those based only on past values of monthly volatility (equivalent to setting beta to zero in equation (1)).

The empirical results were mixed. The performance of the forecasting equation (1) was somewhat dependent on the period and the stock chosen.

For AT&T the regression (1) was often statistically insignificant or had a negative beta coefficient, especially in the first half of the 1994-1999 period. Forecasts based on equation (1) were somewhat less accurate (higher RMS error) than those based on a simple average of past volatility. Knowledge of V_{PE} did not help in predicting AT&T's volatility.

For Exxon, more favorable results were obtained, as shown in Chart 6 and Table 7. Forecasts incorporating V_{PE} had a smaller RMS error (0.0492 versus 0.0609) than those not using this variable. However, the implied volatility from the option markets was an even better predictor (Chart 8 and Table 7). This is perhaps not surprising since implied volatility is considered by many people the best, most difficult to improve upon, volatility forecast.

As is standard in the volatility forecasting literature, encompassing regressions were used to further compare volatility forecasts. (Recent papers that have used this technique include Figlewski (1997), Lamoureux and Lastrapes (1993), Day and Lewis (1992), Harvey and Whaley (1992)). The actual volatility is regressed on the various predictors to see who the "winner" is (i.e. the best predictor). For Exxon from 3/96 to 11/98 the result was

$$\sigma = -0.01781 + 0.970578 * IV + 0.140951 * VOLP$$

$$t=4.15 \qquad t=0.78$$

NOBS=31, Adj. R2= 0.595

Source: xonKau25.xls

This shows that Implied Volatility is superior to VOLP, the volatility predictor based on equation (1). The coefficient of VOLP is not statistically different from zero, meaning that the best policy would have been to ignore VOLP altogether and use only IV as our forecast.

In summary, the calculation of Path and Number of Price Changes for a stock may have some ability to forecast volatility. However, further investigation is required into why the method works for some stocks and time periods and not for others. Also, the tests run here were limited to NYSE stocks; we have seen in section 5.1.3.2 that Path and

NEPC for Nasdaq stocks behave differently. For the moment, we can only conclude that Path and NEPC are perhaps not useless in forecasting volatility, although the option market already takes this information into account.

6.0 Conclusions

The main conclusions of this paper are.

(1) Using close-to-close standard deviation, stock volatility was low in 1994, higher than usual in late 1998 and early 1999.

(2) The number of [mid-]price changes has increased enormously and steadily from 1993 to 1999. In the author's opinion this is what traders and market makers have in mind when they claim that stock volatility has been soaring in recent years. If so, they are using the term "volatility" in a different sense than the conventional academic definition. The more frequent small price changes we are seeing are not contributing much to day-to-day volatility.

(3) When intraday volatility is measured by Parkinson's High-Low indicator, by half-hourly volatility, or by the dispersion around the VWAP (Volume Weighted Average Price), there is no evidence that intraday volatility has deteriorated compared to daily volatility in recent years. (On the contrary, for NASDAQ stocks the excess half-hourly volatility (whether measured from transaction prices, or from prices adjusted for bid-ask spread) has been decreasing. Nevertheless NASDAQ stocks' MECs remain higher than those of NYSE stocks, so that NASDAQ stocks remain more expensive to trade than NYSE stocks).

(4) A new measure of intraday volatility, called Path, has promise but also some problems. Empirical adjustments for these problems were suggested. Path and

Number of Price Changes when combined together contain some information about future volatility.

This paper has illustrated the proposition that looking at measures of volatility other than the conventional close-to-close standard deviation can be worthwhile. A single statistic cannot capture all aspects of stock market volatility.

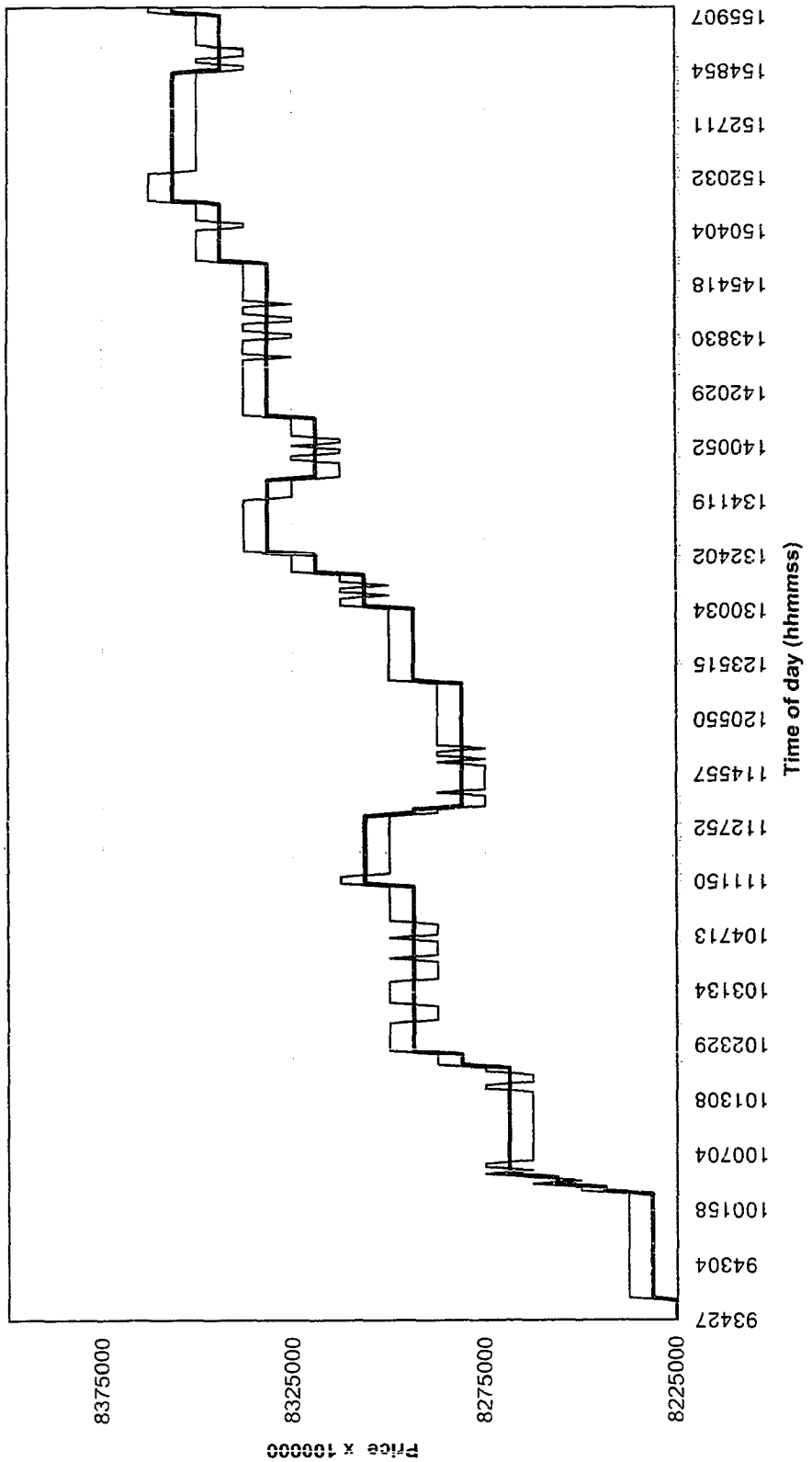


Chart 1. XON 1996/08/01. Transaction price from TAQ data (thin line), price after removal of bid-ask spread using Lee-Ready algorithm (thick line)

Chart 2. Scatter Diagram. Ranking by Daily CC Std Deviation vs Ranking by Total Path
87 Stocks, 1996 (low rank=highly volatile)

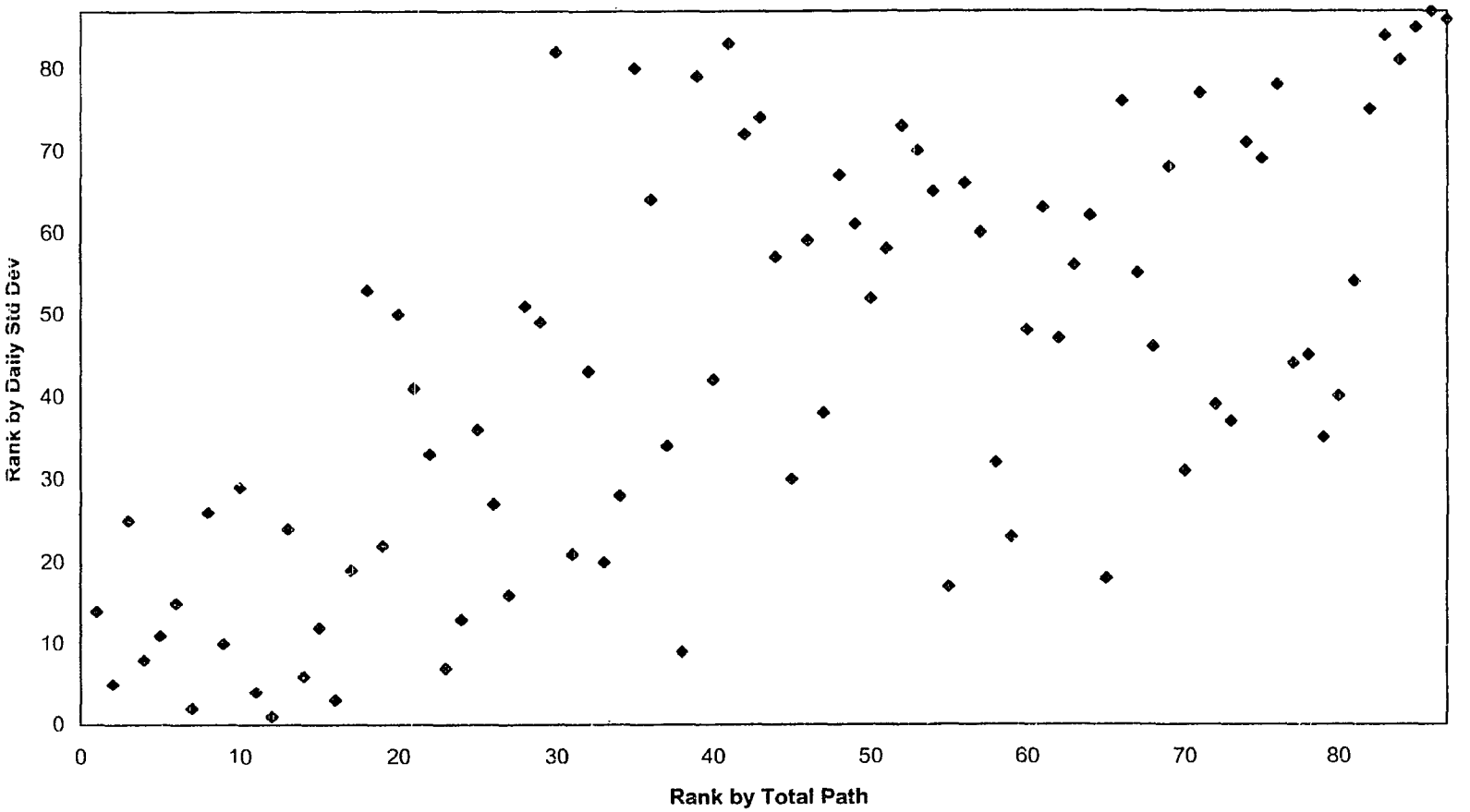


Chart 3. Scatter Diagram. Daily CC Std Deviation vs Total Path
87 Stocks, 1996 (square=NASDAQ, round=NYSE)

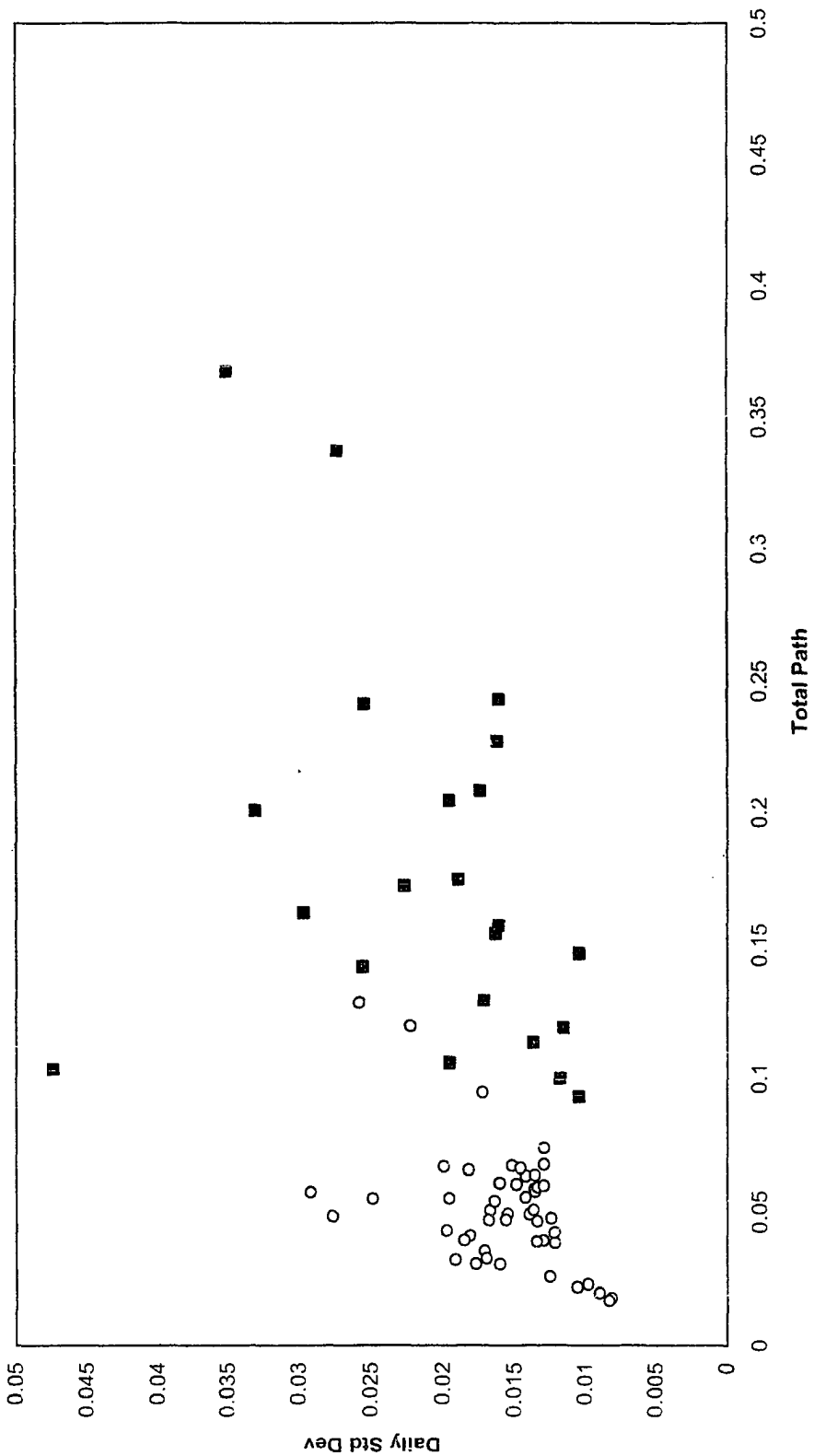


Chart 4. 87 Stocks, 1996 (NYSE=diamond, NASDAQ=square)
Actual OC standard deviation vs Standard deviation implied by Path and #Pr.chgs

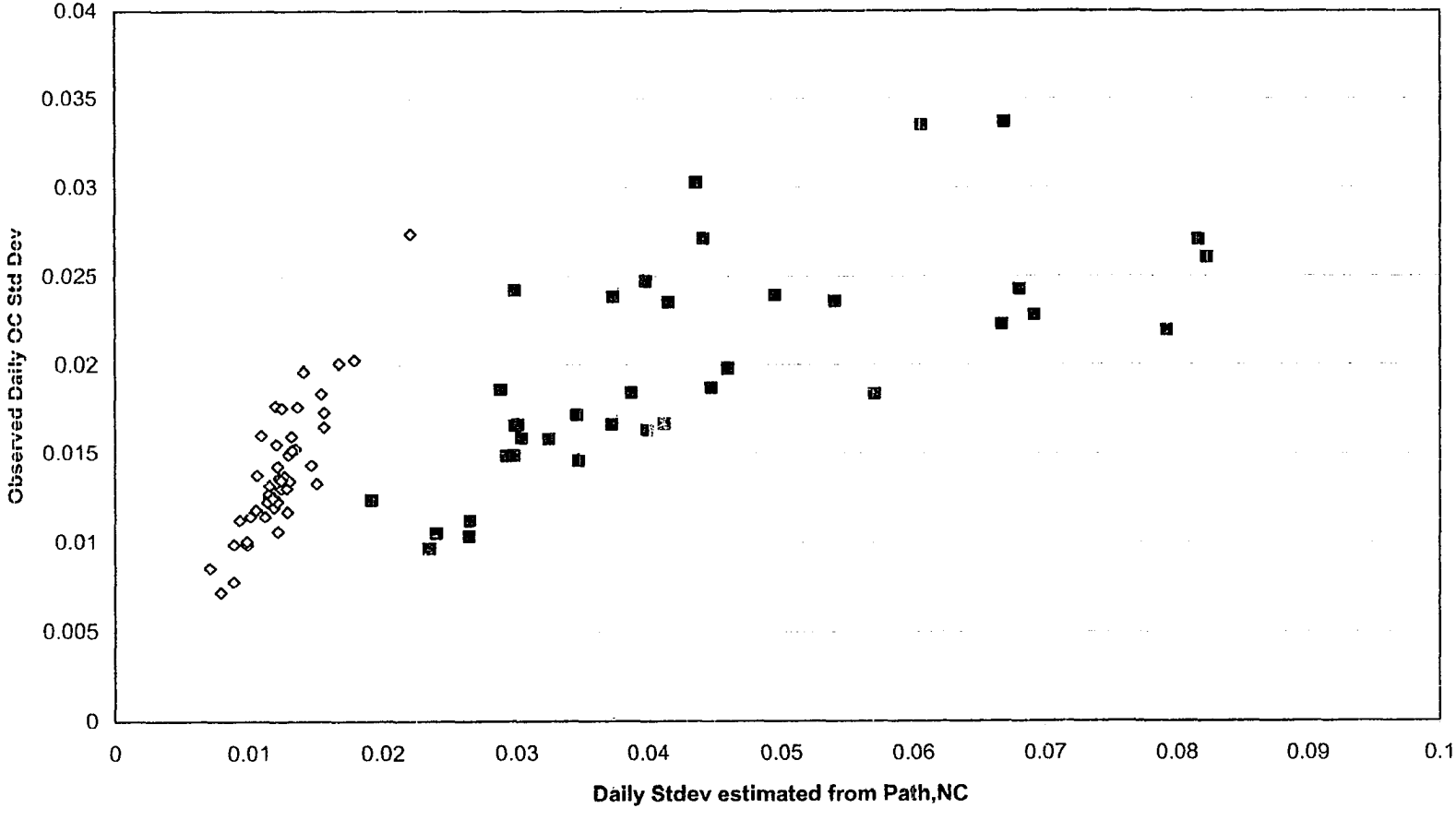


Chart 5. 87 Stocks, 1996 (NYSE=diamond, NASDAQ=square)
Actual OC standard deviation vs Empirical Formula using Path and #Pr.chgs

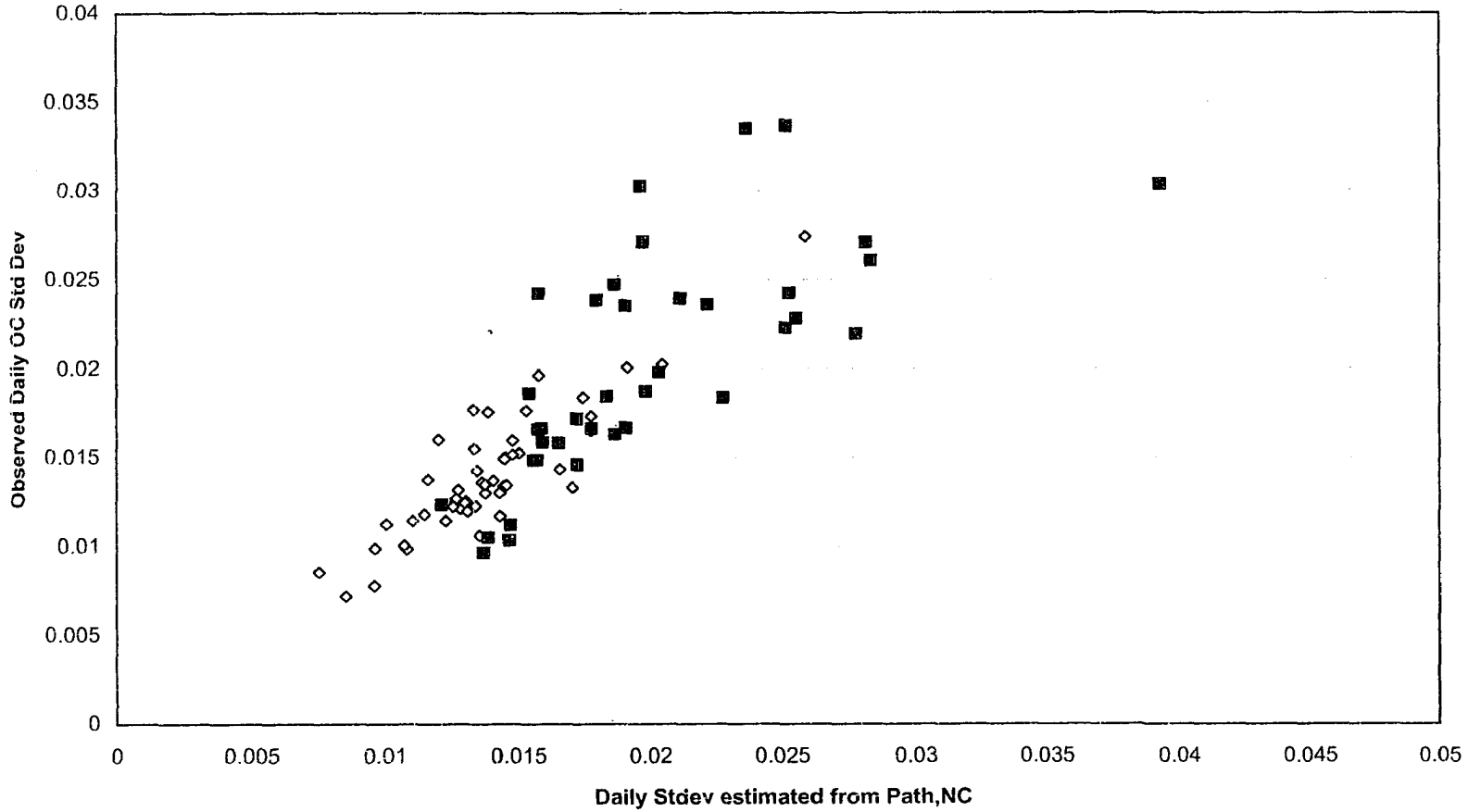


Chart 6. Forecasting XON volatility
(solid: actual volatility, dashed: pve forecast [eqn 1, sec 5.1.4], thick: avg last 24 mo.)

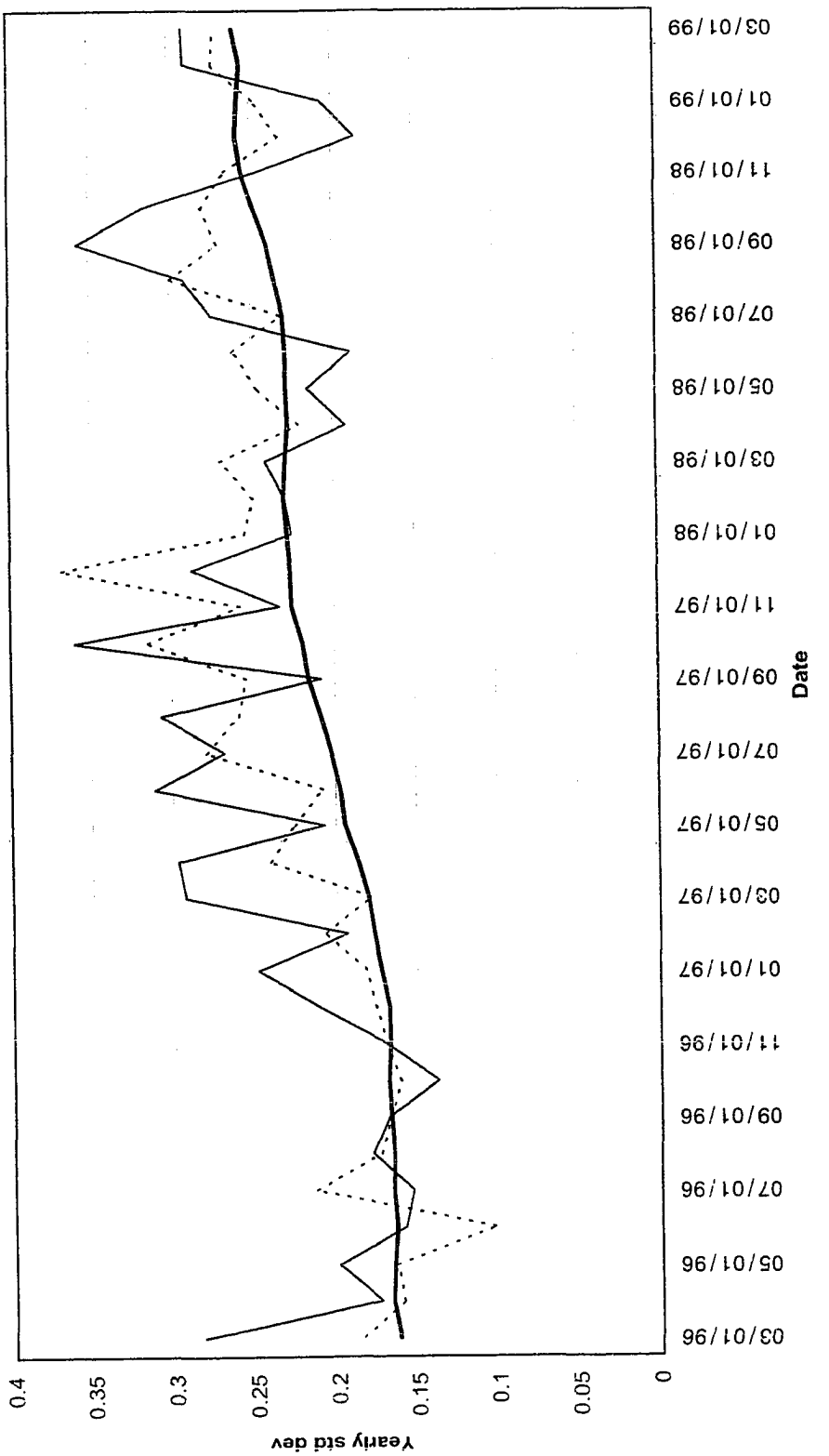
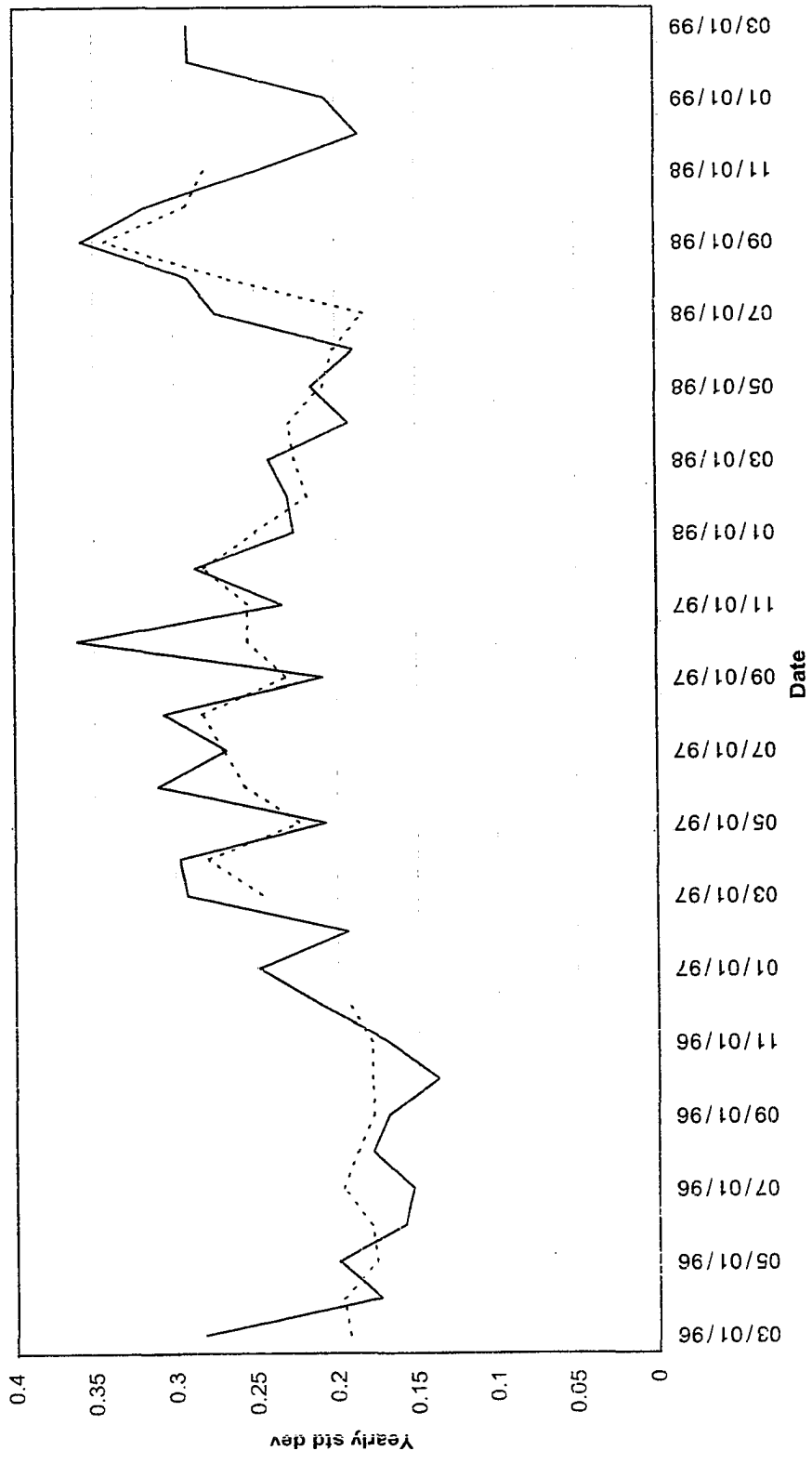


Table VII. Exxon (XON) Volatility Forecasting

Once a month, three forecasts of annualized volatility over the next month are calculated (first three columns). The actual outcome for the next month is given in the last column. The forecasts are: a 24 month moving average, equation (1) section 5.1.2 which takes into account the stock's intraday Path, and the volatility implied by the market for options. It can be seen that the Path based forecast is an improvement over the moving average but not as good as the implied volatility.

Date	24 month avg forcast	Equation (1) forecast	Implied Volatility	Realized volatility
3/15/96	0.1624	0.1846	0.1934	0.2830
4/19/96	0.1665	0.1601	0.1977	0.1739
5/17/96	0.1657	0.1638	0.1762	0.2000
6/21/96	0.1638	0.1032	0.1798	0.1586
7/19/96	0.1656	0.2135	0.1974	0.1536
8/16/96	0.1653	0.1736	0.1883	0.1786
9/20/96	0.1673	0.1676	0.1781	0.1686
10/18/96	0.1685	0.1608	0.1793	0.1377
11/15/96	0.1675	0.1695	0.1792	0.1694
12/20/96	0.1678	0.1758	0.1932	0.2107
1/17/97	0.1726	0.1823		0.2486
2/21/97	0.1769	0.2069		0.1934
3/21/97	0.1805	0.1792	0.2472	0.2926
4/18/97	0.1866	0.2409	0.2795	0.2971
5/16/97	0.1944	0.2257	0.2238	0.2070
6/20/97	0.1969	0.2081	0.2567	0.3106
7/18/97	0.2027	0.2796	0.2700	0.2682
8/15/97	0.2089	0.2594	0.2830	0.3068
9/19/97	0.2161	0.2546	0.2319	0.2083
10/17/97	0.2195	0.3142	0.2547	0.3602
11/21/97	0.2262	0.2579	0.2553	0.2336
12/19/97	0.2268	0.3676	0.2814	0.2870
1/16/98	0.2290	0.2551	0.2499	0.2262
2/20/98	0.2306	0.2492	0.2178	0.2301
3/20/98	0.2293	0.2690	0.2253	0.2416
4/17/98	0.2276	0.2212	0.2293	0.1921
5/15/98	0.2284	0.2461	0.2082	0.2151
6/19/98	0.2290	0.2609	0.2016	0.1888
7/17/98	0.2302	0.2318	0.1826	0.2738
8/21/98	0.2353	0.2988	0.2696	0.2917
9/18/98	0.2400	0.2700	0.3427	0.3574
10/16/98	0.2478	0.2802	0.2926	0.3161
11/20/98	0.2553	0.2654	0.2799	0.2462
12/18/98	0.2585	0.2325		0.1856
1/15/99	0.2574	0.2483		0.2065
2/19/99	0.2557	0.2726		0.2902
3/19/99	0.2597	0.2712		0.2910
RMS error (common dates)	0.0625	0.0509	0.0383	

Chart 8. Forecasting XON volatility
(solid: actual volatility, dashed: implied volatility)



Appendix A – Discussion of the new volatility measure "Path"

A.1 Overview

In simple terms, "Path" measures the total distance by which the price of a stock moved during a trading session. To give a simple example if the price of IBM fell by 1% during the morning and then rose by 2% during the afternoon (with no other changes), the path of IBM on that day would equal 3% (= |-1%| + 2%). Note that this is not the same as the net movement during the day, which is approximately 1% in this example. Path takes into account all of a day's price movements, whether or not they offset each other. Even a stock that ends the day unchanged will have a nonzero path if the price was not constant throughout the day.

A.2 Motivation

Path is one of the simplest measures of price movement that takes into account all trades that occurred. Path is intended to be a robust measure in the sense that it

- Does not rely on the assumption that the price trajectory is approximately a Brownian Motion; in particular it does not assume that price increments are independent and normally distributed. Path does not require any hypothesis about the stochastic process that is generating prices. Path simply measures absolute percentage changes on the assumption that any change is economically significant.
- Should not be thrown off by small timing differences. If IBM rises by 0.1% now and by a further 0.1% a few moments later, Path treats it the same as a rise by 0.2% now. This appears sensible from an economic point of view. In contrast a conventional volatility measure would give different results in these two cases, with the difference depending on the precise length of time between the two successive price movements.
- Path handles volatility bursts correctly. Compare two cases: in Case A there is information about IBM arriving in the market at a steady rate throughout the day. In

case B there is no information at all arriving in the morning and the same information as in Case A arrives in speeded up fashion in the afternoon. In Case B the graph of prices is flat in the morning and quite volatile in the afternoon. Cases A and B would give the same value for Path, which is intuitively appealing. The conventional volatility measure would give a higher volatility for Case B than for case A, even when measured over the whole day. In other words Path satisfies the axiom that the Path of an interval is equal to the sum of the Paths of the sub-intervals, while standard deviation does not. The conventional volatility measure assumes that volatility is constant, and is thrown off when actual volatility changes. A simple numerical example can be used to illustrate this fact. In Figure A, two cases are shown, with identical information events occurring at equally spaced intervals (Case A) or concentrated in the last half of the day (case B); the per trading session standard deviation is higher in Case B. The Path (0.70%) is the same in both cases.

A.2 The Path of an Index

Just as we can compute the Path of individual stocks, we can compute the Path of an index, say the Dow Jones index. How is the Path of an index related to the Paths of the underlying stocks?

Theorem: The dollar Path of an index is equal to the weighted average of the dollar paths of the stocks in the index.

By "dollar Path" is meant that it is the absolute values of actual price changes that are being added together (rather than the percentage price changes).

Proof: Consider the process of updating the Path of the index and the Paths of the underlying stocks whenever information about a new stock trade is received. Suppose a trade in XON occurs at a price p_2 . This value is used to overwrite the previous price p_1 of XON; the dollar Path of Xon is updated by $|p_2 - p_1|$. Since only the price of Xon has

changed, the index is incremented by $w_x(p_2 - p_1)$ where w_x is the weight of XON in the index. The dollar Path of the index is incremented by $w_x|p_2 - p_1|$. Clearly the update to the index dollar Path is the same as to XON's dollar path times the factor w_x.

As each stock trades, a similar calculation takes place: an increment to the stock path and a proportional increment to the index path.

At the end of the trading session, the dollar path of the index will be a weighted average of the dollar Paths of the constituent stocks:

$$\$Path_{index} = (N_A w_A \$Path_A + N_B w_B \$Path_B + \ldots + N_X w_X \$Path_X) / (N_A + \ldots + N_X)$$

Where N_A is the number f trades in Stock A. The individual Paths are weighted both by the index weights w_I and by the number of trades that take place in each stock. QED

With the usual definition of Path as a percentage (rather than a dollar amount), the above result does not hold. The Path for XON increases by $|p_2 - p_1| / p_1$, the Path for the index by $w_x|p_2 - p_1| / i_1$ where i_1 is the previous value of the index. These values are not proportional.

However over the short run (such as one trading session) p and i do not change very much (only by a few percent) and generally in the same direction, so the ratio p/i is roughly constant. Therefore the two terms above are roughly proportional, with proportionality constant $w_X p_0 / i_0$ where p_0 is a typical price of XON stock (say at the beginning of the day) and i_0 is a typical (say, beginning of day) value of the index. So we have the following approximate relationship:

Theorem: The Path of an index is approximately equal to a weighted average of the Paths of the stocks that make up the index:

$$Path_{index} \approx (N_A w_A p_{0A} Path_A + \ldots + N_X w_X p_{0X} Path_X) / (N_A + \ldots + N_X) i_0$$

Calculations with actual Path data show that this approximation is reasonably accurate in practice. Therefore simply taking an average of the Paths of several stocks gives a reasonable measure of overall market volatility.

This property of Path makes it rather different from other measures of volatility. The half-hour variance of an index, for example, is usually below the average half-hour variance of stocks in the index. That is the familiar diversification effect. Path, on the other hand is not much affected by diversification.

A.3 Approximating Path from O-H-L-C prices

Calculation of Path requires knowledge of all trades that have occurred. One sometimes has available only the Open, High, Low and Closing prices over some period of time. If these periods are sufficiently short, it is possible to approximate Path during the period by the following expression

$$\text{Path} \approx 2(h - l) - |\, o\text{-}c \,|$$

Where h,l,o,c are the logarithms of the high, low, open and close prices respectively. This calculation will always result in an underestimation of Path.

Figure A.1

Case A

Time	Descr	Impact	Price	Log Price	Path Calc	Var Calculation(1)
9:30	Market opens		100	4.60517		
10:48	Event 1	0.20%	100.2	4.607168	0.001998	7.37E-05
12:06	Event 2	-0.25%	99.9495	4.604665	0.002503	0.000116
13:24	Event 3	0.15%	100.0994	4.606164	0.001499	4.15E-05
14:42	Event 4	0.10%	100.1995	4.607163	0.001	1.84E-05
16:00	Market closes		100.1995	4.607163	0	0
				stdev per session(2)=		0.003675
				Path per session=	0.70%	

Case B

Time	Descr	Impact	Price	Log Price	Path Calc	Var Calculation
9:30	Market opens		100	4.60517		
13:24	Event 1	0.20%	100.2	4.607168	0.001998	2.46E-05
14:03	Event 2	-0.25%	99.9495	4.604665	0.002503	0.000231
14:42	Event 3	0.15%	100.0994	4.606164	0.001499	8.3E-05
15:21	Event 4	0.10%	100.1995	4.607163	0.001	3.69E-05
16:00	Market closes		100.1995	4.607163	0	0
				stdev per session=		0.004511
				Path per session=	0.70%	

Note 1: H8 =(E8-E7)^2/(A8-A7)
Note 2: G15 =SQRT(((A12-A7)/5)*SUM(F8;F12))

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Footnotes

[1] Leslie Rahl, MIT Hedge Fund Meeting, New York, May 24, 2000

[2] Since our study was started the same authors have followed up their foreign exchange paper with a similar one for stocks: Andersen, T. Bollerslev, F.X. Diebold, H. Ebens (1999). It was later published in Journal of Financial Economics, July 2001, Vol 61, pp. 43-76.

Chapter III: Stock Market Volatility and The On Line Investor

1.0 Introduction

Online investing is a relatively new phenomenon. The early adopters of online investing have concentrated their attention on a fairly narrow subset of stocks. We study some of these stocks at the microstructure level and examine whether their short-term behavior differs from those of other stocks. Specifically, our study concentrates on volatility and shows some differences in volatility behavior for stocks favored by online investors.

2.0 The rise of the "new retail investor"

A number of interrelated developments in the last 2-3 years have given retail (that is non institutional) investors a bigger prominence in the U.S. stock market than they had previously[1]. In this section we will review these developments and point out how the behavior of retail investors has been affected.

2.1 The advent of E-brokers

The term E-brokers refers to brokerage firms (such as Charles Schwab, E-trade, Ameritrade, TD Waterhouse) that have made it possible for their customers to buy and sell stocks cheaply over the Internet. The number of such online accounts has increased rapidly, to 9.7 million at the end of 1999[2]. Because of lower commissions, greater convenience and other factors, online investors trade more frequently than traditional investors (Barber and Odean, 1999).

The day-trading firms (such as All-Tech, Momentum Securities, Heartland Securities) deserve separate mention. These firms provide offices in major cities from which investors can trade directly with market makers, with no broker in between. Typical day trading strategies involve making large numbers of trades (dozens per day), each involving a few hundred shares and lasting a few minutes, in an attempt to capture price movements of a few ticks. There are estimated to be 4000 to 5000 day traders in the United States[3].

A high activity in buying and selling characterize both online investors and day traders, although to a different degree.

2.2 The New Media (ex. CNBC, Yahoo!Finance)

Continuous coverage of the stock market has expanded greatly in recent years (Shiller, 2000). The cable channel CNBC provides a steady stream of live stories throughout the day. Although the stories are intended to be objective and factual, many who watch CNBC report that they have a powerful emotional component as well. CNBC tends to focus on the most exciting story of the moment, on the stock that is going up the most, or falling the most. The viewer gets the impression that important events are taking place and a subtle invitation to participate in those events. In spite of the fact that millions of other people are getting the same information, the typical viewer feels privileged and better informed than anyone else.

Investment oriented Internet sites are the other example of the "new media. Four popular sites are Yahoo!Finance, Raging Bull, The Motley Fool and Silicon Investor. These sites offer free and constantly updated information about the stock market. In addition discussion groups allow users to post messages about specific stocks that other users can read.

Psychologists have used the expression "the illusion of knowledge" to describe the effect of giving people large amounts of information concerning a situation. Even when the information makes only a modest contribution to an accurate understanding of the situation, people report feeling knowledgeable and more confident about their decision making in the given situation (Plous, 1993).

To summarize, the new media provide a channel for written material to be quickly disseminated to the new style investors. The material has both factual and emotional content.

2.3 Early stage companies going public

In recent years many companies having only a short operating history have gone public. The new retail investor has been an enthusiastic buyer of such IPOs.

CNBC and other news media have played a big role in publicizing the stocks of early stage companies. The combination of investors who consider themselves

technology savvy and media who have become inadvertent publicity machines for new offerings may have been a key factor in the recent boom in unseasoned technology companies going public.

An important characteristic of early stage companies (whether they be technology based or not) is that their cash flows are far in the future and extremely uncertain. As a result, there are will be large differences of opinion among investors about the price per share at which an early stage company should trade. This will be a key point in what follows.

2.4 The investment style of the new retail investor

Anyone perusing messages in Internet boards and reading about the new investors in the press quickly forms a general impression of the investment style that is popular with online investors. Empirical research can then be used to verify these impressions. For our purposes the key observations are the following.

Online investors believe in trends. They believe what has gone up will continue to go up, and vice versa. For this reason they tend to act as momentum investors or positive feedback traders. A rise in price (momentum) will attract more buyers and a fall in price will attract sellers. The new investors are value insensitive, they seek to buy the best companies at any price[4].

The new investors read the new media mentioned previously (CNBC and Internet investment sites). We can expect a certain amount of herding, or common action by investors based on these sources.

The new investors have concentrated their interest in the new-technology companies because of their personal interest and knowledge in this area. Specific industries they favor are: all manner of Internet related industries (infrastructure, business to consumer, business to business), genetic engineering, pharmaceutical, telecommunications, media, fuel cells.

In terms of the traditional investment style classification (Growth Vs Value, Large Cap vs Small Cap, Momentum vs Contrarian), the online investors are Growth and Momentum oriented, with perhaps some bias towards Small Cap.

2.5 Why this matters – the limits of arbitrage

Although the peculiarities of today's online investors make for interesting and entertaining reading, there are grounds for believing that such things make no difference in a well functioning financial market. Those who claim that "it makes no difference", that is that the market works the same whether it contains unsophisticated investors or not, have two powerful arguments: arbitrage and Darwinian selection.

A simple example of arbitrage is the following. Suppose there are two securities with identical payoffs, A and B. Both promise to pay $1 a year from now. Security A is priced at 0.95, while security B is priced higher than that because of an irrationally strong demand for it (perhaps CNBC has just done a story on it). This situation cannot last: arbitrageurs will short sell security B and buy security A. In this way the prices of A and B are brought back together again.

This example is persuasive as far as it goes. But somewhat different assumptions can weaken it considerably.

Suppose the time required for the payoff is not one year, but is random and may be considerably longer than a year. The arbitrageur must embark on a voyage with a known destination but no clear time of arrival. As Shleifer and Vishny (1997) assume, suppose also that the arbitrageur is using capital provided by third party investors. Then the arbitrageur faces a significant risk, the risk that the mispricing they have bet against actually increases in the short run. In such a situation the arbitrageur needs more capital to meet margin requirements (and if need be increase his position), but the outside investors will be reluctant to supply it in view of the bad performance of the arbitrageur so far. The main conclusion of Shleifer and Vishny's model is that the arbitrageur may have to liquidate his position at the worst possible time. This risk (which ironically is created by the presence of the irrational traders themselves) discourages arbitrage in the first place. Shleifer and Vishny observe that this problem is likely to be especially severe if the time horizon is long and if the fundamental prices are quite noisy. Both conditions are met in the case of early stage companies in a new industry.

Another circumstance where arbitrage may not work well is specific to the funding of early stage companies. If a company goes public at an outrageously high price, other entrepreneurs have an incentive to start similar companies and go public

also. This new supply of shares will help correct the overvaluation. But in an industry where there is a strong first mover advantage, say because of economies of scale, the first company only will be successful. Then the idea of a second company replicating the first may not work.

Put differently, the classic arbitrage argument assumes that any given payoff can be reproduced exactly (or at least closely approximated) by arbitrageurs who detect a mispricing situation. But in being the first to take advantage of an (assumed) irrational IPO market to raise a large amount of funds, and then investing in a business with economies of scale, an enterpreneur could create an asset that would be difficult for others to reproduce. I will call this the unique-asset obstacle to arbitrage.

The Darwinian argument against irrational pricing states that by trading incorrectly irrational investors will bankrupt themselves and disappear from the scene. A classic source is Milton Friedman (1953). Undoubtedly this is valid in the long run, but it carries less weight in the present unusual situation where a new category of investors using new approaches has come forward. They may indeed disappear, but since they are fairly numerous it may take quite some time, and their effects on the market may be observable.

Another critique of the Darwinian argument is in DeLong, Shleifer, Summers and Vishny (1990). In their model the unpredictability of noise traders' beliefs creates a new risk, which deters arbitrageurs from betting against them. This allows the noise traders to survive and even earn a risk premium in equilibrium; this risk premium is based on risk that they themselves create. "The noise traders create their own space". The result holds because arbitrageurs have a finite horizon, while the return of prices to rational levels can be postponed indefinitely.

Based on the above, we will accept that irrational investors might affect prices and proceed to look for empirical evidence of this.

2.6 Related work

Authors who have studied the behavior of online investors or the recent changes in the behavior of investors in general include: Barber and Odean (1999), Shiller (2000),

Hirschey et al. (2000), Blanchard (2000), and more recently D'avolio et al. (2001) and Ferguson (2001).

Barber and Odean (1999) studied a sample of 1600 investors who switched from phone based to online trading in the years 1991 to 1996. These investors were quite active before the switch, with a turnover of 74% per year. After they began trading online, their turnover briefly surged to 120%, then settled back to 95.5% per year. The investors' average round trip commissions dropped from 3.3% to 2.5% after they went online. But as a result of the higher activity their investment performance (after transactions costs) actually dropped.

3.0 Implications and testable hypotheses

If the online investors act as described above, we might expect them to affect some stocks and not others. Specifically we expect to see the following.

Stocks in which the new investors are active ("affected stocks") will show a lot of small trades (500 shares or less). Technology stocks are the place to look, especially early stage companies where arbitrage has difficulty undoing the effect of noise traders.

For such stocks, periods of time with a large activity by small investors will have a high volatility. We expect no such result for established, industrial stocks.

The price impact of small trades will be larger for the affected stocks than for other stocks. Far from ignoring small trades, the market maker for such a stock pays attention to them in adjusting his price.

We expect to see more correlation of trade direction for the affected stocks. Because the drivers of online investor behavior are the same, these investors will tend to take similar actions. At some times many online investors will be buying and at other times many will be selling.

3.1 Volatility of Internet stocks

It has been discussed above, and it has been mentioned in the press as well, that some of the most volatile stocks have been Internet companies listed on Nasdaq. The press has described how, thanks to improved technology and lower commissions, many small

investors have begun to actively trade these stocks. Whether described as "online traders" or "day-traders" these investors are said to be a major force behind the high volatility of Internet stocks. What hard evidence is there for these assertions?

Average Trade Size versus Volatility

Chart A shows average trade size and volatility for 5 Internet stocks and 5 conventional technology stocks in November 1998. Not only do the Internet stocks have a smaller trade size than the other stocks, but there is an inverse relation between trade size and volatility for these stocks. The most volatile stock, Ebay, is also the one with the smallest trade size.

The distribution of trade sizes for Ebay and Microsoft on a particular day (November 19, 1998) was as follows:

	Ebay	MSFT
Trades of 100 shs	39% of trades	25.8%
200 shares	30%	12%
201 – 500	18%	21.7%
501- 1000	9.4%	27%
1001-5000	2.4%	11%
5001-20000	0.1%	1.6%
20000+	0%	0.3%

Note that 87% of Ebay's trades are for 500 shares or less, versus only 59.5% for Microsoft. Hereafter we will consider any trade of 500 shares or less as a "small trade".

4.0 A model of small trades and volatility

There is an obvious difficulty in interpreting the above evidence. What is the direction of causation, and what is the mechanism behind it? For example individual traders could be attracted to volatile stocks and institutions could shun such stocks. Or the dynamics of

certain stocks could be affected by the presence of small traders, perhaps resulting in higher volatility.

4.1 Theory and Hypotheses

In most economic models, the participation of a large number of small traders in a market is a favorable development, which results in lower volatility. At its simplest, the more small traders there are the more liquid the market and the closer prices will be to the equilibrium price. If traders make independent errors in their private estimates of the value of the good being traded, a large number of traders will entail a smaller pricing error.

The well known model of Tauchen and Pitts (1983) formalizes this idea. These authors are concerned with the link between volume and volatility. In their model each trader has a private estimate of price (which generally differs from the market price) and trades accordingly; traders also revise their estimates based on information they receive in each period. Tauchen and Pitts conclude that three different things can happen: when there is a large revision in price estimates that is common across all investors (for example all investors receive the same public information) there will be a large price change and zero trading volume, when there is a large revision in price estimates that differs across investors there will be a large price change and large trading volume, and when there is an increase in participation (that is more investors) there will be a smaller price change and more trading volume.

An example of the third effect occurs in any new financial market during its rapid growth phase. Tauchen and Pitts cite the case of the Tbill Futures market in the early 80's. They show that there was an increase in the number of market participants, leading both to higher volume and to lower volatility. Essentially the market was becoming more liquid and hence closer to a perfect market.

An alternative to this theory has not been carefully formalized but is often heard in the press or among stock market professionals. It is that large numbers of small know-nothing traders can somehow destabilize the market, perhaps because they tend to copy

each other or to react to recent price patterns in the same way (that is, correlated trading in the absence of information).

For example Michael Traynor, a manager with the VBS brokerage house said in discussing online trading: "[The crowd mentality] takes strong hold in an online chat room where a number of investors start hyping and getting behind a particular stock". The operation of such an online group was described in an article in the Wall Street Journal of March 18, 1999; the leaders of the group would watch for positive developments on some small stock, then egg on the other group members to buy. The rapid messaging capability of the Internet makes it possible for investors to quickly influence each other, and the availability of up to the moment quotations makes it possible to engage in what DeLong Summers Shleifer and Vischny (1990) call "positive feedback trading".

4.2 Empirical investigation of small trades and volatility

Battalio, Hatch and Jennings ("SOES trading and Market Volatility", 1997) used Granger methods to analyze the link between small trades and volatility. Our methodology is similar. The trading day is divided into 1 minute intervals; for each interval the volatility VOL and the fraction of trades that are small (500 shares) FSMALL, are computed. VOL_i, the volatility of the stock during the one minute period i is defined as the logarithm of V_{MAX} / V_{MIN} , where V_{MAX} and V_{MIN} are the highest and lowest value of the stock during the one minute interval. The stock value is the bid-ask midpoint at the time a trade takes place. If the stock does not move at all or is not traded during the one minute period, then VOL will be zero.

Unlike Battalio et al., who used a pooled sample of stocks (52 stocks for 2 months), we will consider eight stocks separately over a longer period of time (12 months). This will allow independent conclusions to be drawn for each stock. The period chosen was the year 1998. We will also consider a single stock at two different points in time (1994 and 1998) to detect any changes over time.

4.2.1 First Step: Correlation analysis

When we examine the cross correlations of VOL and FSMALL, two different patterns emerge: For PG (Procter & Gamble), XN (Exxon) and GE the correlations are negative: a high FSMALL is associated with a low VOL and vice versa. This is consistent with the null hypothesis mentioned above (that a large number of small traders makes the market price more stable). The most negative correlation is the contemporaneous one, although there are negative correlations at other leads and lags as well. All these correlations are statistically significant. A typical correlation diagram (for GE) is shown in Chart B.

For another set of stocks, consisting of EGRP (E*Trade Group), YHOO (Yahoo!), AMZN (Amazon), ATHM (At Home), and EBAY the correlations are positive, and again statistically significant. There appears to be a direct relationship between our two variables. A typical diagram (for EGRP) is shown in Chart C. The other stocks' diagrams are qualitatively similar, except for Yahoo which shows a flatter curve with no depression at k=0.

Examining the autocorrelations, VOL is more persistent (autocorrelated) than FSMALL. Both of these autocorrelations are somewhat higher for the first group of stock than for the second.

Comparing cross correlations for Microsoft in 1998 with those of 1994, we find that both are negative, the 1998 cross correlations being more negative. In other words Microsoft shows the "conventional" pattern. The 1998 chart especially is very similar to the one for GE.

4.2.2 Second Step: Statistical Model

The variables chosen for the model are nearly identical to those used by Battalio et al. (1997):

The equation for FSMALL contains:

- 1 constant
- 12 lagged FSMALL values
- 4 lagged VOL values
- 3 lagged Number of Trades values
- Logarithm of Stock Price

6 Time of Day dummies

The equation for VOL contains:

1 constant
8 lagged FSMALL values
12 lagged VOL values
3 lagged Number of Trades values
Logarithm of Stock Price

In almost all cases we found bidirectional Granger-causality between Volatility and FSMALL (the fraction of trades which are small). The one exception is Procter & Gamble where the causality runs from Small trades to Vol but not vice versa.

Thanks to the large amount of data used (about 95000 observations per stock) the F-statistics are highly statistically significant. They are summarized below:

	Vol causes Small Trades		Small Trades cause Vol	
Stock	F-value	Prob	F-value	Prob
GE	16.7	0.112E-12	34.2	0.333E-15
Yahoo	36.4	0	10.3	0.147E-13
Exxon	5.00	0.501E-03	6.00	0.977E-07
Proct&Gamble	0.847	0.495	15.1	0.555E-15
Etrade Grp	6.30	0.459E-04	11.3	0.444E-15
Ebay	11.5	0.253E-08	5.53	0.511E-06
AtHome	44.1	0.00	7.31	0.919E-09
Amazon	124.0	0.00	34.1	0.555E-15

(These are F-tests for the null hypothesis that all vol coefficients are zero in the equation that predicts fsmall (or vice versa)).

The t-statistics of the individual regression coefficients are as follows:

Prediction of small trades

t-statistics for 4 lagged volatility terms

	VOLATILITY			
	[1]	[2]	[3]	[4]
GE	-4.19	-2.67	-3.21	-2.59
Exxon	-4.16	-0.87	0.12	0.24
Proct&Gamble	-1.53	0.80	0.61	-0.45
Yahoo	5.39	5.14	2.18	3.65
Etrade Grp	1.57	-1.06	1.26	3.97
Ebay	4.36	2.51	0.92	0.36
AtHome	6.62	2.24	3.51	5.65
Amazon	12.33	5.80	5.72	4.64

Prediction of volatility

	Fraction of small trades							
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
GE	-16.27	0.00	-1.51	0.22	0.26	0.47	1.20	0.58
Exxon	-6.21	-0.84	-0.11	0.81	0.03	1.58	1.03	-2.11
Proct&Gamble	-10.36	-1.53	0.65	0.52	-1.06	0.35	1.32	2.57
Yahoo	2.30	1.61	2.43	2.02	1.21	2.07	2.69	3.33
Etrade Grp	0.57	2.52	2.88	3.76	3.06	3.37	1.42	2.50
Ebay	4.31	0.79	-0.55	1.51	1.75	2.20	0.84	0.12
AtHome	3.09	2.81	2.03	2.57	1.68	1.10	1.42	1.72
Amazon	6.11	3.25	4.80	2.66	3.29	2.45	3.30	3.65

We conclude there is a major difference between the traditional industrial stocks (GE, Exxon and Procter & Gamble) and the five internet stocks.

For GE, XN, PG, there is a negative relationship between FSMALL and VOL. In particular a high proportion of small trades predicts a lower volatility for the next 1 minute or so.

For the five internet stocks the relationship between small trades and volatility is positive in both directions. A period of high volatility tends to be followed by a higher than usual proportion of small trades. Conversely a high proportion of small trades is followed by higher volatility. These effects are spread out over several minutes, unlike the very short term effects for GE, XN, PG.

4.2.3 Some conclusions

We have documented a previously unknown distinction among stocks based on the effect of small trades on volatility. The stocks we examined fall into two distinct groups when a Granger-causality test is performed on volatility and small trade time series.

The results we obtain for such stocks as GE are very similar to Battalio's results: little or no effect of small trades on volatility, and only in the very short term. The effect of small trades is a reduction in volatility for these stocks.

For stocks such as Yahoo there is positive causality in both directions between VOL and FSMALL. A considerable number of lagged values of FSMALL (up to eight) influence volatility positively, showing the effect is somewhat spread out over time.

4.2.4 Discussion and possible explanations

What is the significance of classifying trades into small vs. large? As was shown by Lee and Radhakrishna (2000), trade size is a proxy for the type of investor who is initiating

the trade. Large trades are more likely to be submitted by institutional investors, small ones by individual investors.

We have shown that the small investors who trade internet stocks behave differently from those who trade the other stocks in our sample. Their trading activity increases following moments of high volatility. Although we could say that these individual investors are responding to common information, that information would have to be somehow specific to individuals, since the larger, institutional investors, are not acting upon it. Another, more plausible explanation is that some individual traders are following strategies that are based on short term price movements (which they can continuously monitor through their computer systems). When they see prices move, they trade. (The next section will look at whether their trades are positive-feedback (price destabilizing) or negative-feedback (price stabilizing)).

We have also shown that for the Internet stocks, a high fraction of small trades Granger-causes an increased volatility, although the number of coefficients of FSMALL that are statistically significant varies somewhat from stock to stock. For industrial stocks a reverse (negative) effect on volatility is observed, and then only in the short run. In the next section we will analyze more closely the impact of small trades on stock prices.

5.0 An investigation of market impact of small trades

In market microstructure studies, a distinction is made between the temporary and the permanent impact of a trade. The temporary impact is sometimes called the price of immediacy. It is a trading cost to the initiator of the trade and a source of profit to the market maker or trader who steps up to take the other side of the trade. A price movement occurs which is unfavorable to the person requesting the trade, but the price soon returns towards its unconditional equilibrium value.

The permanent impact, on the other hand, is related to the information content of a trade. The trade reveals information in the sense that it permanently affects the stock price. As informed traders trade, the permanent impacts of trades result in the stock price

closing in on the (unobservable) intrinsic value of the stock, a process sometimes referred to as price discovery.

Any trade is likely to have both a temporary and a permanent impact, but the two components can be distinguished by using appropriate methodologies.

In this study we computed market impacts for large trades and for small trades. The null hypothesis would be that the large trades have a bigger permanent impact than small trades. Small trades' impact, on the other hand, should be mostly temporary, for two reasons. First of all, anyone with significant private information is likely to want to put on a large trade. Second, institutions, which trade in larger size, are more likely to have done the research and analysis needed to uncover information; individual investors are more likely to trade for liquidity or 'noise' reasons.

5.1 Empirical investigation of price impacts

A methodology similar to that in Handa, Schwartz and Tiwari (1998) was used. The first step is to classify trades as buyer initiated or seller initiated, by reference to the bid and ask prices. (Lee and Ready, 1994). Each trade is also classified as large or small. We can then determine the trajectory of transaction prices for 15 trades before and 15 trades after the trade of interest. Handa, Schwartz and Tiwari (1998) define the permanent impact as the price change between trade –15 and trade +15, where "price" refers to the bid-ask midpoint; the temporary impact as minus the change from the transaction price for trade 0 to the price for trade +15. Separate trajectories can be drawn for small trades, small buy trades, etc.

Sample results are shown in Charts D and E. These two charts (for GE and YHOO) are dramatically different:

For GE, consistent with the theoretical considerations above, the effect of small trades is entirely temporary. Large trades on the other hand have a large permanent impact and a smaller temporary impact.

Overall the hypothesis that large trades carry information and small trades do not is supported.

For Yahoo, in the case of sells, the effect of small and large trades is identical: both a temporary and a permanent effect. For buys, large buys have a somewhat larger permanent effect than small buys; nonetheless small buys have a permanent effect (even if not as pronounced as large buys).

The conclusion is: the market reacts very differently to small orders for GE and YHOO. For GE the possibility that a small trade contains information is completely ruled out and no permanent price adjustment takes place. For YHOO on the other hand a small trade is treated not very differently from a larger trade, resulting in a permanent price impact.

It is perhaps only a matter of semantics whether we say that small YHOO trades have as much information as large ones or that large YHOO trades have as little information as small ones (just like saying that two people are equally short or equally tall).

The results for all eight stocks are summarized in the following table:

Summary of price impacts (trading costs)
Temporary vs. Permanent
Small Trades vs. Big trades

	A	B	C	D	
Stock	**temp small**	**temp big**	**perm small**	**perm big**	**C / D**
GE	0.000250	0.000059	0.000103	0.000547	0.188
XON	0.000604	0.000514	-0.000058	0.000256	-0.227
PG	0.000220	0.000065	0.000279	0.000877	0.318
YHOO	0.000680	0.000703	0.000149	0.000294	0.507
EGRP	0.002332	0.001887	0.000860	0.001542	0.558
EBAY	0.001193	0.001873	0.000593	0.000173	3.428
ATHM	0.001713	0.001549	0.001052	0.001223	0.860
AMZN	0.000904	0.000967	0.000281	0.000444	0.633

For industrial stocks the permanent impact of small trades ranges from essentially none (Exxon) to 30% of the impact of large trades.

For Internet stocks the permanent impact of small trades is always at least 50% of the impact of large trades. (In one case, EBAY, small trades had, paradoxically, a bigger impact than large trades).

Trade Similarity

Another type of diagram introduced by Handa, Schwartz and Tiwari (1998) is the Trade Similarity diagram. This measures the tendency for trades close to trade 0 to be in a similar direction to trade 0. For example if trade 0 is a buy, what is the probability that trade +15 is also a buy? If trade directions were completely random we would expect all these probabilities to equal 0.5, meaning the direction of trade 0 has no predictive value for the direction of nearby trades. In empirical work the probabilities are often found to be greater than 0.5, implying clustering of trades of the same type.

The results of applying this technique to the two stocks in question are shown in Charts F and G. Both show some clustering of successive trades. For GE the next trade is in the same direction as the current trade about 66% of the time for large trades and 58% of the time for small trades. For YHOO the same numbers are 64% and 64%. These results are very similar. A difference emerges when the current trade is compared to trade +15: no relationship for GE (similarity of 50%), versus 54.8% for YHOO.

To summarize there is evidence of trade direction correlation for YHOO that lasts for an extended time (i.e. not just between one trade and the next, but over 15 trades). Large impact of small trades and correlation of small trades as to direction offer a possible mechanism by which small trades may impact volatility.

6.0 Summary and conclusions

We have identified a small number of stocks that are highly traded and that experience volatility out of proportion to historical norms for highly traded stocks. The average trade size for these stocks is small, suggesting a retail clientele, and specifically retail investors trading online.

We have also shown that the short-term price dynamics of these stocks (which we called the Hyper Vol Stocks) are different from those of the typical industrial stock. The main findings are:

(1) A positive correlation between the fraction of small trades and the volatility for Hyper Vol Stocks

(2) Evidence of positive feedback trading for the Hyper Vol Stocks. (After a volatile period small trades increase, also after a buy there is a slightly higher probability of buys for the next 15 trades)

(3) The difference in information content between small and large trades is not very pronounced for our Hyper Vol Stocks. Small trades participate in the price determination process for these stocks almost to the same extent as large trades. For traditional stocks on the other hand, small trades have no permanent impact whatever.

These observations support the idea of a clientele effect on volatility, at least in some cases (i.e. for a particular group of stocks). Stocks that are favored by online investors appear to behave differently, at a micro-structure level, from other stocks. We have been able to observe the "fingerprints" of the new online investor in the trading data for such stocks.

Appendix A - Application: assessing volatility after adjusting for small trades

In the main part of this paper a correlation was found between small trades and volatility. As a check on these results a wider sample containing 95 stocks was chosen. Intraday trade and quote data was obtained. Volatility at 5 minute intervals was measured as

$$VOL5 = \log (M_{HI}) - \log (M_{LO})$$

Where M_{HI} and M_{LO} are the highest and lowest bid-ask midpoint. The proportion of trades that are small (less than or equal to 500 shares) was also computed for each 5 minute interval and will be denoted Fsmall5. Average values of Vol5 and Fsmall5 were computed for the year 1998 and are plotted in figure A.1.

Using least squares regression a statistically significant positive relationship was found, as follows:

N=95 Adjusted-R^2=0.4648 F=82.6 (Prob < 0.001)

Constant= -0.00038

Slope= 0.00558 (T-statistic= 9.1)

The simplest explanation for this relationship is that small investors are particularly interested in volatile stocks, while institutions do not show such a preference. Small investors might, for example, experience difficulty in borrowing; they could view investing in volatile stocks as a convenient substitute for leverage (Black (1993)).

A.2 Small-trade adjusted volatility

If we accept that an Fsmall effect exists, we can adjust for it, that is remove this effect and examine the remaining volatility. This could be called the adjusted or inherent volatility, not associated with small trades. An open question is whether all volatilities are the same after this adjustment or whether there is substantial variation left and what factors account for it.

We will estimate an equation that explains (in a statistical sense) the volatility in a five minute window as a function of the fraction of small trades and of dummy variables specific to each stock. The coefficient estimated for each dummy variable will be taken

as the measure of adjusted volatility for that particular stock. Mathematically, the equation is

```
Vol5 = alpha +beta*fsmall5 + … Stock specific dummy variables
```

The coefficient of fsmall5 captures the average effect of small trades, in the sense that we have imposed the same linear relationship between fsmall5 and volatility for all stocks and all time periods. Individual differences in stock volatility, on the other hand, are captured by the individual dummy variable coefficients.

One dummy variable had to be omitted to avoid multi-collinearity, so there are 94 dummy variables. (The omitted stock was GE).

We analyzed the 94 dummy variable coefficients, to identify factors that cause these measures of volatility to be high or low. The factors considered in this study were four in number and each is described by a dummy variable, as follows:

dNYSE – 1 if stock trades on the New York Stock Exchange,
0 if it trades on the Nasdaq exchange

dBigCap – 1 if stock has a large market capitalization (more than $5.18 B on 1997/12/31), 0 otherwise

dHiTurn – 1 if stock has a high turnover, 0 otherwise. Turnover is defined as the total number of shares traded divided by the total number of shares outstanding (this definition is consistent with Lo & Wang (2000), Lee and Swaminathan (2000) and other studies). High turnover was defined as 0.34% per day or above.

dTMI – 1 if the company belongs to one of the following sectors: Technology, Medical or Internet, 0 otherwise.

The 94 stocks were divided into two groups; those having a dummy variable coefficient larger than the median (High Adjusted Volatility, "avol=1" group), and those smaller than the median ("avol=0"). Two by two contingency tables were produced showing how avol interacts with four variables describing basic characteristics of the stocks involved.

The proper method to analyze these contingency tables is Fisher's Exact Test (Siegel, 1956); the Chi-Square test can also be used and will give similar results for large enough samples. These tests address the question whether the row and column classifications are independent. The results are presented in Table A.1.

In Panel A of this table we see that there is no statistically significant relationship between the exchange on which the stock trades (NYSE or NASDAQ) and the adjusted volatility. In Panel B a significant relationship ($p<5\%$) is found between market

capitalization and adjusted volatility. BigCap stocks are more volatile than SmallCap stocks. Panel C evidences a highly significant ($p<1\%$) and positive relationship between relative volume and adjusted volatility. Panel D concerns the stocks of Technological, Media or Internet companies relative to all the others; they are found to be more volatile and the results are highly significant ($p<1\%$).

In summary, even after adjusting for the fraction of small trades, there are significant differences in volatility among major groups of stocks. However, contrary to popular opinion, NASDAQ stocks are not inherently more volatile than NYSE stocks; some NASDAQ stocks appear highly volatile, but statistically speaking this is better explained by different levels of participation by small traders rather than exchange per se.

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Chart A - Volatility vs Avg Shares per Trade
(10 NASDAQ stocks, November 1998)

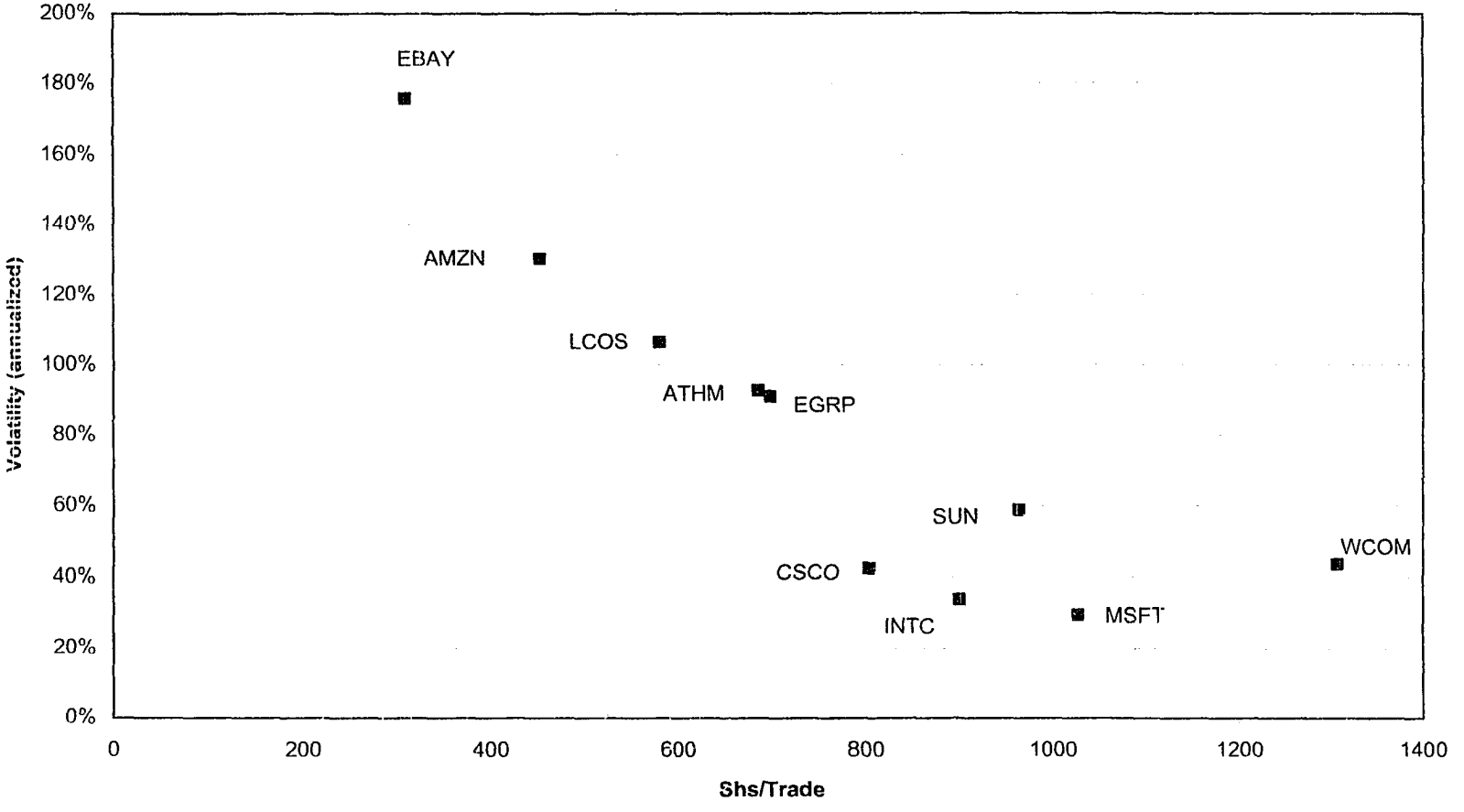

Chart B. GE 1998. Crosscorrelation of fsmall [fraction of small trades] w/ volatility lagged by k minutes. The correlation is negative at all lags.

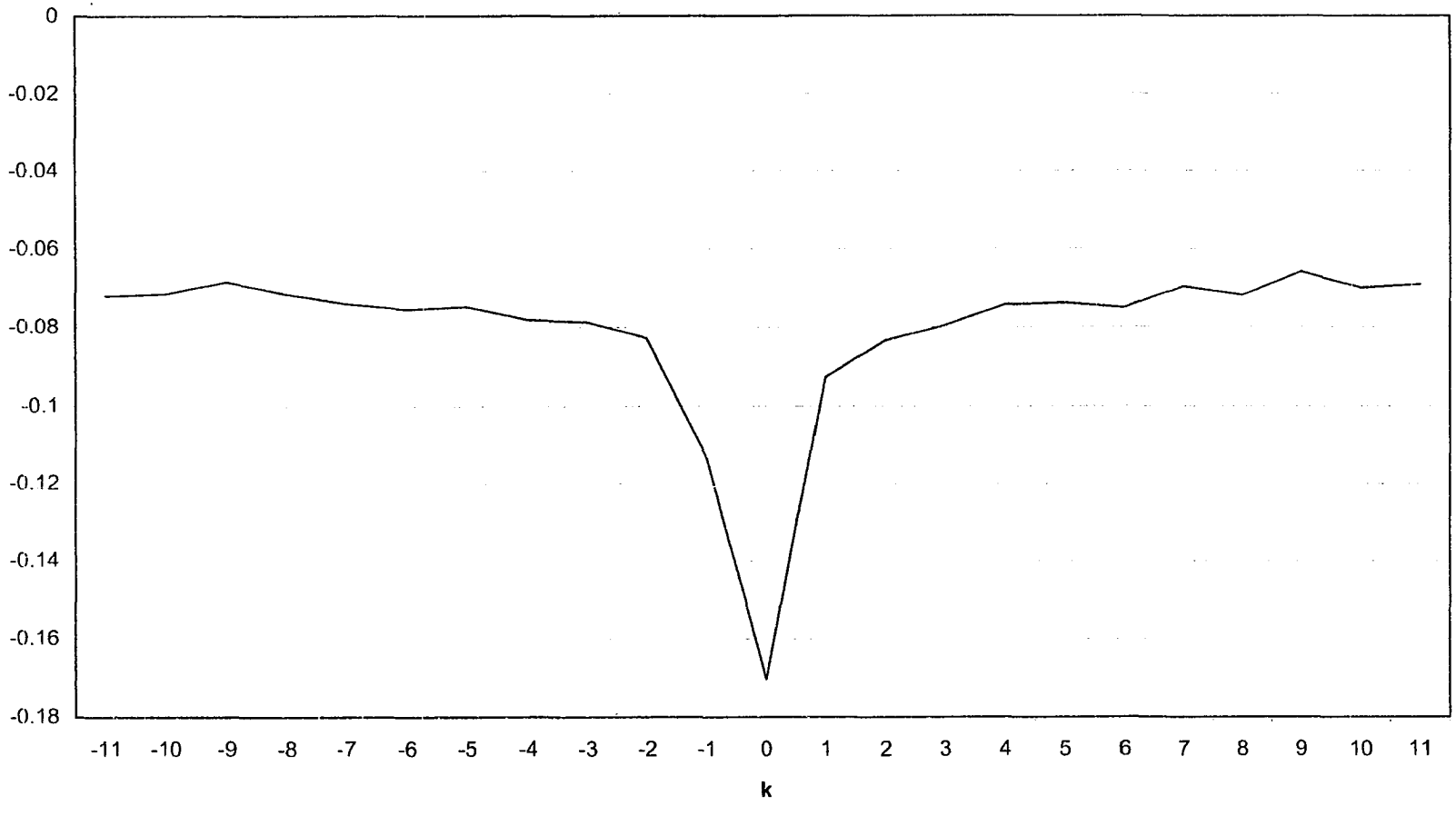

Chart C - YAHOO 1998. Crosscorrelation of fsmall [fraction of small trades] w/ volatility lagged by k minutes. The correlation is positive at all lags.

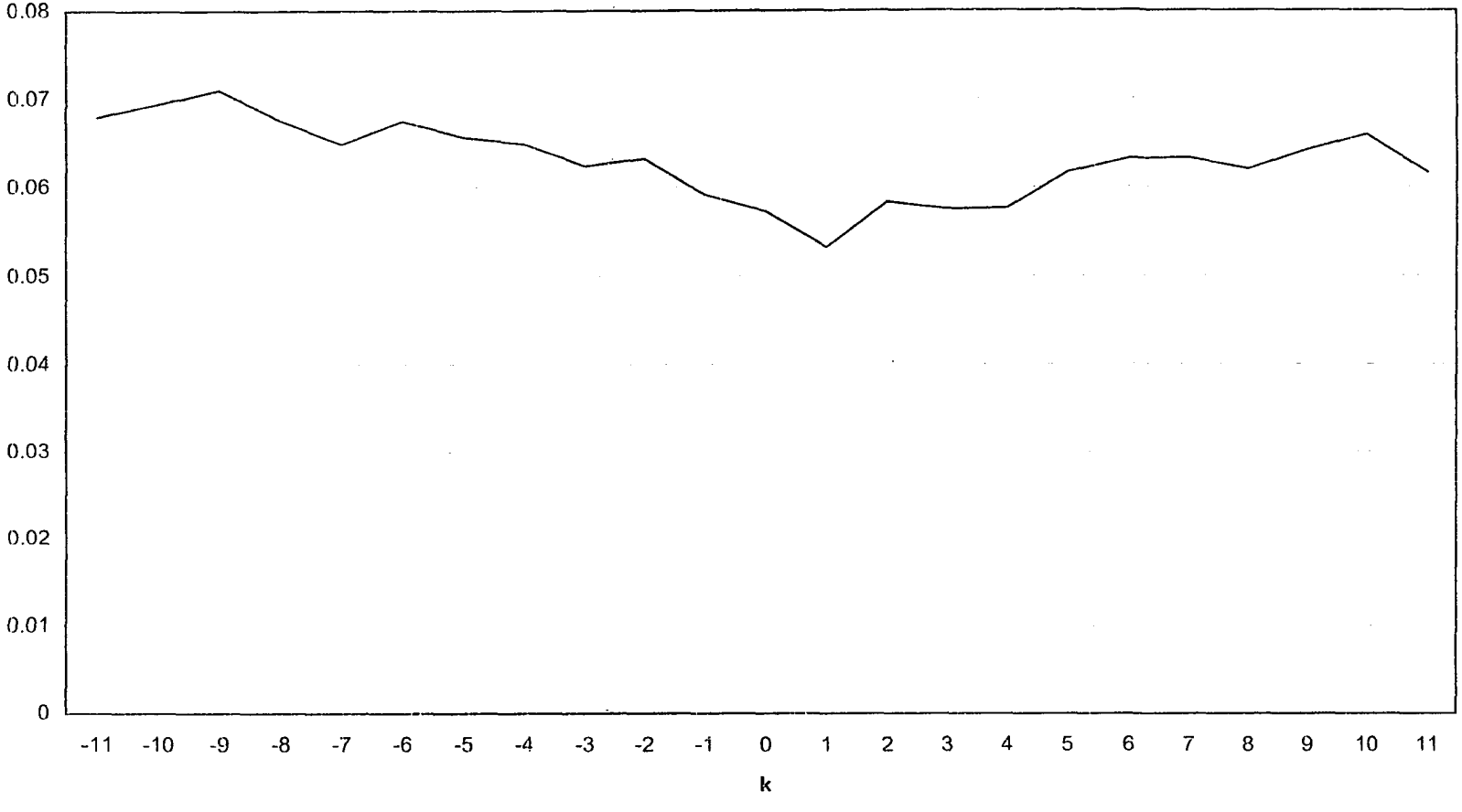

Chart D - GE 1998. Price behavior around each trade
(S/L/A=Small/Large/AllSizes; B/S/T=Buy/Sell/AllTrades)

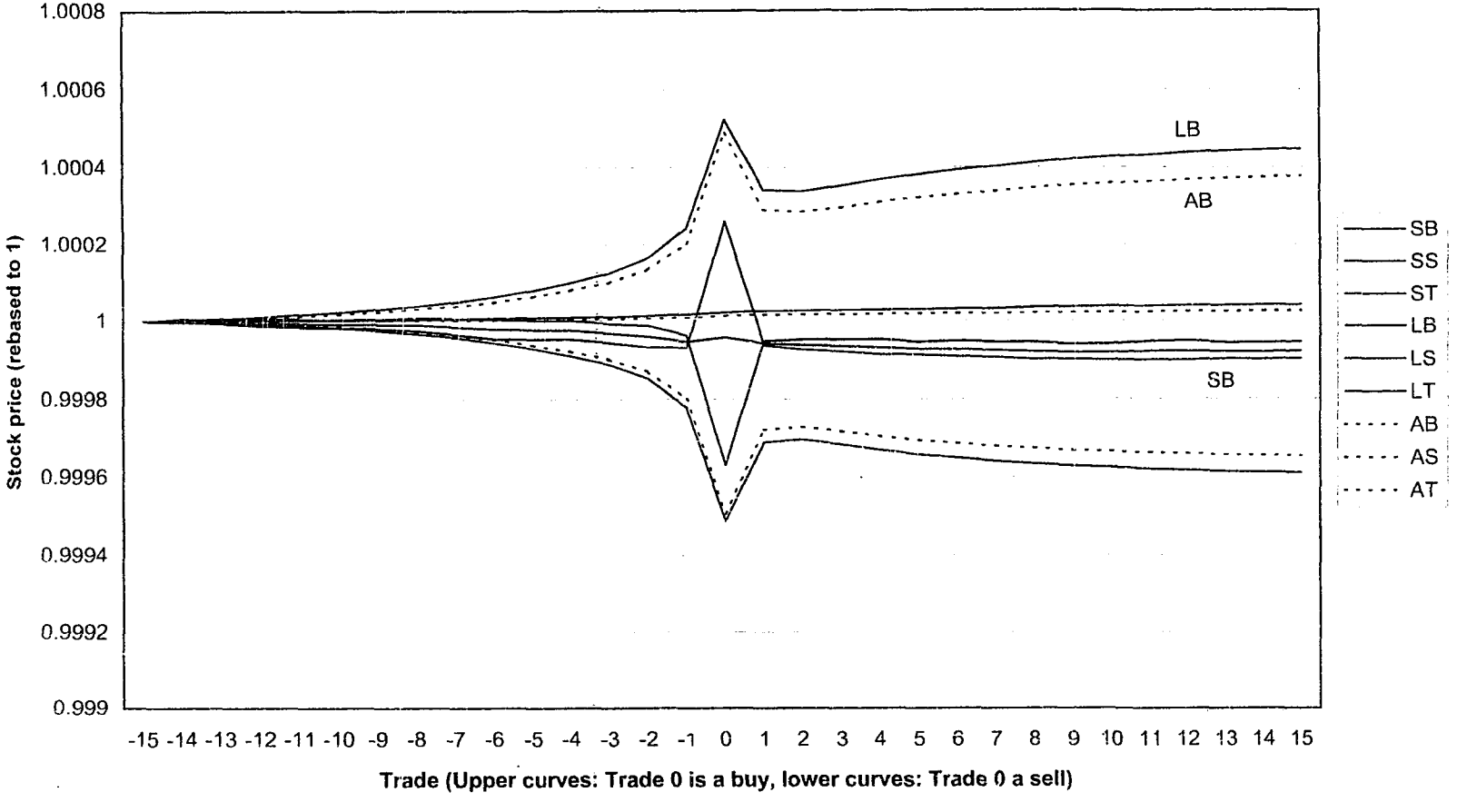

Chart E - Yahoo 1998. Price behavior around each trade
(S/L/A=Small/Large/AllSizes; B/S/T=Buy/Sell/AllTrades)

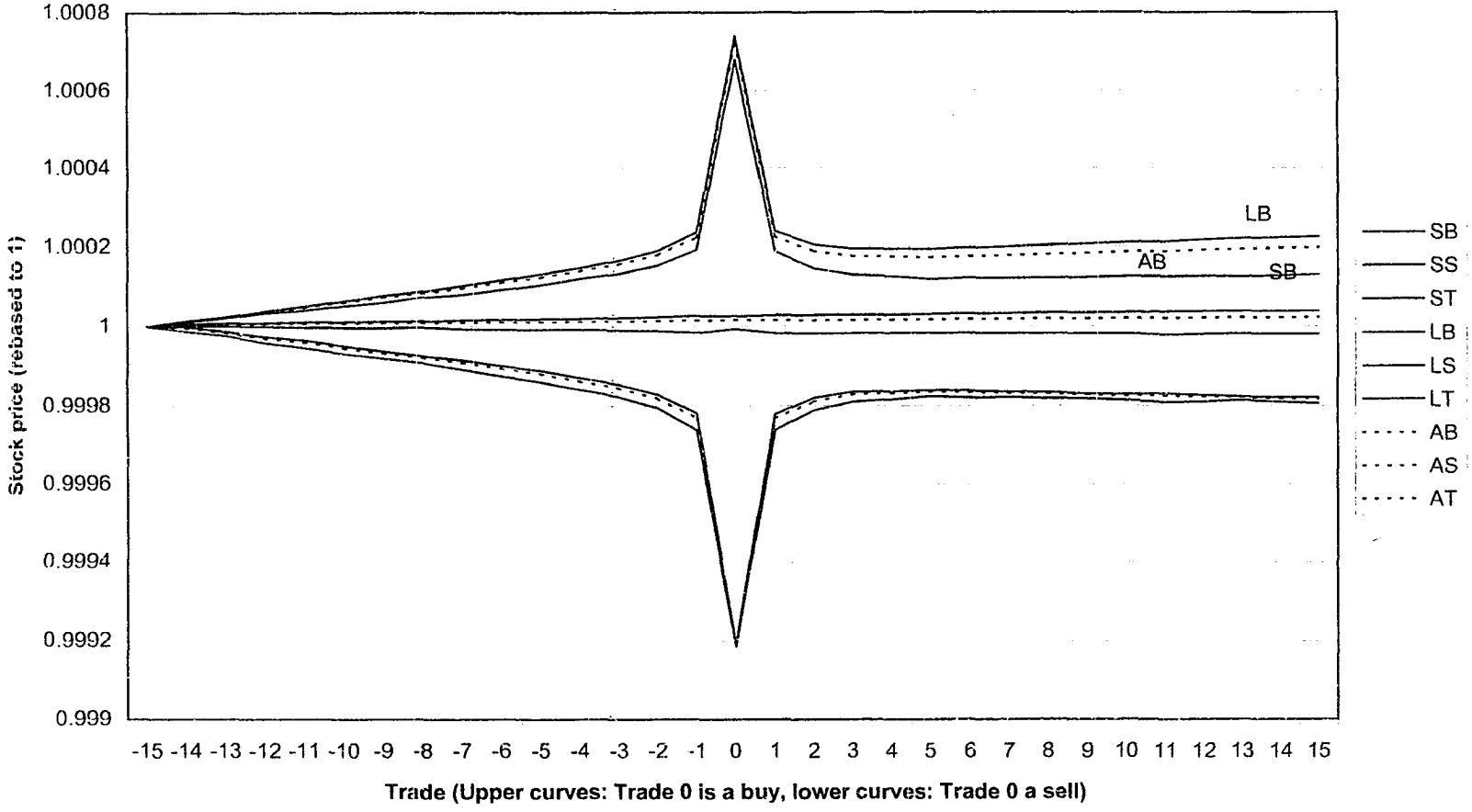

Chart F - GE 1998. Trade direction similarity
Probability that trade j is in the same direction (buy or sell) as trade 0

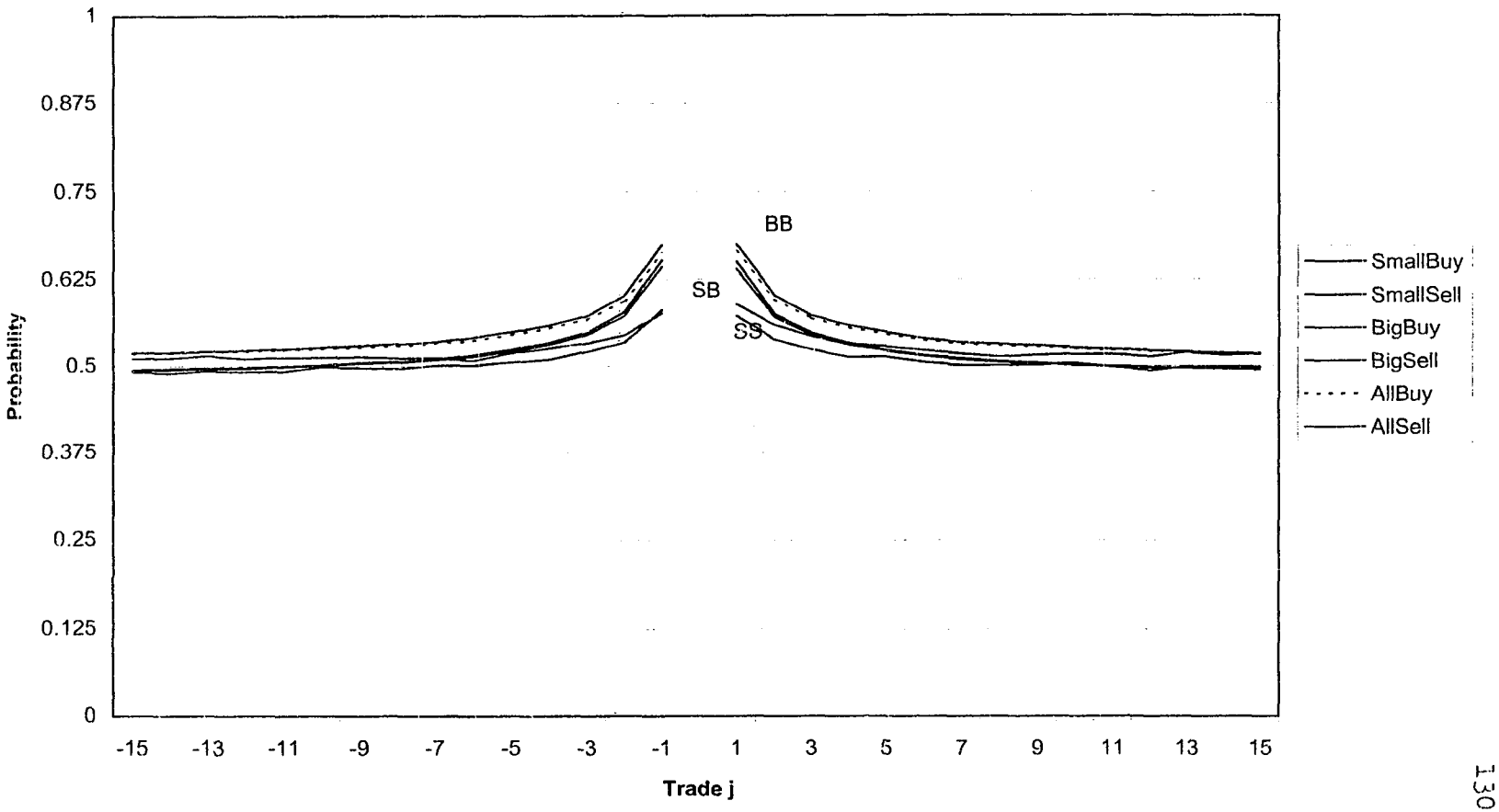

Chart G - Yahoo 1998. Trade direction similarity
Probability that trade j is in the same direction (buy or sell) as trade 0

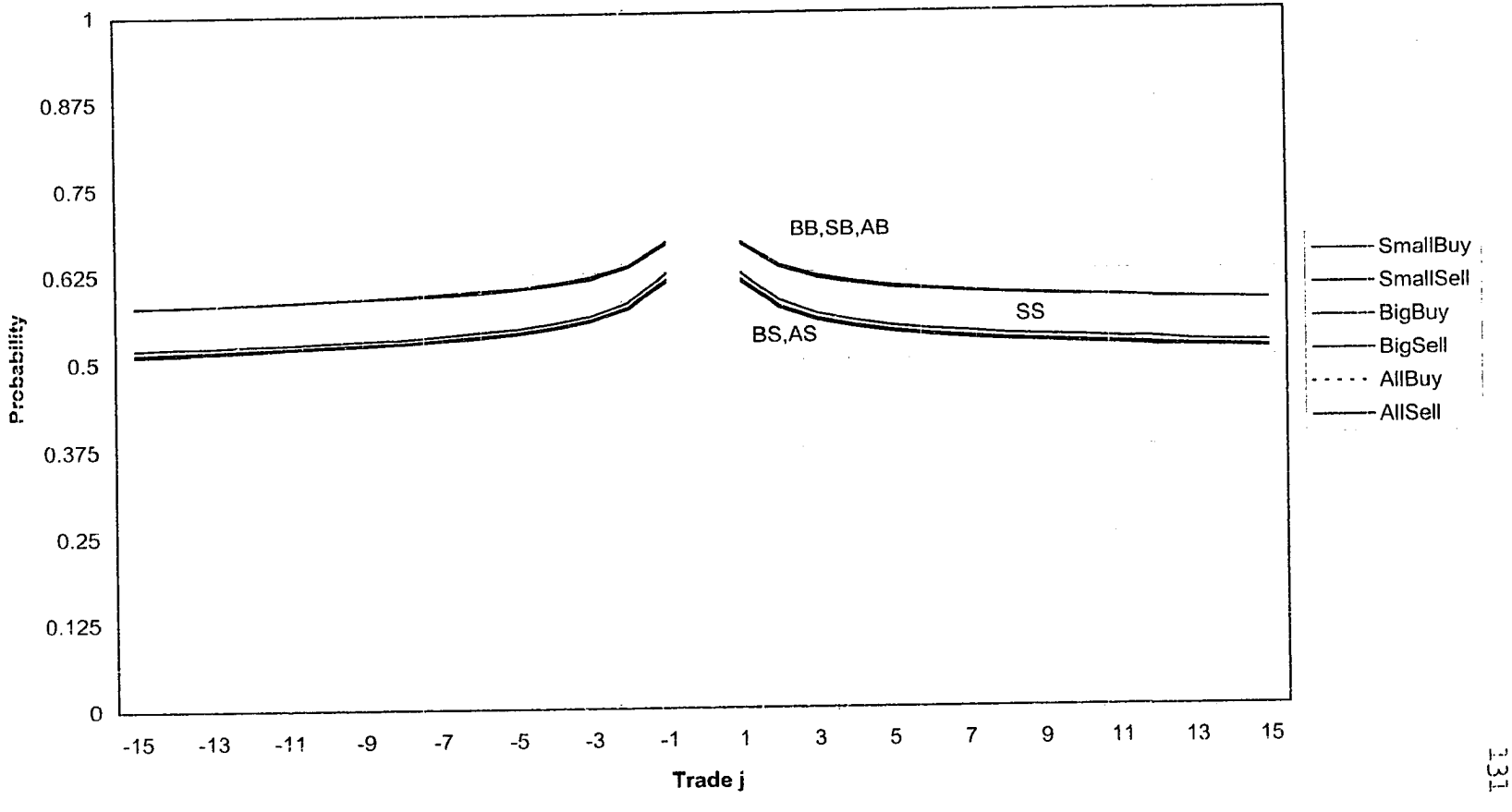

Figure A.1

Five minute volatility (y axis) vs Fraction of small trades (x axis)
for 95 stocks in 1998

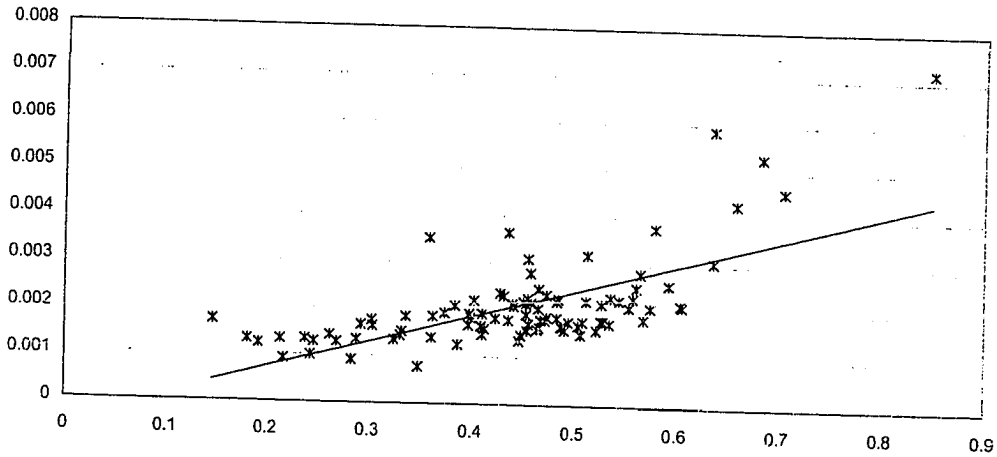

Table A.1
Characteristics of stocks having Low or High adjusted volatility (94 stocks, 1998)

Panel A: Exchange (NYSE vs NASDAQ)

	NYSE		
avol	No	Yes	Grand Total
Low	19	28	47
High	26	21	47
Grand Total	45	49	94

FISHER'S EXACT TEST
Two tail prob= 0.215218

Panel B: Market Capitalization (Big Cap: >$5.1B)

	BigCap		
avol	No	Yes	Grand Total
Low	30	17	47
High	17	30	47
Grand Total	47	47	94

FISHER'S EXACT TEST
Two tail prob= 0.012891

Panel C: Trading volume relative to shares outstanding

	HiRelVolu		
avol	No	Yes	Grand Total
Low	28	19	47
High	14	33	47
Grand Total	42	52	94

FISHER'S EXACT TEST
Two tail prob= 0.006668

Panel D: Technology/Medical/Internet stocks vs other stocks

	TechMedInet		
avol	No	Yes	Grand Total
Low	37	10	47
High	24	23	47
Grand Total	61	33	94

FISHER'S EXACT TEST
Two tail prob= 0.009001

[1] According to the Federal Reserve's Survey of Consumer Finances the proportion of households investing directly in equities rose from 15% in 1995 to 19% in 1998.

[2] These accounts generated nearly 40% of all retail trades in 1999. These figures are from the SEC (Barron's, April 11, 2000). A more disaggregated picture of the number of accounts at the end of 1999 is: Charles Schwab 6.6 million accounts, Etrade 1.56 million accounts (as of September 30, 1999), Ameritrade 0.686 million accounts.

[3] The North American Securities Administrators Association issued a report on day trading in August 1999. (www.nasaa.org). The 4000-5000 day traders estimate is contained in this report, where it is attributed to the Electronic Traders Association, a trade group. The reliability of this figure has not been independently verified. The ETA also estimated that day traders collectively make 150,000 to 200,000 trades per day.

[4] Online investors show signs of confusing good companies with good stocks, or at least do not make the distinction underlined in Statman & Stolt (1989) "Good Companies, Bad Stocks", *Journal of Portfolio Management*. Blanchard (2000) describes online investors thus: "Ils achètent les actions des compagnies en expansion, quelle que soit la somme: acheter Microsoft, Amazon ou Genzyme, c'est acheter l'avenir, ça n'a donc pas de prix. Ils achètent à la hausse: si les actions ont monté dans le passé, elles monteront à l'avenir. Ils vendent à la baisse.".

Chapter IV: Investigation of Changes in the Cross-Section Of Stock Volatility

1.0 Introduction

The phrase "In today's volatile stock market..." has become almost a cliché of newspaper and magazine articles published in the last few years. Price declines in particular are often described as being among the largest on record. This could be simply dismissed as a misperception by the general public, who tend to focus on point moves of the Dow Jones average instead of looking at daily percentage returns. But even among investment professionals concerns about abnormally high volatility are often heard; for example at the recent Baruch Conference on Market Structure, the head of Nasdaq trading at Bear Stearns, Aldo Parcesepe, said he had never seen such high volatility in his career[1]. The issue of recent stock market volatility therefore deserves a closer look.

When asked to back up their claims investors often cite Nasdaq stocks, or high technology stocks as examples of unusually high volatility. They draw attention to possible culprits such as SEC rule changes for Nasdaq that went in effect on September 27, 1997, or increased activity by retail traders operating through on line computer systems. Before addressing the causes, however, we need to document to what extent volatility has changed.

We proceed as follows: we examine the past volatility of the S&P500 and NASDAQ Composite (Section 1.1); we then define "popular stocks" and examine their volatility. This points out the emergence in recent years of a number of stocks with unprecedented high volatility (Section 1.2.3). We find that stocks which existed in 1984 are not appreciably more volatile now. It is the addition of new stocks to the "popular stock" universe which has brought about an increase in the median volatility of individual stocks. To reconcile the fairly steady volatility of the broad averages with the increased volatility of the median stock, we turn to an examination of the correlation of individual stock returns and market wide returns; we find some evidence that the correlation has decreased in recent years. Other authors who have addressed the same topic include

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[1] A summary of Parcesepe's remarks appears in Schwartz (2001), p. 47

Campbell and Lettau (2000), Xu and Malkiel (1999), although our research began independently.

1.1 Aggregate stock market volatility

Figure 1 shows calendar month volatility of the S&P500 and the NASDAQ composite based on daily closing prices. For the S&P500 average, claims of unusual volatility in the last 5 years receive only partial support. There is evidence of an upward spike in volatility in August-September 1998 and an irregular decline thereafter; this episode and its connection to the Russian default and the near failure of the hedge fund LTCM are discussed in detail in a separate chapter of this dissertation. It also appears that volatility in 1997 was somewhat higher than in 1994, but from a long term point of view the 1994 volatility appears depressed compared to the early 1990's, and the rise from 1994 to 1997 could be viewed as a return to more normal levels rather than a departure into uncharted territory. Although it is true that NASDAQ volatility is higher than S&P500 volatility, this is not a new phenomenon, but one that has recently increased.

Broad stock market averages are not the end of the story, however. Even if the volatility of the Standard & Poor 500 has not changed a great deal, it may still be the case that volatility could have increased for individual stocks.

1.2 The cross-section of individual stock volatilities

Since one of our hypotheses is that the universe of available stocks is changing, we cannot measure the volatilities of a predetermined group of stocks, such as the S&P500 or all the stocks in the CRSP tape. These lists of stocks change slowly based on the policies of Standard & Poor's and CRSP, and not necessarily based on investor behavior. The present study is based instead on a dynamically defined universe of stocks, with the list of stocks to be examined changing from year to year based on data available at the beginning of each year.

1.2.1 Definition of the universe: the "popular stocks"

Since the general public perceives the stock market to have become more volatile, it is logical to examine the stocks that are most often traded. These are in some sense, the most popular stocks at a point in time, the ones that are most followed and are considered representative by most investors.

We need a precise definition of "popular" or "much traded" stocks. Number of shares traded could be used, but clearly the volume of trade in dollars (rather than in number of shares) is a better indicator of economic significance of trading. Also, specific corporate events, such as an IPO, a merger, or an important announcement can cause a large volume of trading for a few days, but that would not make a stock a "popular stock" in a long term sense. Therefore we define a "popular stock" as a stock which consistently appears on the list of the day's biggest dollar volume stocks over a significant length of time, namely a year.

Another wrinkle in the definition concerns exchange traded versus NASDAQ stocks. As many researchers have pointed out, volume figures for NYSE/AMEX and NASDAQ stocks are not directly comparable. The multiple market-maker system on NASDAQ causes its volume to be overstated. According to Atkins and Dyl (1997) the overstatement is by a factor of two. Therefore we measure popularity using 'adjusted volume', which is the same as actual volume for NYSE/AMEX stocks, but is equal to half actual volume for NASDAQ stocks.

We defined two samples of stocks: The Popular 30 stocks and the Popular 1000 stocks. The 30 stock sample lets us examine and discuss the stocks individually, while the 1000 stock sample will be used for a more aggregated statistical comparison. The procedure is similar in both cases and uses the CRSP daily tape. To determine the Popular X stocks on 1/1/1985, we ranked stocks on each day of 1984 based on adjusted dollar volume. The number of appearances each stock makes among the top X (30 or 1000) is then computed for all of 1984. We classified as 'popular' or 'highly traded' stocks the X stocks that appear most often in the top X.

1.2.2 A small sample: the Popular 30

Examination of these lists shows that the identity of the popular 30 stocks, and their volatilities have changed in interesting ways over the years. The main conclusions are as

follows. (See Table 1, which shows the volatilities in 1984 and 1999 of the popular 30 stocks of 1/1/1984, and Table 2 which presents the popular 30 stocks of 1984 and the popular 30 stocks of 1999 side by side).

1.2.2.1 The rise of NASDAQ

On 1/1/1984, out of 30 stocks on the popular list, only one was traded on NASDAQ. Most were well established industrial companies. By 1/1/1998 the number of NASDAQ stocks had increased to nine. These, as well as some of the NYSE stocks, could be described as Technology stocks (in industries such as software and personal computers) rather than traditional manufacturing companies. Also the 1998 list included more "new" stocks, that is stocks with relatively less price history on the CRSP tape. So there was a qualitative shift in the kinds of stocks on the list.

1.2.2.2 Same stock, similar volatility

If we follow the 1984 popular stocks in the following years, we find that their volatility has varied over time, but not by a large amount (Table 1).

For example, we see that their average volatility increased from 29.97% in 1984 to 36.85% in 1998. We see therefore that on a "same stock" basis there was an increase in volatility (by 23%) during this period. Recall that August and September of 1998 were particularly volatile. The 1984 popular stocks were affected by this "macro" phenomenon.

1.2.2.3 The appearance of new, more volatile stocks

On the other hand if we compare the volatility of 1984's popular stocks to the volatility of 1998's popular stocks (Table 2) we see that the increase in volatility is greater (from 29.97% to 46.04%). Therefore one of the ways in which the stock market has changed in recent years is that a new set of stocks with high volatility have become popular.

In summary, from 1984 to 1998 there were two separate phenomena affecting popular stock volatility. There was an increase by 23% due to macro phenomena, and there was a further increase of 25% due to changes in the composition of the popular stock list. New high volatility stocks that appeared on the list included Sun Microsystems (1998 volatility 51%), Oracle Corp. (56%), Dell Computer (56%), CBS Corp (51%), Iomega (84%), Micron Technology (70%), Compaq Computer (51%), Seagate (69%), 3Com (58%), Bay Networks (59%) and Ascend Communications (58%). Most of these stocks are relatively new high technology stocks. A characteristic of such stocks is that their revenues and earnings are growing at a fast but highly variable rate; their future earnings are particularly difficult to predict, and thus the stocks are difficult to value.

If we had looked only at a fixed list of stock names (such as the Dow Jones stocks), we would have underestimated the increase in volatility during 1984-1998, and have attributed it mainly to the peculiar events of August and September of 1998. We would have missed the fact that the public has chosen to trade a new set of stocks that are highly volatile.

The most volatile popular stock on 1/1/1984 was Pan Am, with a volatility of 46% the following year. By contrast for the most recent popular stocks the highest 1999 volatility was Iomega with 84%, and several other stocks had volatilities well above 46%. In other words the cross sectional distribution of volatility has widened, with the most volatile stocks being new names that are even more volatile than the ones that could be considered highly volatile in the past.

1.2.3 A large sample: the Popular 1000

If we choose 1000 popular stocks, we have available 1000 volatilities, and it becomes possible to plot the cross-sectional distribution of volatilities using the Kernel Density Estimation procedure (Silverman(1986) is a reference for this technique).

1.2.3.1 NASDAQ vs NYSE

In 1984 154 of the Popular 1000 stocks were on the NASDAQ; by 1999 this had increased to 268. These 268 stocks were almost completely new: 259 were not in the 1984 list, versus only 9 that were.

So the NASDAQ component of the Popular 1000 increased in importance, and also underwent very high turnover (as a result of three forces: exit from the popular list, transfer to the NYSE, or rise to popularity of new stocks).

1.2.3.2 Same stock, similar volatility

Chart 3 is in some sense the equivalent of Table 1. It shows the distribution of volatilities for 1000 popular stocks in 1984 (dotted line), and for those very same stocks in 1999. Actually, out of the 1000 stocks on the 1/1/1984 list, more than half disappeared during the intervening years, so that 461 are included in the curve labeled 1999 volatility.

We do not expect a perfect agreement between the two curves (overall volatility was higher in 1999 than in 1984, and stocks with different volatilities may have disappeared at different rates between these dates). Nonetheless, the graph shows that there is qualitatively a good agreement in the shape of the two curves.

1.2.3.3 The appearance of new, more volatile stocks

Chart 4 is the equivalent of Table 2. It shows volatilities measured in 1999 for two groups of stocks: the stocks that survive from the Popular 1000 of 1984 (this is the same graph as appeared in Chart 3), and the Popular 1000 of 1999. Put another way, the first curve represents the stocks available to a stick-in-the mud investor who refuses to buy any stocks other than those he knew about when he began his investing career in 1984; while the second curve represents the stocks available to an up-to-date investor who is fully in touch with today's fashions on Wall Street. The curves could also be labeled "Old Economy" and "Today's Economy".

It is clear that the second curve is much more skewed than the first (Skewness of 5.53 versus 3.07). Stocks with 1999 volatilities higher than 45% are more common in the second curve than in the first. It appears that between 1984 and 1999 the menu of stocks available to investors has been revised to include a greater number of highly volatile stocks.

1.2.3.3.1 Significance testing

The skewness of volatilities for the 1999 popular stocks (5.33) is higher than the skewness for the 1984 popular stocks (2.77) (see Table 8). Is this result statistically significant or could it be due simply to chance? To answer this question, a Monte Carlo experiment was carried out.

We start with the approximately 1000 volatilities of 1984 and repeatedly perform the following two steps: (1) Select a volatility at random and eliminate it from the population. Each volatility is equally likely to be chosen. (2) Create a new stock with volatility equal to one of the existing volatilities chosen at random.

After performing these steps 654 times, we have obtained the volatility distribution that would have been observed in 1999 if popular stocks had been dropped and replaced at random. The skewness of the simulated distribution can then be computed.

When this experiment was performed 10,000 times, the skewness was never as high as 5.33 (the highest observed value was a little above 4), therefore we can conclude that at 1% significance level, the observed results are not due to random deletion/replacement of stocks with the same volatility distribution. In other words the increase in skewness is significant.

1.3 The co-movement of stocks

How to reconcile the existence of more hyper-volatile stocks (sections 1.2.2.3 and 1.2.3.3) with the fact that broad stock market indexes (such as the S&P 500) have seen little change in their volatility (section 1.2)? A first step is to examine whether stocks move together more or less than they used to. (Similar investigations have been carried out by Freund and Webb (1998) and Campbell, Lettau, Malkiel, Xu (2000)).

1.3.1 Market correlations

We can apply the market model

$R_{it} = A_i + B_i * M_{it} + eps_{it}$

Where M_{it} is the return on the CRSP Value Weighted Index. This equation was estimated by least squares for each of the 1000 Popular Stocks using 252 daily returns.

The most interesting parameter is the R**2 for the regression, which tells us what percentage of the variance of returns is explained by the market factor M_{it}.

A graph of the average R**2 as a function of time is shown in Chart 5. The highest average R**2 was 0.36, which occurred in 1988. The lowest was 0.10 in 1993 and 1994. There was a downward trend for most of this period, but the average R**2 has since returned to a level very close to what it was in 1984. The standard deviation of R*2 varied from 0.16 to 0.06 depending on the year.

The R-squareds tend to increase in highly volatile years (such as 1987 and 1998) making it difficult to judge the overall long term trend. Nevertheless the visual impression from Chart 5 is of a mild long term decline in average R**2.

1.3.2 Synchronicities

A simple measure of the extent to which stocks move together is the "synchronicity" defined by Morck Yeung and Yu (1999). It is the percentage of stocks that move in the same direction during a period, here taken as one week. Formally synchronicity is defined as

$$F_t = \mathrm{Max}[\, n_t^{UP}, n_t^{DOWN} \,] / (n_t^{UP} + n_t^{DOWN})$$

Where n_t^{UP} and n_t^{DOWN} represent the number of stocks with positive or negative return during week t. Synchronicity ranges between 0.5 and 1.0. Using CRSP data we computed synchronicity for the 1000 Popular Stocks on a Wednesday to Wednesday basis from 1984 to 1999. The synchronicity varies erratically from week to week, so a one year moving average was applied before plotting the data in Chart 6.

There is an irregular downward trend in synchronicity during this period. The synchronicity increases during volatile periods, but these peaks are becoming lower and lower. Although the synchronicity increased in 1998 and 1999, it is actually surprisingly low when one considers that this was a high volatility period. We conclude that synchronicity has declined during the period under review, especially when we compare say 1987 to 1998 or 1988 to 1999.

1.3.3 Conclusions on co-movement

Using both Correlations and Synchronicities, there is some visual evidence of a decreased tendency for co-movement among popular stocks during 1984-1999. In other words

stock price movements are somewhat more idiosyncratic and somewhat less systematic than was the case earlier (and this matches the conclusions of Malkiel et al (2000) and others). This partially helps explain why the S&P 500 volatility has not increased very much while enormous individual stock volatilities were increasingly being observed.

However, this explanation is not completely satisfactory and we are led to consider the possibility that the hyper-vol stocks are a new group of stocks that is not included in the S&P500 or other broad averages such as the Dow. This would imply that the S&P500 is becoming increasingly unrepresentative of the stocks that investors actively trade (the popular stocks).

2.0 Some characteristics of hyper-vol stocks

For this section we define a hyper-vol stock as a stock in the Popular 1000 list that had volatility of 70% or greater in 1999. There are 214 such stocks. We will describe their characteristics below.

2.1 Recent popularity

Only 16 of these 214 stocks are also in the Popular 1000 list of 1984, showing that the popularity of hyper-vol stocks is a comparatively new phenomenon.

2.2 S&P500 membership

Again only 16 out of 214 hyper-vol stocks are included on the Standard & Poor 500 list as of the end of 1998. In other words the S&P list largely excludes such stocks.

2.3 Nasdaq membership

A majority, 69%, of hyper-vol stocks are listed on the Nasdaq. Specifically there are 61 on the NYSE, 5 on the Amex and 148 on Nasdaq. The preponderance of Nasdaq stocks and paucity of S&P 500 stocks helps explain why in Chart 1 the volatility of the Nasdaq Composite is increasingly diverging from that of the S&P 500.

2.4 Recent IPO

The earliest date for which the CRSP database gives pricing data for a stock usually coincides with the Initial Public Offering date for the stock (although there can be exceptions). As of 1/1/1999 the median length of price data for a hyper-vol stock was 5.5 years. Therefore half of these stocks have gone public between June 1993 and December 1998. Many are even younger, for example one quarter of the hyper vol stocks went public in 1996, 1997 or 1998 (i.e. during the previous three years).

2.5 Concentration in *Technology and Telecommunications industries*

The 4 most common SIC codes for hyper-vol stocks are: 7370 (Computer and Data Processing Services) 39 companies, 3670 (Electronic Components) 14 companies, 7372 (Prepackaged Software) 12 companies, 3660 (Communications Equipment) 10 companies.

2.6 The probability of long term survival

By "survival" we mean the continued listing of a stock on the CRSP tape under the same Permno. A stock can disappear either because the company goes out of business or is acquired by another company with a different Permno. Generally low-volatility stocks survive longer than high volatility stocks. For example in Table 8 panel A we see that stocks that were popular in 1984 and survived until 1999 had an average volatility of , those that did not survive had a volatility of ... on average in 1984. Among the highest volatility stocks the survival rate is quite low: among 55 popular stocks of 1984 that had vol > 70% only 14 survived as independent companies through 1999. Generally (12 out of 14 cases) they were no longer on the popular list in 1999, even though they were still traded.

If this pattern continues we can expect that only a small fraction of the 215 hyper-vol stocks of 1999 will be around 15 years from now. (Whether shareholders will experience a satisfactory rate of return is another matter, which we do not address).

3.0 Conclusions

To summarize, there is an increased skewness in the distribution of U.S. stock volatilities. We can find stocks today with volatilities so high that they would have been rare or non-

existent 15 years ago. And these are actively traded stocks, not just obscure names that start popping up in the CRSP tape because of efforts by the data base's managers to increase their coverage.

In presenting the results of his study Xu (1999) stated that "the most volatile stocks are becoming more volatile". The findings here go beyond this by showing that we are seeing a new set of stocks exceed in volatility the stocks that were previously considered highly volatile. There is a change in the population of high vol stocks, rather than simply an increase in the volatility of a fixed list of stocks. To use an analogy, suppose a steady patron of a Chinese restaurant tells us that "the spiciest dishes are becoming spicier" there are two ways this could happen: more spice added to existing spicy dishes, or entirely new dishes added to the menu that are spicier than the previous. This study makes clear that, in the U.S. stock market, it is the latter that has taken place.

At the same time, there is a tendency for stock returns to be less correlated than they used to be, although this trend was interrupted by the market-wide turmoil of Summer 1998. Lessened correlations were also found by Freund and Webb (1998), Morck, Yeung and Yu (1999), Campbell el al. (2000); our study simply confirms this using more recent data.

There are a number of possible explanations for these findings. More companies are going public, and at an earlier date than previously; companies with a limited operating history are likely to be volatile (their future cash flows are highly uncertain). The investing public is nonetheless willing to bear this risk, both because of greater personal wealth and greater diversification. The risk of this kind of company is likely to be idiosyncratic and hence easily diversifiable.

The decline in correlations may have a number of other causes. More information may be one. Better informed investors mark the prices of stocks up or down based on company specific information rather than on broad economy-wide or industry-wide factors. Morck and Yeung show this to be true across both developed and emerging stock markets. In addition U.S. company strategies are more focused than they used to be, with the conglomerate or multi-business type of company almost disappearing from

the scene and more and more businesses pursuing niche strategies. The new companies mentioned earlier, in particular, are almost always single product companies.

This study has implications for investors, regulators and academics. Investors should be aware that the individual volatilities of the most volatile stocks today are quite high by historical standards. These stocks are a different animal altogether compared to the volatile stocks of 15 or more years ago. Also, because correlations are lower than previously, a larger number of stocks is required to achieve a given level of portfolio diversification.

Regulators may want to ask whether the general public is fully aware of the risks inherent in today's volatile stocks. If not, what educational or information disclosure initiatives would be appropriate?

Academics should supply a better theoretical explanation for the changes in stock volatility that we are seeing.

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Tables and Figures

See following pages.

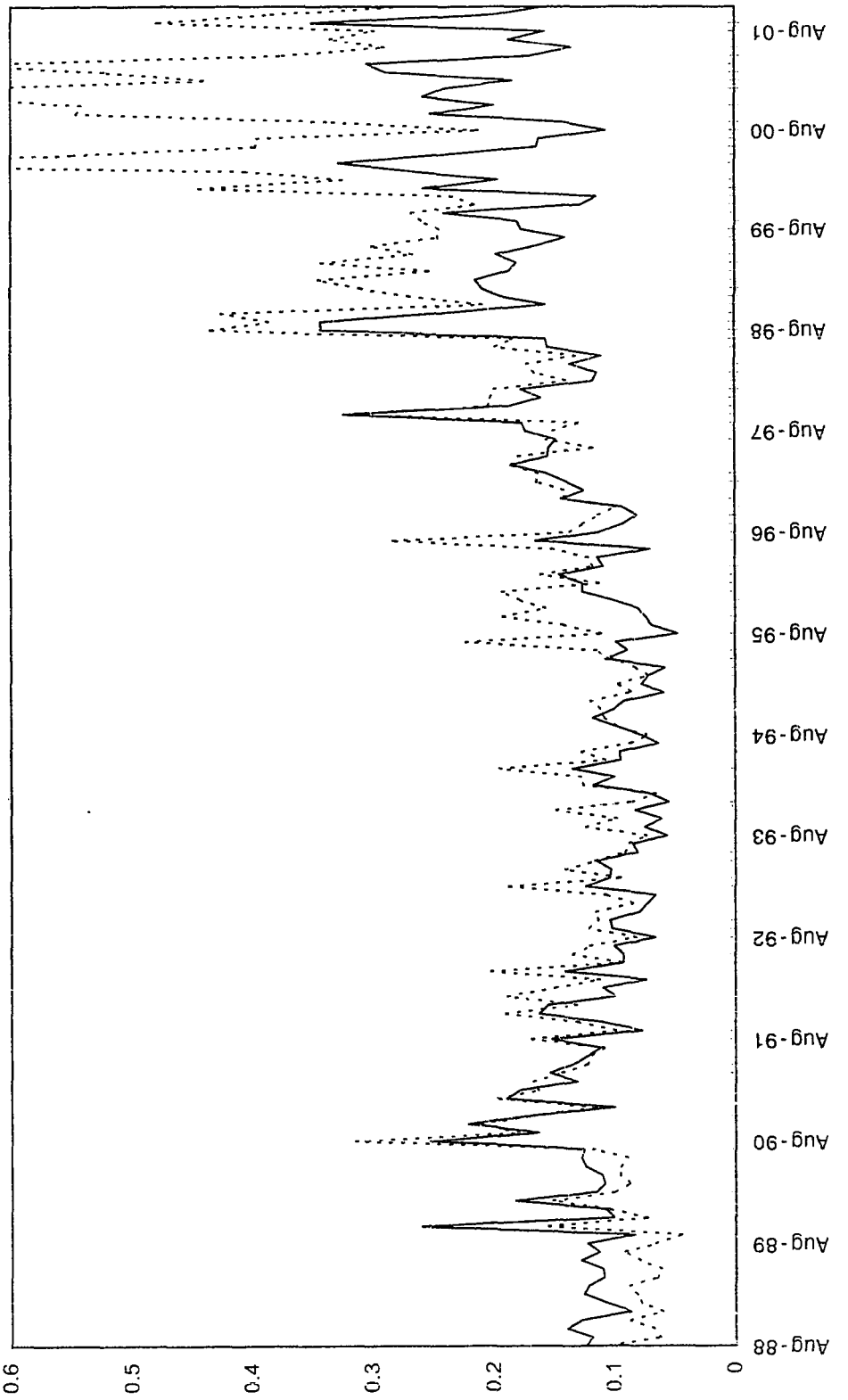

Chart 1. 1988-Nov 2001. S&P 500 volatility (monthly, annualized)
NASDAQ volatility [dashed line]

Table 1
Volatility in 1984 and 1998 for 30 stocks highly traded in 1983

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Permno	Name	1984 CC Volatility	1984 Resid Vol	1984 R^2	1984 Beta	1998 CC Volatility	1998 Resid Vol	1998 R^2	1998 Beta
10401	A T & T Corp	0.2459	0.2204	0.1789	0.752	0.3222	0.2844	0.2126	0.913
10604	Atlantic Richfield Co	0.2284	0.2229	0.1813	1.070	0.2954	0.2740	0.2136	0.678
11260	Chrysler Corp	0.4164	0.3292	0.3725	2.561	0.4886	0.4004	0.2483	0.931
11754	Eastman Kodak Co	0.1900	0.1660	0.1467	0.647	0.3311	0.3124	0.1064	0.622
11850	Exxon Corp	0.1852	0.1684	0.2370	0.802	0.2574	0.2539	0.3684	0.948
12060	General Electric Co	0.2058	0.1406	0.4736	1.345	0.2891	0.1794	0.6247	1.285
12079	General Motors Corp	0.2111	0.1510	0.4800	1.344	0.3263	0.2646	0.3023	0.905
12490	Ibm Corp	0.1917	0.1149	0.5572	1.303	0.3045	0.2465	0.4291	1.318
12749	K Mart Corp	0.2742	0.2171	0.3252	1.559	0.4924	0.4235	0.1576	0.934
13856	Pepsico Inc	0.1922	0.1677	0.1779	0.749	0.4297	0.3815	0.2976	1.121
14090	R C A Corp	0.2727	0.1998	0.3638	1.636				
14322	Sears Roebuck & Co	0.2874	0.2289	0.4602	1.748	0.4001	0.3293	0.3466	1.219
14541	Chevron Corp	0.2380	0.2188	0.2358	1.114	0.2928	0.2810	0.2827	0.853
15560	Tandy Corp	0.3441	0.3222	0.1473	1.296	0.4817	0.4245	0.2688	1.182
15966	Mobil Corp	0.2600	0.2405	0.2600	1.142	0.3099	0.2935	0.3107	0.870
16432	Goodyear Tire & Rubr Co	0.2638	0.2115	0.3008	1.368	0.3041	0.2616	0.2993	0.831
20626	Dow Chemical Co	0.2635	0.2130	0.2958	1.373	0.2559	0.2143	0.3746	0.798
20853	Unicom Corp Holding Co	0.2471	0.2347	0.0801	0.549	0.2013	0.2113	0.1511	0.600
20984	Pan Am Corp	0.4645	0.4269	0.1319	1.482				
21020	A M R Corp Del	0.3898	0.3219	0.2603	1.845	0.4365	0.3623	0.2877	1.049
21709	Superior Oil Co	0.2082	0.2027	0.1013	1.008				
22111	Johnson & Johnson	0.2634	0.2294	0.2194	0.977	0.2650	0.2203	0.4421	1.036
25785	Ford Motor Co Del	0.3272	0.2370	0.4643	2.022	0.3944	0.3170	0.2969	1.012
38551	Warner Communications Inc	0.3923	0.3677	0.0706	0.933				
43916	*Digital Equipment Corp*	0.3095	0.2542	0.2158	1.577	0.4555	0.4566	0.1607	1.195
47079	Citicorp	0.2706	0.2170	0.2928	1.445	0.5581	0.4370	0.3941	1.529
50404	M C I Communications Corp	0.5302	0.4701	0.1945	2.262	0.3647	0.2819	0.1063	0.839
51043	Fed Natl Mtg Assoc	0.5293	0.4394	0.3090	2.469	0.3311	0.2541	0.4293	1.201
52919	Merrill Lynch & Co Inc	0.4471	0.3232	0.3979	2.511	0.5622	0.4176	0.5098	1.895
59176	American Express Co	0.3422	0.2555	0.2952	1.745	0.4324	0.3054	0.4782	1.338
	Average	0.2997	0.2504	0.2742	1.421	0.3685	0.3111	0.3115	1.042
	Median	0.2672	0.2259	0.2602	1.357	0.3311	0.2889	0.2985	0.980
	SEE of Average	0.0181	0.0161	0.0234	0.100	0.0191	0.0154	0.0251	0.057

See Table 2 for Column descriptions

Table 2
1984 Volatility of 30 stocks highly traded in 1983 (left)
1998 Volatility of 30 stocks highly traded in 1997 (right)

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Permno	Name	1984 CC Volatility	1984 Resid Vol	1984 R^2	1984 Beta
10401	A T & T Corp	0.2459	0.2204	0.1789	0.752
10604	Atlantic Richfield Co	0.2284	0.2229	0.1813	1.070
11260	Chrysler Corp	0.4164	0.3292	0.3725	2.561
11754	Eastman Kodak Co	0.1900	0.1660	0.1467	0.647
11850	Exxon Corp	0.1852	0.1684	0.2370	0.802
12060	General Electric Co	0.2058	0.1406	0.4736	1.345
12079	General Motors Corp	0.2111	0.1510	0.4800	1.344
12490	Ibm Corp	0.1917	0.1149	0.5572	1.303
12749	K Mart Corp	0.2742	0.2171	0.3252	1.559
13856	Pepsico Inc	0.1922	0.1677	0.1779	0.749
14090	R C A Corp	0.2727	0.1998	0.3638	1.636
14322	Sears Roebuck & Co	0.2874	0.2289	0.4602	1.748
14541	Chevron Corp	0.2380	0.2188	0.2358	1.114
15560	Tandy Corp	0.3441	0.3222	0.1473	1.296
15966	Mobil Corp	0.2600	0.2405	0.2600	1.142
16432	Goodyear Tire & Rubr Co	0.2638	0.2115	0.3008	1.368
20626	Dow Chemical Co	0.2635	0.2130	0.2958	1.373
20853	Unicom Corp Holding Co	0.2471	0.2347	0.0801	0.549
20984	Pan Am Corp	0.4645	0.4269	0.1319	1.482
21020	A M R Corp Del	0.3898	0.3219	0.2603	1.845
21709	Superior Oil Co	0.2082	0.2027	0.1013	1.008
22111	Johnson & Johnson	0.2634	0.2294	0.2194	0.977
25785	Ford Motor Co Del	0.3272	0.2370	0.4643	2.022
38551	Warner Communications In	0.3923	0.3677	0.0706	0.933
43916	Digital Equipment Corp	0.3095	0.2542	0.2158	1.577
47079	Citicorp	0.2706	0.2170	0.2928	1.445
50404	M C I Communications Corp	0.5302	0.4701	0.1945	2.262
51043	Fed Natl Mtg Assoc	0.5293	0.4394	0.3090	2.469
52919	Merrill Lynch & Co Inc	0.4471	0.3232	0.3979	2.511
59176	American Express Co	0.3422	0.2555	0.2952	1.745
	Average	0.2997	0.2504	0.2742	1.421
	Median	0.2672	0.2259	0.2602	1.357
	SEE of Average	0.0181	0.0161	0.0234	0.100

Permno	Name	1998 CC Volatility	1998 Resid Vol	1998 R^2	1998 Beta
10078	Sun Microsystems Inc	0.5077	0.4397	0.3102	1.662
10104	Oracle Corp	0.5596	0.5001	0.2257	1.675
10107	Microsoft Corp	0.3806	0.2712	0.4043	1.250
10401	A T & T Corp	0.3222	0.2844	0.2126	0.913
11042	Mci Worldcom Inc	0.3970	0.2936	0.2973	1.223
11081	Dell Computer Corp	0.5658	0.4327	0.3958	1.953
11260	Chrysler Corp	0.4886	0.4004	0.2483	0.931
11308	Coca Cola Co	0.3122	0.2543	0.4458	1.128
11850	Exxon Corp	0.2574	0.2539	0.3684	0.948
12060	General Electric Co	0.2891	0.1794	0.6247	1.285
12490	Ibm Corp	0.3045	0.2465	0.4291	1.318
12749	K Mart Corp	0.4924	0.4235	0.1576	0.934
13856	Pepsico Inc	0.4297	0.3815	0.2976	1.121
13901	Philip Morris Cos Inc	0.3017	0.2920	0.2399	0.980
15368	C B S Corp	0.5098	0.4415	0.2376	1.145
22752	Merck & Co Inc	0.2945	0.2338	0.4056	1.158
22779	Motorola Inc	0.4155	0.3684	0.2864	1.314
25785	Ford Motor Co Del	0.3944	0.3170	0.2969	1.012
27828	Hewlett Packard Co	0.4055	0.3604	0.3021	1.227
45891	Iomega Corp	0.8367	0.8173	0.0724	1.075
53613	Micron Technology Inc	0.6992	0.6375	0.1986	1.745
55976	Wal Mart Stores Inc	0.3630	0.2611	0.3934	1.135
59328	Intel Corp	0.4130	0.3356	0.3431	1.417
68347	Compaq Computer Corp	0.5155	0.4483	0.3158	1.743
69607	Seagate Technology	0.6874	0.6172	0.2064	1.673
76076	Cisco Systems Inc	0.4601	0.3298	0.4528	1.669
76129	3Com Corp	0.5852	0.5229	0.2289	1.657
76171	Columbia Hca Healthcare	0.4464	0.4015	0.1409	0.875
76754	Bay Networks Inc	0.5943	0.5535	0.2509	1.891
80506	Ascend Communications In	0.5843	0.4992	0.1599	1.506
	Average	0.4604	0.3933	0.2983	1.319
	Median	0.4380	0.3749	0.2971	1.239
	SEE of Average	0.0252	0.0257	0.0209	0.059

Column descriptions
CC Volatility: Close to Close Volatility annualized. The next three columns are based on the market model R(t) = A+B*RM(t)+EPS(t) estimated by least squares using a year of daily data
Resid Vol: Standard deviation of the residual EPS(t) annualized
R^2: R Squared from the market model regression, ie the percentage of return variance that is explained by the CRSP Value Weighted Index
Beta: Coefficient B estimated from the market model

Chart 3 - Distributions of Volatilities for Popular 1000 Stocks of 1/1/1984 In 1984 [dashed line]. In 1999 [black line] (survivors only)

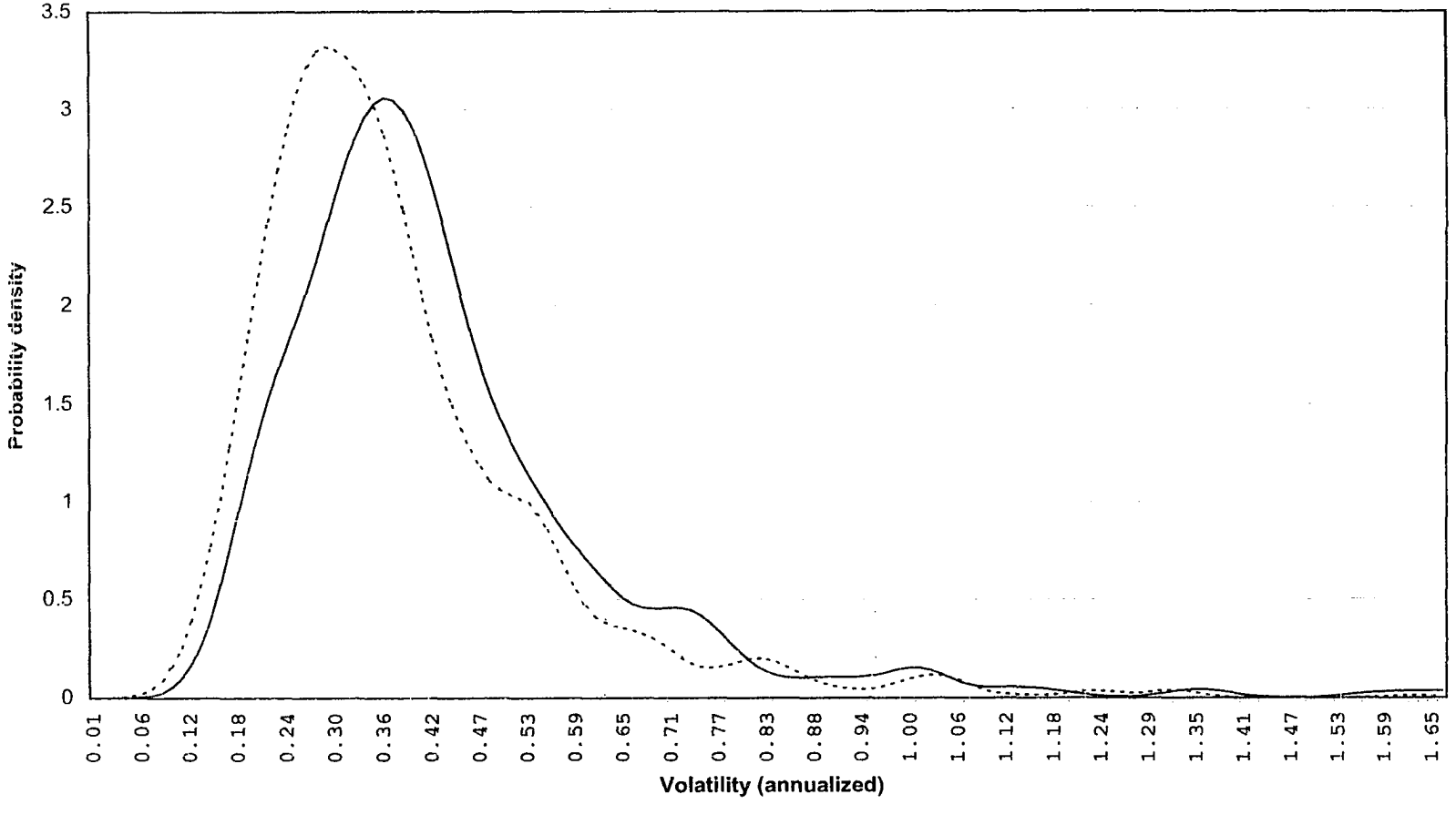
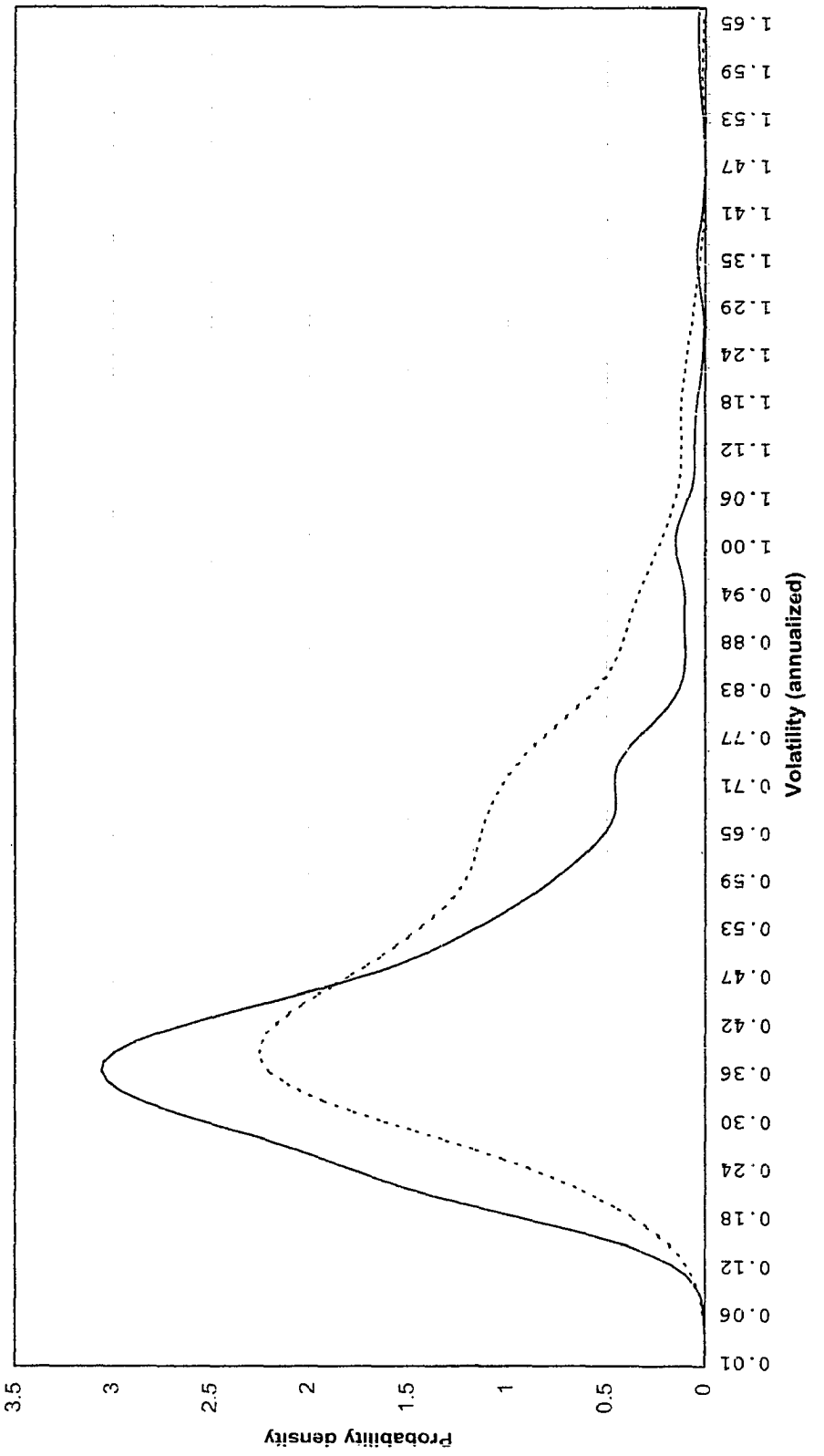


Chart 4 - Distributions: Volatilities of 1000 popular stocks of 1/1/1984 in 1999 (survivors)
Volatilities of 1000 popular stocks of 1/1/1999 in 1999 [dotted line]



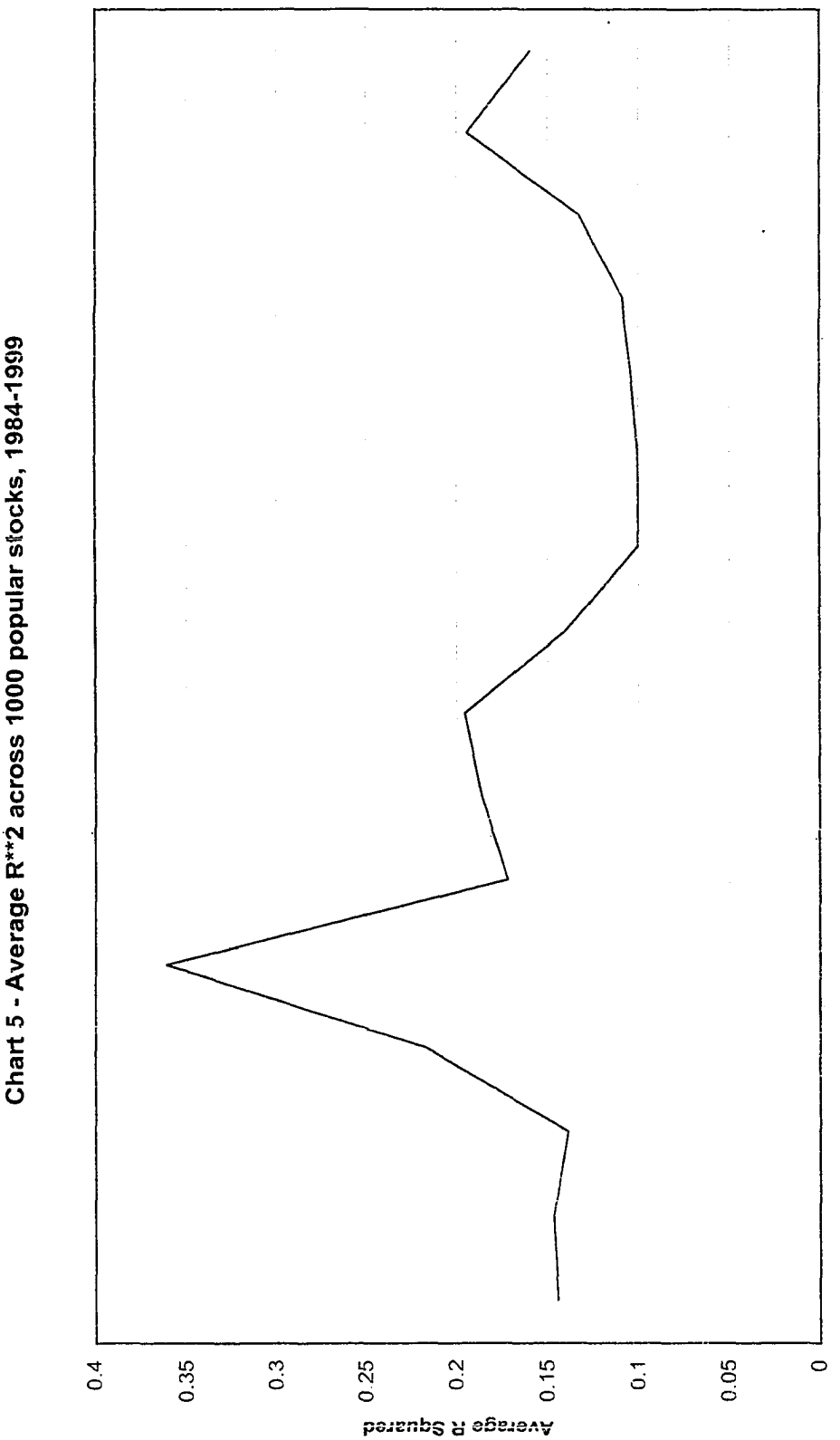


Chart 5 - Average R**2 across 1000 popular stocks, 1984-1999

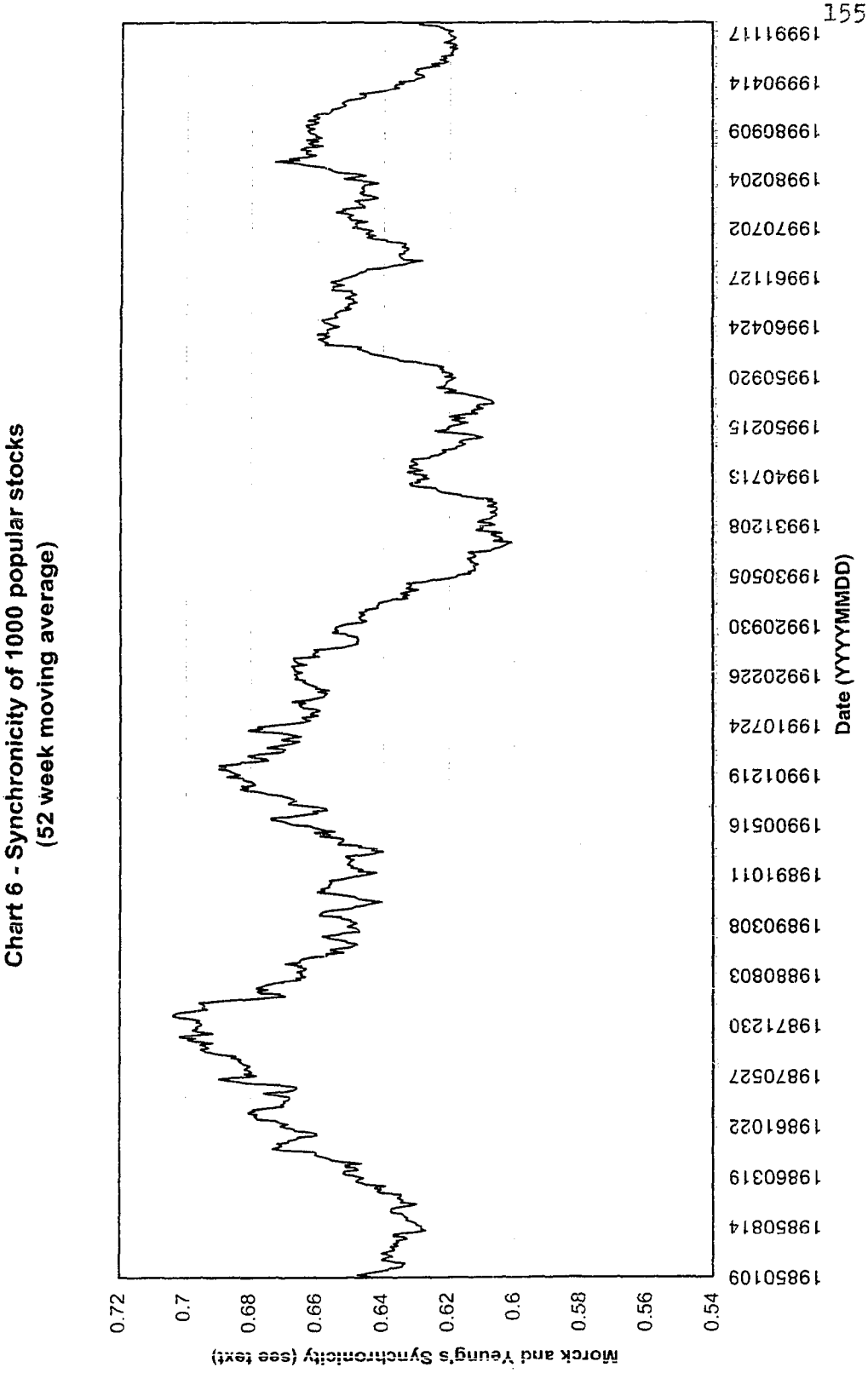
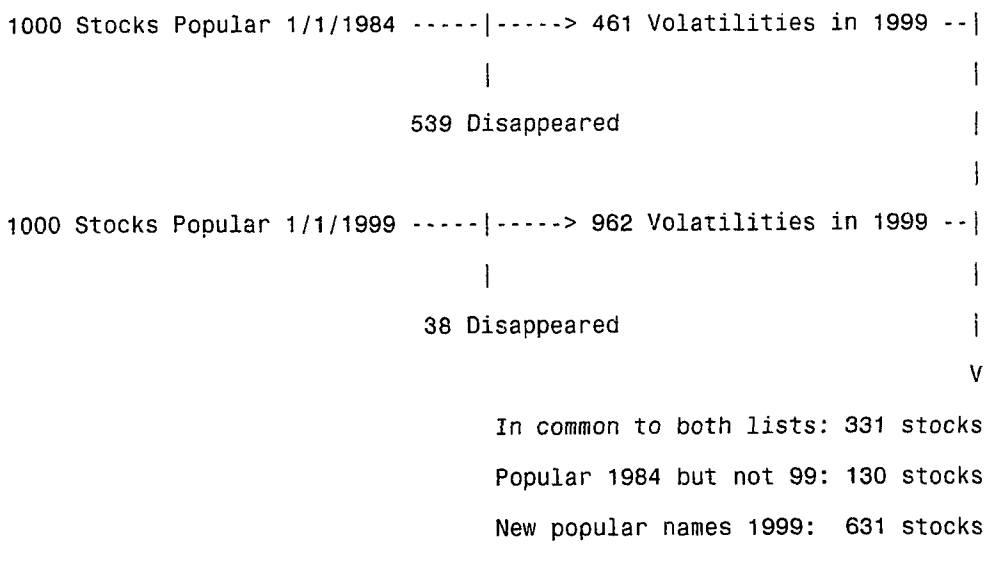


Table 7

Panel A. Relationship among Popular 1000 of 1984 and Popular 1000 of 1999



Panel B. Fate of Popular 1000 of 1984

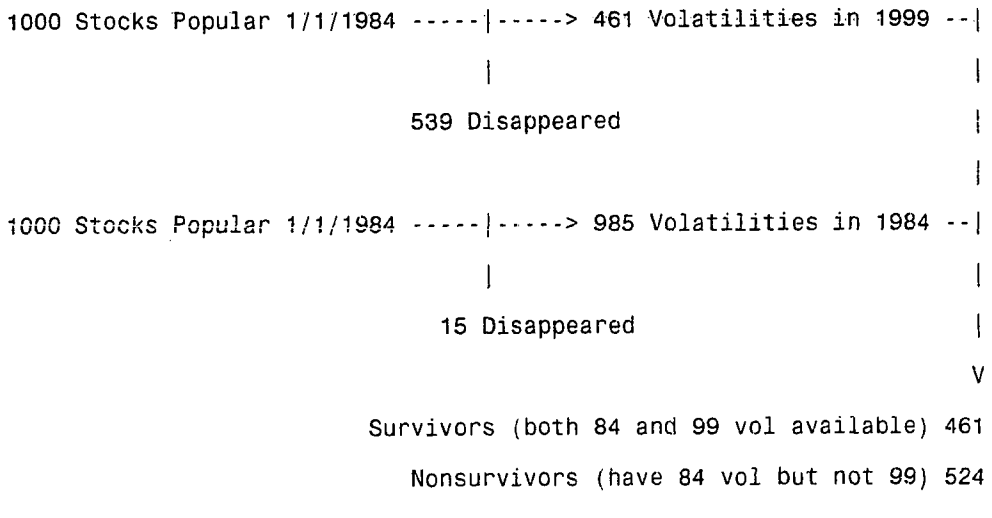


Table 8

Descriptive Statistics for Various Volatility Populations

Panel A. 1984 Volatilities

Stock population	N	Average	Median	StdDev	Skew
Popular 1984	985	37.897%	33.429%	19.728%	2.77
Pop84 alive 1999	461	33.535%	30.432%	14.558%	1.61
Pop84 not alive 99	524	41.735%	36.525%	22.679%	2.77
Pop84 unpop 1999	130	41.029%	36.821%	18.674%	0.98

Panel B. 1999 Volatilities

Stock population	N	Average	Median	StdDev	Skew
Pop84 alive 1999	461	43.862%	38.371%	24.450%	3.07
Popular 1999	962	55.117%	47.546%	33.079%	5.53
Pop84 unpop 1999	130	53.823%	40.447%	37.926%	2.04
Pop84 and pop99	331	39.950%	37.438%	14.717%	1.58
Pop1999, not 84	631	63.073%	56.462%	37.035%	5.45

Panel C. Pairwise differences: 1999 Volatility Minus 1984 Volatility

Stock population	N	Average	Median	%positive	StdDev
Pop84 alive 1999	461	10.327%	7.657%	78.5%	20.7%

Source: Namanal3.xls, Namanal2.xls

Chapter V: Summary and Conclusions

1.0 Summary

The first chapter concerned the volatility of daily S&P 500 returns during all calendar months from 1928 to 1999. Using two statistical tests (the Lilliefors and Wilk-Shapiro tests) it was shown that the change from month to month in log-volatility is not Normally Distributed. This contradicts the most common theoretical models of volatility change, which assume a volatility that drifts according to a Geometric Random Walk. Instead the data show very large (non-normal) increases and decreases in vol, with a preponderance of large increases (i.e. a positive skewness). A third statistical test, using the volatility of volatility during rolling 6 month periods, came to similar results. We then presented a series of graphs documenting the occurrence in the historical record of volatility spikes consisting of a very rapid increase (usually in 1 month) and a slower (2 to 6 months or so) return to normal.

Applying the Haugen, Torous and Talmor procedure for detection of vol changes showed that during the 1990's (a period not covered in HTT's original paper) there were 19 statistically significant vol changes, compared to 18 during the 1980's. Thus the erratic behavior of volatility noted by HTT has continued (actually increased slightly) since the publication of their paper.

We then reviewed, in narrative form, the events that accompanied the volatility spikes of October 1987 and August-September 1998. Short-term disruptions of liquidity in the financial markets featured prominently in both episodes; while some market participants sought to disengage from market participation, others had an urgent need to transact for risk control reasons. We argue that theoretical models proposed by Pagano in 1989 and Allen and Gale in 1994 that link volatility to the level of market participation are relevant to both episodes.

We propose that Behavioral Finance concepts may be helpful in understanding volatility spikes. As Shefrin and Statman have emphasized the behavior of investors differs depending whether they have gains or losses; as Greenspan and others have stated, investors seek to disengage when uncertainty reaches an extreme level. These asymmetries lead to reduced liquidity during a market decline. If the price of stocks

declines for any reason (perhaps the end of a bubble, perhaps bearish economic news), reluctance to realize losses will mean reduced trading and liquidity. If the circumstances are sufficiently murky and ambiguous that investors temporarily disengage from participating, market liquidity will drop further. All this at a time when other investors still seek to trade for liquidity, information or risk control reasons. A temporary increase in volatility is the result. Further empirical research could be done to confirm this explanation.

Another suggestion for further work would be to derive the critical values for the third statistical test (mentioned above) analytically rather than via simulation.

The second chapter considers multiple measures of intraday volatility for 94 stocks from Jan-1993 to Apr-1999. There is a large and persistent increase throughout this period in the Number of Price Changes per day. Also, the average trade size began to drop in 1997. We suggest that this is due to fragmentation of large orders and perhaps to increased participation by small investors.

The classic measure of volatility, close-to-close standard deviation, was unusually low in 1994, then began to rise by about 2.7 percentage points per year, reaching historically high values in 1998 and 1999. It varied far less than the number of price changes, however.

The half-hour variance was compared to the close-to-close variance, and their relationship was seen to change over the period under review. Initially (1993) the half-hour variance was more than proportional to the close-to-close variance, suggesting (consistent with previous studies) some negative correlation of returns in successive half-hour intervals. Later (1999) the half-hour variance was almost exactly proportional, as a near zero correlation would imply. The MEC (Market Efficiency Coefficient) showed a similar change towards apparent greater efficiency. A possible explanation is that mean reversion after large trades (negative correlation) is being masked by increased momentum trading (positive correlation), the result being near zero correlation on average. A practical implication is that buying and selling through limit orders is less advantageous to investors now than six or seven years ago.

Parkinson's measure of volatility based on the high and low of the day was compared to the close to close volatility and no clear trend was detected over time. Thus there was no evidence that intra day high and lows are drifting further and further apart over time, although this conclusion is dependent on price changes being (and remaining) normally distributed. Further research is needed to reconcile this result with recent findings about highs and lows in a study by Shapiro and Schwartz that used different data and methods.

When we examined groups of stocks we arrived at three conclusions: (1) The upward trend in close-to-close volatility is most pronounced among big cap stocks, (2) The decline in average trade size has affected all stocks (big cap and small cap, NYSE and Nasdaq), and (3) As of 1999 Nasdaq stocks have a lower Market Efficiency Coefficient (higher trading costs) than NYSE stocks.

Robert A. Wood's novel measure of volatility, Path, was also examined. The combination of Path and Number of Mid-Price Changes per Day has potential as a measure of intra-day volatility. It behaved differently for Nasdaq and NYSE stocks, making comparisons across the two different trading platforms difficult, although we proposed an empirical adjustment to deal with this problem.

The third chapter is concerned with stocks popular with retail investors in 1998 compared to a control group of stocks. The first comparison used a Granger model of the relationship between small trades and volatility. For the control stocks small trades have little or no effect on volatility; the effect is short term (1 minute) and an increase in small trades causes a decrease in volatility. For the popular retail stocks small trades influence volatility positively over a period of about 8 or more minutes. In the second comparison, the permanent and temporary price impacts of large and small trades were calculated. For the control stocks the effect of small trades is entirely temporary, large trades on the other hand have a large permanent impact and a smaller temporary impact. For the popular retail stocks both large and small trades have a large temporary and a small permanent impact. In sum both comparisons show that for certain stocks (such as Yahoo) small trades can have an impact on volatility and price (albeit largely temporary).

The fourth chapter found a major change in the population of stocks that are heavily traded by investors. On January 1 of each year from 1984 to 1999 we formed a list of stocks that were heavily traded in the previous year, then computed their volatilities in the current year. We found that the cross sectional distribution of volatility has widened, with the most volatile stocks being new names that are even more volatile than the ones that could be considered highly volatile in the past. For example we found 214 stocks with a volatility of 70% or greater in 1999 (vs. only 55 in 1984). Some characteristics of these stocks include: Nasdaq membership (69% of cases), relatively short trading history (median of 5.5 years as of 1/1/1999), and concentration in Technology and Telecommunications industries.

We also confirmed the results of other studies showing that correlations among stocks have trended lower during this period.

2.0 Conclusion

A common theme emerges from the previous four chapters: the instability of stock market volatility. This has several implications. (1) In forecasting volatility, point estimates may be misleading. Some investors forecast volatility for the next three months by taking realized volatility during the last three months and adjusting it up or down for mean reversion. This ignores the possibility of a sudden volatility increase. It would be better to give a range of volatility estimates, taking into account the kinds of increases that have occurred in the past. This will require looking at considerably more than 3 months of past data. (2) Since illiquidity affects volatility, measures taken by regulators to increase liquidity and maintain confidence at stressful times are to be applauded. (3) We may wonder whether ordinary investors fully realized that the stocks which went public in the mid 1990's had unprecedented levels of volatility and that online trading boosted trading propensities enormously. As researchers studying financial markets we support financial innovations but we should also educate and warn the public when speculative enthusiasm is getting out of hand.

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