ASSET PRICE BEHAVIOR IN COMPLEX ENVIRONMENTS

by

William A. Brock[1]
Department of Economics
The University of Wisconsin, Madison
August, 1995
Revised, December, 1995
This Revision, April 9, 1996

1. Introduction

Eight years ago, the Santa Fe Institute organized a conference called The Economy as An Evolving Complex System" and produced a book with the same title. The purpose of that conference was to bring together "free spirits" who were willing to examine the economy using techniques from "complex systems theory."

"Complex systems theory" is hard to define, but I shall use the term to refer to recent methods of time series analysis which are inspired by dynamical systems theory as well computer assisted analysis of complex adaptive systems consisting of many interacting components. Complex systems analysis as used here includes neural nets, genetic algorithms, as well as artificial life analysis such as Arthur etal. (1993). I shall sometimes speak loosely and use "complex systems theory" to denote the research practices of complex system theorists including those at Santa Fe.

This paper gives a brief review of the use of complex systems techniques in the study of asset price dynamics and related subjects since the SFI conference. The paper is organized by listing the facts we wish to explain, followed by explanation of works that address those facts. For lack of space, I shall concentrate on works by myself, my coauthors, and my students. The reader should be warned that finance is a huge field that contains many researchers and that the use of "complex systems techniques" in this field has grown rapidly. Hence there is a vast amount of work that we shall not be able to discuss in this article. I shall give frequent reference to recent surveys to give the reader a port of entry into the literature. Many of the works discussed here give extensive discussion of the work of others.

1.1 TIME SERIES ANALYSIS

One set of research practices which are associated with complex systems scientists, in which SFI affiliated researchers played a major role in developing, supporting, and popularizing, is the study of time series data using tools inspired by dynamical systems theory and related methods that are tailored to the study of "deep" nonlinearity.

A survey of this type of work up to 1991 is contained in the book by Brock, Hsieh, and LeBaron (1991). Two recent surveys with an emphasis on methods of testing for "deep" nonlinearity are contained in Abhyankar etal. (1995), and LeBaron (1994a). Excellent general surveys on financial time series findings, which include findings on nonlinear dynamics, are Goodhart and O'Hara (1995), and Guillaume etal. (1994)

SFI affiliated researchers also played a major role in developing statistical methods to detect nonlinearities in data. Many of these methods use versions of "bootstrapping" type ideas from statistical theory. Examples of this kind of work include Brock, Lakonishok, and LeBaron (1992), LeBaron (1994a,b), and Theiler etal. (1992).

Let us be clear what we are talking about here. At an abstract level, *all* serious analysis of time series data is inspired by "dynamical systems theory." We are concerned here, with methods that study, for example, nonlinear stochastic dynamical systems where the nonlinearity is so "deep" that it cannot be dealt with by minor modifications of linear techniques such as (i) change of variables after "detrending," (ii) adaptation of linear techniques to conditional variances (e.g. ARCH-type models, c.f. Bollerslev, Engle, and Nelson (1994)), and (iii) stochastic analogues of "Taylor" type expansions where all remaining nonlinearity is tucked into the "remainder" terms and treated as "errors" in econometric models.

INITIAL REACTIONS TO EMPHASIS ON "DEEP" NONLINEARITIES

Before I give a discussion of research findings, let me give a few remarks on the initial reaction to the new methods that were inspired by dynamical systems theory. Eight years ago, I think it is fair to say that there was some controversy over whether application of dynamical systems theory and related nonlinear techniques would add much of value to received methodology in time series econometrics in economics and finance. I believe the main reason for this opposition is the following.

Many economists believe that the strength of "deep" nonlinearities in financial data is small enough relative to the size of non forecastible nonstationarities that reliable detection could not be had with the datasets available. After all, if such predictively useful nonlinearities were present, they would be found and exploited by expert trading houses. Such activity would cause asset prices to move to eliminate any predictive structure in such nonlinearities. Furthermore, nonlinear prediction algorithms were widely available before methods were developed which were based upon dynamical systems theory, so there was no reason to believe that these newer methods would find structure that had not been already found by earlier, perhaps cruder, methods.

I believe that there is rough evidence that opposition to using "fancier" technology including methods based upon dynamical systems theory, neural nets, genetic algorithms, and the like, has fallen faster in areas where better data has become available at a more rapid rate.

For example, "high technology" groups such as Olsen and Associates (cf. Corcella (1995) for a cover story on Olsen) which are quite common in High Frequency financial applications seem less common in Low Frequency financial applications as well as in aggregative macroeconomics applications such as business cycle analysis and analysis of economic growth.

However, while academics initially debated the usefulness of the new methods, at least some practitioners appeared to rapidly adopt and use the new methods. Not only did some researchers associated with the Santa Fe Institute form their own company (The Prediction Company) but also many other like minded companies and groups have emerged in recent years (see, for example, Ridley (1993)).

While the debate on the value added of methods such as neural nets, genetic algorithms, and dynamical systems theoretic time series analysis has not yet died down in academia, it appears that the rate of adoption of the new methods by academics has increased rapidly in the last few years. The recent surveys by Abhyankar, Copeland, and Wong, (1995), LeBaron (1994a), Creedy and Martin (1994), Goodhart and O'Hara (1995), and Guillaume etal. (1994) lists many recent studies in academia that use "complex system techniques" as defined here

Why did this rather silly (viewed from hindsight from the vantage point of the widespread adoption by sectors that "have to meet the bottom line") opposition (especially in academia) to the use of "high nonlinear" technology occur and what has caused the change in attitude? Manski, in his well known paper (1993), stresses that when there is not enough data to resolve issues one way or another, divergent beliefs can be held very firmly. When large and widely held investments in established techniques are threatened, opposition can run deep.

But, in finance, the availability of high quality high frequency datasets such as that collected and made widely available by the Olsen Group (cf. Corcella (1995) and Ridley (1993) for popular articles on the Olsen Group) have made it possible to detect usuably predictable "nonlinearities" in financial data. In fields such as aggregative macroeconometrics, there is still a widely held attachment to linear methods. But aggregative macroeconometrics as a field does not have access to data of such quality and plentitude as does high frequency finance.

Of course, much of the opposition will melt away against those techniques which prove useful in more conventional practices which have nothing to do with "deep" nonlinearities such as chaos. An example is the use of the BDS test (which originally had its roots in chaos theory) as a specification test for GARCH-type models which have nothing at all to do with complex systems theoretic techniques. See Bollerslev, Engle, and Nelson (1994) for a discussion of the use of the BDS test as a specification test.

Someone once cynically said that scientific advances take place "funeral by funeral." Viz. when the powerful old guard dies off younger and more open minded scientists can fill the vacated niche space. While there may be some truth to this, I believe instead that economic science advances dataset by dataset rather than funeral by funeral because the evidence can be adduced with more precision when more and better data become available.

This is especially true in situations where the goal function of scientific activity is more precise. For example, corporations and government agencies may be subject to a stronger practical performance discipline to understand how the "system actually works" (e.g. better "prediction and control") than academics. Even in that much maligned institution, government, there is strong pressure to understand how the system really works.

In agencies such as private corporations and government departments academic paradigm attachment may not matter as much as delivery of useful results. This may be so because there is an incentive structure operating in these environments that resembles more the profit motive in conventional competition analysis then the incentive structure in academic environments.

I also believe that the SFI meeting of 1988 and subsequent activities by SFI-affiliated researchers played a key role in popularizing new "high technology" ideas in economics and finance. Turn now to a list of stylized facts we wish to explain.

A LIST OF STYLIZED FACTS WE WISH TO EXPLAIN

Before any theorizing is done we should ask the following questions: (i) What are the facts and regularities that we wish to explain? (ii) What are the goals of the explanation? While a standard commerical goal is prediction for the purpose of generating trading profits, we shall take the position here that we are only interested in understanding the stochastic properties of stock returns and trading volume and the forces that account for those properties. This basic scientific understanding is essential to design of intelligent regulatory policy. It also has practical commerical value for the management of risk.

Here is a list of stylized facts. Most of these concern high frequency data, ranging from the tic by tic frequency to the weekly frequency. The facts are taken from the book by Brock, Hsieh, and LeBaron (1991), and articles by Guillaume etal. (1994), Goodhart and O'Hara (1995), LeBaron (1994a,b), and Brock and de Lima (1995). We especially stress the article by

Guilaume etal. (1994) for an excellent list of high frequency facts.

FACT 1: Complexity. Using estimated correlation dimension and lack of predictability as a measure of complexity, financial asset returns are highly complex.

I.e. the estimated correlation dimension is high (and is also unstable across subperiods, in some cases) and there is little evidence of low dimensional deterministic chaos. Evidence against low dimensional chaos includes not only high estimated (and unstable) correlation dimension, but also very little evidence of out of sample predictability using nonlinear prediction methods that have high power against low dimensional deterministic chaos. Here the term "low dimensional deterministic chaos" is used for chaos that is not only "low dimensional" but also "usably" low dimensional in the sense that nonlinear short term prediction can be conducted out of sample.

We doubt if anyone in finance believes that asset returns are wholly a deterministic chaos. The issue is whether there might be a chaos of low enough dimension and "regular" enough lurking in the sea of nonstationarity and noise that marginally effective short term prediction might be possible. Unfortunately the evidence for even this rather limited notion of chaos is weak.

FACT 2: Nonlinearity. There is good evidence consistent with nonlinearity, but effort must be made to avoid confusion of evidence of nonlinearity with evidence of nonstationarity. Much of the evidence of nonlinearity is also consistent with evidence of neglected nonstationarity.

Although evidence for low dimensional deterministic chaos is weak, there is, however, evidence of stochastic nonlinearity. Let "IID" denote "Independently and Identically Distributed." There is extremely strong evidence against IID-linearity and there is weaker evidence against MDS-linearity. Here a stationary stochastic process $\{X_t\}$ is said to be IID-linear (MDS-linear) if $X_t=\sum a_j\varepsilon_{t-j}$, $\sum a_j^2<\infty$, where $\{\varepsilon_t\}$ is an IID stochastic process (Martingale Difference Sequence, i.e. $E\{\varepsilon_t|\varepsilon_{t-1},\varepsilon_{t-2},\ldots\}=0$, all t). While the evidence may be due to nonstationarity rather than nonlinearity, many studies reviewed in, for example, Abhyankar etal. (1995), Hsieh (1991), and Guillaume etal. (1994) attempt to control for nonstationarities by adjusting for known seasonalities from higher to lower frequencies such as daily seasonalities in the bid/ask spread, volatility and volume over the trading day to the January Effect.

Guillaume etal. (1994) introduce a rescaling of time, which they call "theta" time, which shortens periods with little trading activity and magnifies periods with a lot of trading activity. They show that this device is very useful for controlling for nonstationarities. It is also sensible from an economic point of view and plays an important role in the Olsen group's vision of how the markets work--a vision which emphasizes trader heterogeneity at all time scales.

Studies such as Abhyankar etal. (1995), and Hsieh (1991) adjust for other types of nonstationarities by studying the pattern of rejections of nonlinearity by frequencies. At a very rough level of expository approximation one may describe their results as showing that the pattern of rejections of linearity have a "self similar" structure. I.e. the pattern of rejection is similar at all frequencies. This forces some discipline on heterogeneous belief or heterogeneous characteristics theories of traders.

Evidence of nonsymmetry such as skewness allows rejections of many models of the form $X_t = \sum a_j \varepsilon_{t-j}$, for example $\{\varepsilon_t\}$ Gaussian. Gallant, Rossi, and Tauchen (1993, p. 873), adduce evidence against a Vector AutoRegressive model driven by AutoRegressive Conditionally Heteroskedastic errors, abbreviated as VAR-ARCH in stock price and volume data by showing that the symmetry imposed by such a model conflicts with "the instrinsic nature of the price-volume relationship." In general as Gallant, Rossi, and Tauchen (1993) show for asset returns and volume data, and as Potter (1991) shows for macroeconomic data, nonlinear dynamic impulse response analysis coupled with a bootrapping type of statistical significance analysis is a good way to adduce evidence against linear models.

FACT 3: Predictability. Evidence of out of sample predictability is weak.

The studies of Diebold and Nason (1990), Meese and Rose (1990) put a damper on the effort to find reliable out of sample predictability in asset returns. They showed that evidence for predictability out of sample beyond that of simple random walk models was nil.

Later studies such as Brock, Lakonishok, and LeBaron (1992), LeBaron (1992) for stock market indices, Antoniewicz (1993) for individual stocks; and LeBaron (1994b) and Guillaume etal. (1994) for foreign exchange showed that evidence for short term out of sample predictability is good *provided* conditioning was done on the "right" information sets.

If opportunities for such predictability were rare enough over the whole sample, they would be hard to detect in bulk average measures of predictability over the whole sample. Tests such as the BDS test (Brock, Dechert, and Scheinkman (1987)) are useful for exhibiting evidence for such "pockets of predictability" but more refined tools such as bootstrapping economically motivated quantities such as profits from different trading strategies under null models whose development was guided by structural economic modelling (e.g. Brock, Lakonishok, and LeBaron (1992)) are required to locate such pockets and measure the "statistical and economic" significance of such conditional predictability. Blind application of nonlinear high technology is not likely to be successful.

As we said before, there is evidence of short-term predictability provided one conditions on the "right information sets." For example, LeBaron (1992a) has shown, for stock indices and for foreign exchange, that predictability increases when near-past volatility and volume decreases. He has also shown, LeBaron (1994b), that certain technical trading rules have predictive power for foreign exchange. But this predictive power drops when central bank intervention periods are deleted.

Lagged volume has predictive power for near future returns. Recall that volume and volatility measures are contemporaneously correlated for both indices and individual stocks (see Antoniewicz (1992, 1993) for documentation for a large collection of individual stocks). For indices LeBaron (1992a) (LeBaron (1992b)) showed (for several indices and for IBM stock returns) that decreases in lagged volatility (volume) are associated with increases in first order autocorrelation of returns. To put it another way, price reversals tend to follow abnormally high volume.

Conrad etal. (1992) find the following for weekly returns on individual securities: "returns autocovariances are negative only for last period's heavily traded securities; autocovariances in returns are positive if trading declined last week." Campbell, Grossman, and Wang (1993) give a theoretical story for this type of finding and document it for indices and some data on individual firms.

Campbell, Grossman, and Wang (1993) consider the regression

(R) $r_t=\alpha_0+(\alpha_1+\beta_1^M V_{t-1}^M)r_{t-1}+\varepsilon_t$,

where r, V denote returns and detrended turnover and find $\alpha_1>0$, $\beta_1^M<0$ for the NYSE/AMEX value weighted index. While they also study some individual firms, Antoniewicz (1993) runs regressions of the form (R) for a large sample of individual firms, for more lags, and for individual firm specific volume as well as market volume.

The theoretical story consists of two classes of mean variance investors, one type has constant risk aversion, the other type has random risk aversion. The constant risk aversion types serve as "liquidity providers" and they must be rewarded for this task. There is no heterogeneity of beliefs. Since the random risk aversion process is persistent, a burst of volume signals not only an innovation to the random risk aversion process but also an increase in expected returns which must revert to the "normal" level. This leads to a volume spike predicting a decrease in first order autocorrelation of future returns. As we said before, Campbell, Grossman, and Wang (1993) find evidence consistent with the theory using data on indices and individual firms.

Antoniewicz (1993) has shown that "spikes in aggregate volume do *not* influence the serial correlation for large capitalized securities. For smaller securities, episodes of abnormally high firm specific volume can induce a change from negative serial correlation to positive serial correlation in returns. The effects from market volume and firm specific volume on the serial correlation in returns depend on firm size and the sign of the previous day's return." Her findings may be consistent with the presence of different types of "liquidity providers" for large securities than for small securities. The differential presence of derivative securities such as put and call options across different size classes may play a role in the apparently different volume/return dynamics for large capitalized securities.

SIMPLE HETEROGENEOUS BELIEF STORIES TO "EXPLAIN" VOLUME AND AUTOCORRELATION

A very simple story based upon sequences of two period temporary equilibria under heterogeneous beliefs may help point the way towards building models that may help explain some of the Antoniewicz findings for smaller securities. Let one set of traders have belief biases away from the fundamental where the bias process is persistent. The traders which have no bias serve as the "liquidity" providers. Volume increases when there is an exogenous shock to the bias process. Since this exogenous shock is persistent, this generates positive first order serial correlation in returns even though fundamental returns have no serial correlation.

A simple story based upon three period temporary equilibrium adds the new ingredient that expectations must be formed by the "fundamentalists" on how many biased traders will be around next period when they wish to trade. One can tie down the sequence of equilibria by having the "fundamentalists" believe that values will revert to fundamental values three periods from now. This kind of model can induce endogenous changes in the quantity of risk in the system especially when it is coupled with the modelling strategy laid out in Brock (1993a) where the interaction between intensity of choice and the desire to choose strategies used by people most like yourself can create large movements in the strategy mix induced by small differences in the payoff measure to each strategy.

FACT 4: Autocorrelation Functions of Returns, Volatility of Returns, Volume Measures, and Cross Correlations of these measures have similar shapes across different securities and different indices.

Autocorrelation functions of returns are roughly zero at all leads and lags. This is a version of the Efficient Markets Hypothesis. However, at high frequencies, autocorrelations of returns are slightly negative for individual securities and for foreign exchange at small lags. This may be due to bid/ask bounce (Ross (1992)). For stock indices, autocorrelations of returns are slightly positive at small lags. This is, at least, partly due to non synchronous trading effects (Ross (1992)). I.e. stocks which have most recently traded have adjusted to the latest "news" whereas sluggishly traded stocks have not adjusted. Their slow adjustment leads to a move in the same direction later on. This "non synchronous trading" effect leads to positive autocorrelation in returns. Yet if one tried to trade on it, the typically wider bid/ask spread and higher liquidity costs of the sluggish securities may wipe out the apparent profits.

Autocorrelation functions of volatility measures are positive at all lags with slow (approximately hyperbolic) decay for stock indices and foreign exchange. The decay is more rapid for individual securities.

This is the famous stylized fact that lies behind the huge ARCH literature surveyed by Bollerslev, Engle, and Nelson (1994). Microeconomic explanations for this stylized fact, which we call the "ARCH" fact, are discussed by Brock and LeBaron (1995).

Autocorrelation functions of volume measures look similar to those of volatility measures. Cross autocorrelations of volatility with volume are contemporeneously large and fall off rapidly at all leads and lags. There is some asymmetry in the fall off. Antoniewicz (1992, 1993) documents many of these facts as well as others for a large collection of individual NYSE/AMEX and NASDAQ stocks. She also surveys many other studies documenting similar facts for indices and individual assets.

SOME THEORETICAL STORIES FOR THE ARCH-FACT

Models of endogenous belief heterogeneity (where belief types are driven by profitability of trading on those beliefs) by Brock and LeBaron (1995) for short lived assets and multiple time scales, and de Fontnouvelle (1995a) for long lived assets and one time scale are shown to produce time series roughly consistent with Fact 4 which includes the ARCH-Fact. The general phenomenon of volatility bursting in complex interconnected systems has been recently treated by Hogg etal. (1995).

FACT 5: Seasonalities and Other Predictable Nonstationarities; Non Predictable Nonstationarities.

Seasonalities include the widening of the bid/ask spread at daily open and daily close, increase in volatility and trading volume at daily open and daily close as well as spillover effects across major international markets as they open and close over the trading day. See Goodhart and O'Hara (1995). The major theories are asymmetric information and differential arrival rates of information to portfolio rebalancing and peak load pricing of trading services. Guillaume etal. (1994) show that use of an appropriate rescaling of chronological time into "economic" time is very useful for removing many seasonalities. They also show how estimates of objects like autocorrelation functions are badly contaminated and how statistical inference is damaged if these seasonalities are not removed.

FACT 6: Lead/lag relationships (Linear and Nonlinear)

Lo and MacKinlay (1990) have documented that large firms in the same industry tend to lead smaller ones in returns. Conrad etal. (1992) references work documenting similar leading effects for conditional variances. Kleidon and Whaley (1992) reviews evidence that futures markets on stock indices tend to lead cash markets on stock indices. Abhyankar (1994) and Hiemstra and Jones (1994a) have recently used nonlinearity tests based upon U-statistics theory and correlation integrals to document lead-lag relationships over and above those documented by linear methods.

Let us digress here to explain the correlation integral-based tests of Hiemstra and Jones (1994a) and Abhyankar (1994). We do this by expositing a simple special case of the general method.

Let $\{X_t\}$, $\{Y_t\}$ be a pair of stationary stochastic processes, let "Pr{E}} denote the "probability of event E," and let it be desired to test the proposition

$$\Pr\{X_t|Y_{t-1}\}=\Pr\{X_t\}, \text{ using data } \{X_t\}, \{Y_t\},$$

i.e. X_t is independent of Y_{t-1}. While one can do this by constructing estimators of $\Pr\{X_t,Y_{t-1}\}/\Pr\{Y_{t-1}\}$, $\Pr\{X_t\}$ and setting up a test of the null hypotheis: $\Pr\{X_t|Y_{t-1}\}=\Pr\{X_t\}$ using these estimators, one can alternatively set up a test based upon

$$H_0: \quad \Pr\{|X_t-X_s|<\varepsilon, |Y_{t-1}-Y_{s-1}|<\varepsilon\}/\Pr\{|Y_{t-1}-Y_{s-1}|<\varepsilon\}=\Pr\{|X_t-X_s|<\varepsilon\}.$$

Now any object of the form $\Pr\{|Z_t-Z_s|<\varepsilon\}$ can be estimated by the correlation integral estimator,

$$U_T=(1/T^2)\sum\sum 1\{|Z_t-Z_s|<\varepsilon\},$$

using data $\{Z_t, t=1,2,\ldots,T\}$, where $\sum\sum$ runs over $s,t=1,2,\ldots,T$. Here $1\{A\}$ is 1 if event A occurs, zero otherwise.

For the univariate case Brock, Dechert, and Scheinkman (1987) showed that statistics of the form U_T are U-statistics and tests for IID can be set up using such statistics. Brock, Dechert, Scheinkman, and LeBaron (1991) later showed that such statistics had the same first order asymptotic distribution on *estimated* residuals as on the true residuals of IID-driven estimated models on data. This made such statistics useful for model specification tests (cf. Bollerslev, Engle, and Nelson (1994)).

Baek and Brock (1992) extended this analysis for the multivariate case, including proofs of invariance theorems on estimated residuals. Hiemstra and Jones (1994) showed how to test H_0 by replacing each population value in H_0 by a corresponding correlation integral estimator like U_T, taking the difference and multiplying it by $T^{1/2}$, and using the statistician's Taylor series approximation method, which statisticians call "the delta method", and working out the null distribution. Hiemstra and Jones (1994) faced the challenge of dealing with a long and complicated formula for the variance because, unlike Baek and Brock (1992), they did *not* have an IID maintained hypothesis.

Using this test for "nonlinear casuality of Y for X" where the word "casuality" here is used in the narrow sense of incremental predictive ability of past Y's given, above and beyond, that already contained in past X's, they found evidence consistent with the proposition that daily stock returns help predict trading volume and trading volume helps predict daily stock returns.

I.e. they found evidence consistent with bidirectional causality. However, Gallant, Rossi, and Tauchen's (1993) impulse response analysis showed that returns help predict trading volume, they did *not* find that trading volume helped predict prices. Antoniewicz (1993) using an adaptation of the Brock, Lakonishok, LeBaron (1992) bootstrap test found evidence that trading volume *did* help predict prices. The efficient markets argument would lead one to expect that any test capable of picking up evidence (that presumably would have been erased by traders' actions) that trading volume helps to predict prices would have to be quite subtle.

FACT 7: Nonlinear Impulse Response Functions for Volatility and Volume (Gallant, Rossi, and Tauchen (1993).

Gallant, Rossi, and Tauchen (1993) show that a shock to current volatility leads to an immediate increase followed by a long term decline in future trading volume. However, shocks to current volume have little effect on future volatility. They develop general nonlinear impulse response analysis and apply it to finance. Potter (1991) develops nonlinear impulse response analysis and applies it to macroeconomic time series. Both sets of authors find strong evidence for nonlinear effects that would not be found by standard linear impulse response analysis.

de Fontnouvelle (1994) has developed a heterogeneous agent asset pricing model with endogenous evolution of signal purchasing belief types versus passive investor types (who free ride on the signal purchasers as in Brock and LeBaron (1995)) with infinite lived assets, unlike the finitely lived assets in Brock and LeBaron (1995). His model generates time series output for returns, volume, and volatility that is approximately consistent with some of Gallant, Rossi, and Tauchen's findings on impulse responses as well as Fact 3 on conditional predictability and Fact 4 on autocorrelation and cross correlation structure on returns, volume, and volatility. His model is promising enough for estimation by methods such as the Method of Simulated Moments (cf. Altug and Labadie (1994) for a nice exposition) and specification testing.

FACT 8: Market Micro Structure Effects on Index Returns and Returns on Individual Securities.

Ross (1992) discusses construction of different types of stock market indices and surveys the major indices in use around the world. He discusses the advantage of using value weighted (usually capitalization weighted, i.e., weighted by the value of the capitalization of the company's common stock) indices over other types. The Standard and Poors 500 is a value weighted index. He points out that smaller stocks trade in a less liquid market and trade less frequently than larger stocks. This is called the non trading effect and it induces positive serial correlation in daily index returns. This effect may loom larger in more broadly based indices. An offsetting effect is the "bid-ask" effect which induces negative serial correlation in the returns for individual stocks. This effect looms larger for smaller time intervals and for less frequently traded stocks. Ross points out that in indices where large liquid stocks (which tend to have small bid/ask spreads) dominate the index, the nontrading effect will generally dominate.

An extensive discussion of the impact of different market institutions upon the stochastic structure of returns, volatility, and volume is given in the surveys of Guillaume etal. (1994) and Goodhart and O'Hara (1995).

FACT 9: Evidence of Departures from "Standard" Models