Non-linear puzzles in asset returns

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During the last decade it has become clear to all – investors as well as academics – that we know quite a bit less about the behavior of financial markets and about fundamental asset valuation than it was thought earlier. In retrospect, the 1980s amounted to a humbling experience, both in terms of discredited theory and practical challenge.

The problem was strong and unexplained market volatility. Stock market investors suffered agony (e.g. the 1987 crash in the U.S.) and pain (in Japan). Bond market investors were faced with high and volatile real interest rates. They also learned about the inherent dangers of trading 'junk'. Currency traders lived through the rise and fall of the U.S. dollar. Finally, real estate markets went through a world-wide boom and bust, leaving many financial institutions insolvent or at the mercy of government subsidies. All these developments were unexpected and leave even today many intelligent people bewildered and in disbelief. For instance, at one point, the Japanese communication giant NTT was ostensibly worth more than all companies listed on the Frankfurt Stock Exchange combined. What was the logic of that?

Appropriately, finance theorists talked a lot about managing the new risks. But, while much financial innovation was clever, it did not always deliver the protection that was promised – at least at the times when it truly mattered. More importantly, long and dearly held notions of market efficiency, the positive risk-return tradeoff, and dividend discount models were put into question. Could the variation in stock returns be rationalized by subsequent movements in dividends and interest rates? It seemed not (Shiller [1989]). The magnitude of the return premium of equity over fixed-income instruments became another much investigated puzzle (Mehra and Prescott [1985]). And it appeared that in the cross-section stock returns were surprisingly predictable, but not by beta as the capital asset pricing model would have it (Fama and French [1992]). Instead, new evidence suggested seasonal patterns, reliable differences between small and large firms and between neglected and 'glamour' companies, and short- and long-term mean reversion (De Bondt and Thaler [1989]). The predicted returns were frequently negative, in clear contradiction to standard equilibrium theory.

Where do these disturbing findings and the experience of the 1980s leave us? Certainly, with more respect for the old view that prices and values are not always one-and-the-same thing. Modern finance is built around the economic delusion that both people and markets are perfect. It leaves out the institutional framework and it snubs the human factor. Security analysts,

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however, – chartists as well as those in the tradition of Graham and Dodd [1934] – emphasize differing trader beliefs and market psychology.

Perhaps, through careful study, investors are capable to pin down the intrinsic values to which prices tend in the long run. In the near term, such calculations are often disappointing. It is worthwhile to remember how the Keynesian metaphor of the stock market as a beauty contest relies on the sobering insight that "it needs more intelligence to defeat the forces of time and our ignorance of the future than to beat the gun" [1936, p. 157]. Frequently, the market takes on a life of its own. This means that, to the degree that people want wealth without risk *now*, it is impractical to overlook 'the state of the market'. Surely, money managers are aware that they can ignore the crowd only at the peril of their own jobs! This perspective is the conceptual foundation of technical analysis (Levy [1966]), as well as other active investment strategies.

In the past, finance theorists have paid only limited attention to shortterm price-volume dynamics and "technical corrections". But that is no longer possible. To retain its old glory, asset pricing theory needs a major rebuilding effort. In particular, future models must explain (i) why prices move so much and (ii) why investors trade so much. The organizers of this symposium on chaos theory, neural networks, and complex dynamics in financial time-series are aware of the formidable task that lies ahead and they are to be congratulated. Much of the new research on nonlinearity is motivated by investor heterogeneity in information and knowledge. These studies promise the development of more realistic pricing models. As it happens, the theory has already moved beyond its early stages. The data are suggestive. The implications for investment strategy may be profound.

This paper serves as an introduction to nonlinear dynamics in asset returns. Inevitably, because of the constraints of time and space, my discussion is rudimentary.[2] However, I hope to motivate the reader to further explore the literature! Section I reviews some fascinating theoretical and empirical facts. Section II asks what challenges the research poses to finance and how progress can be made. Section III concludes.

I Beyond the random walk

A fresh and stimulating advance in finance during the last few years is the application of chaos theory. What is chaos theory? It is a branch of mathematics that studies nonlinear deterministic processes. These processes 'look' random, i.e. chaotic systems yield extremely complex time paths that are similar to stock price fluctuations. For instance, the deterministic sequence of values produced by a simple *tent map* (f:[0,1][0,1]) where

$$X_t = 2X_{t-1} \quad \text{if } 0 \leq X \leq 1/2$$

[2] Other introductory surveys appear in Nichols [1993] and in the October 9, 1993 issue of The Economist.

and where, otherwise,

$$X_t = 2(1 - X_{t-1})$$

has the same autocovariance function as white noise! In general, the trajectories that chaotic variables follow are quite sensitive to initial conditions. Usually, they do not converge to rest points or limit cycles (as with linear deterministic processes, e.g. difference equations).[3]

Why do so many people stand ready to apply chaos theory to financial markets? There are three basic reasons. First, the theory has intuitive appeal. It generates variations in market prices endogeneously (i.e. from within the system), reducing the role of outside information shocks.[4] Yet, the theoretical time paths resemble the sudden bursts of market volatility and the occasionally large crashes that are actually observed. Second, chaotic models arise naturally in finance and economics. They allow investor heterogeneity, the presence of long-lived agents, arbitrage, and competition (see e.g. Deneckere and Pelikan [1986]). Third, there is in fact increasing evidence of nonlinear dependence in asset returns.

Goetzmann [1993] studies long historical series of annual stock index returns on the London (since 1700) and New York exchanges (since 1790). Using autoregression as well as rescaled range (R/S) statistics, Goetzmann finds evidence consistent with nonlinearity and long-term mean reversion in asset prices. Autocorrelation tests can detect long-term dependency if the behavior is periodic and if the periodicity is consistent over time. In contrast, R/S-statistics identify non-periodic cycles. They measure how far a random variable strays from its mean. Peters [1991] believes that significant R/S-statistics argue in favor of deterministic chaos.[5]

However, nonlinear science examines stochastic as well as deterministic dynamic systems. In the case of 'noisy chaos', both are present. Empirically, it is quite difficult to distinguish these systems. Scheinkman and LeBaron [1989] use the methods of Grassberger and Procaccia [1983] and Brock, Dechert, and Scheinkman [1987] (BDS) to examine a weekly value-weighted index of U.S. stock returns. The familiar random walk theory -that the returns are independently and identically distributed (IID) over time- is rejected.[6] Similarly, Hsieh [1989,

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3 The tent map illustrates low-complexity univariate chaos. For practical purposes, high-complexity chaos is indistinguishable from randomness. Introductory discussions of the role of chaos theory in finance and economics are found in Baumol and Benhabib [1989], Brock [1992], and Peters [1991].

4 This is an important modelling feature since the data do not allow us to relate asset return volatility to the release of significant information in a straightforward way. See, e.g., Haugen et al. [1991]. Still, the trading process itself may reveal information that causes a rational (?) reassessment of future payoffs. See, e.g., Genotte and Leland [1990] and Romer [1992].

5 An English hydrologist, Harold E. Hurst, first developed R/S-statistics. A related concept is the so-called 'Hurst exponent' (H). An H equal to 1/2 implies the absence of long-term dependence, i.e., random walk behavior. With monthly data for the S&P-500 (1950-1988), Peters [1989] finds an H equal to .61. This suggests persistent trends in the stock market. See also Peters [1991] and Lo [1991].

6 The stock index is computed by the Center for Research in Security Prices at the University of Chicago. It starts in 1963 and covers all companies listed on the NYSE and the AMEX.
BDS develop a statistic that builds on the notion of the 'correlation integral' (This concept is related to Grassberger and Procaccia's 'correlation dimension', a tool of chaos theory.) The BDS-statistic has power against chaotic as well as stochastic systems. BDS test the null hypothesis that the data are IID. BDS-tests also pick up linear dependence. This difficulty is solved by examining residuals from fitted linear models. For details, see Hsieh [1991].

1991] computes BDS-statistics for daily movements in the exchange rates of five currencies and for eleven series of stock returns. (This includes the S&P-Index measured weekly, daily, and at 15-minute intervals.) The stock returns are filtered by autoregression. In each case, the returns -or filtered data- are not IID. Thus, there is nonlinearity and past returns may help to predict future returns, even while they are uncorrelated.[7]

The rejection of IID is consistent with (i) low-complexity chaos, (ii) nonlinear stochastic processes, e.g. ARCH-type models, (iii) a mixture of both.[8] At this stage, the data clearly favor the second explanation. There is much stronger evidence of conditional heteroskedasticity in returns – i.e. predictable variance changes – than of conditional mean changes, consistent with chaos.[9]

The rejection of linearity leads to theoretical questions about its interpretation, to be addressed later, and empirical questions about the form of the nonlinearity in asset returns. It is worthwhile to list some of the major stylized facts. As mentioned, returns are conditionally heteroskedastic. In addition, volatility is seasonal and there are significant differences between trading and nontrading periods (French and Roll [1986]) Volatility is unusually high as we approach economic recession (Schwert [1989]). Perhaps this occurs because corporate leverage goes up if stock prices are a leading indicator. Finally, the first-order serial correlation in daily and weekly returns is larger when markets are calm than when they are turbulent (LeBaron [1992a])[10]

A related issue is the link between volatility and volume (reviewed by Karpoff, [1987]). Two results stand out. First, absolute price changes are positively correlated with contemporaneous volume (see e.g. Gallant et al. [1992] or Bessembinder and Seguin [1993]). Duffee [1992] argues that the correlation is due to noise traders who drive a wedge between fundamentals and price. Like Campbell et al. [1992], he asserts that price movements are more likely to be reversed if associated with high volume. Second, there is positive comovement between

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7 All the series examined by Hsieh are strongly leptokurtic. In addition, the BDS-statistics in Hsieh [1993] show that the daily log price changes in four currency futures contracts (British pound, Deutschmark, Japanese yen, and Swiss franc) are not IID.

8 In principle, the test results also agree with nonstationarity in the return data. However, this argument raises the question what to make of Hsieh's findings based on 15-minute S&P return data.

9 See, e.g., Akgiray [1989] and Hsieh [1989, 1991]. Not all stochastic models that detect nonlinearity are of the ARCH-variety. For example, Hinich and Patterson [1985] estimate the bispectrum for fifteen U.S. common stocks and find nonlinearities. Engel and Hamilton [1990] use Markov switching models that capture regime shifts to demonstrate persistent trends in the movement of the dollar.
The relative weakness of the evidence for chaos theory is due to (i) low-powered tests and (ii) low-quality data. E.g., long economic time-series are frequently nonstationary.

10 LeBaron's finding agrees with the role of trading frictions. However, there are competing explanations. An interesting fact, reported by Campbell et al. [1992], is that the daily serial correlation of stock returns is lower on high-volume days. The authors suggest that the high turnover reflects the activities of noise traders. The price changes that accompany this volume will tend to be reversed. On the other hand, Morse (1980) finds that for 50 individual securities the autocorrelation in returns is positively related to trading volume. This is surprising since it contradicts Campbell et al. [1992] as well as LeBaron [1992a] if volume and volatility move together.
Cutler et al. [1991] describe further aspects of the characteristic dynamics of asset returns.

volume and price changes per se. Low volume in bear markets may be explained by investor loss aversion (Shefrin and Statman [1985])[11].

The rejection of linearity may offer new respectability to technical analysis. Almost by definition, chartists that look for 'head-and-shoulder' or related patterns are attempting to detect nonlinearity! Three popular trading methods are (i) moving average (MA) rules, (ii) trading range break (TRB) rules, and (iii) filter rules.[12] Brock et al. [1992] study the Dow Jones between 1897 and 1986 (24,771 trading days). A typical MA crossing rule that compares a 1-day to a 50-day MA results in about 40% more buy than sell signals. Ignoring transaction costs, annualized buy returns are about 12 percent; sell returns are -7 percent! TRB-rules also yield statistically significant profits. With support and resistance levels computed over 200 days, the Dow earns a ten-day return that is about 1.2% larger after a buy than after a sell signal.

Levich and Thomas [1991] study foreign exchange futures markets between 1976 and 1990. They test three moving average specifications for five major currencies. The MA-rules yield significant profits in every instance. Levich and Thomas also try filter rules (the filters range between 0.5 and 10 percent). Again, the rules uniformly produce profits. For instance, a 5 percent filter rule on Deutschmark futures earns 8.2% per annum (in U.S. dollars). The statistical tests use Efron [1982] bootstrap methods. Thus, the profits are assessed relative to the empirical distribution of profits for thousands of randomly generated series.[13]

What is the exact logical connection between the profits of technical analysis and nonlinear science? Neftci [1991] formalizes various methods – e.g. MA crossings – using Markov times. These are random time periods that can be determined from current or past information only. Of course, to be unambiguous, well-defined trading rules ought not to depend on future information! Neftci asks under what conditions the rules may be useful for prediction. He shows that no sequence of Markov times can help in prediction – beyond vector autoregressions according to Wiener-Kolmogorov prediction theory – so long as the process $\{X_t\}$ is linear, i.e., $E[X_{t+s}|X_{t-1}, X_{t-2}, ..X_{t-k}] = \alpha_1 X_{t-1} + .. + \alpha_k X_{t-k}$ where $s \geq 0$.[14] An

11 Three more studies of prices and volume are Antoniewicz [1992], LeBaron [1992b] and Wiggins [1991]. These papers agree with the Wall Street aphorism that "it take volume to move prices".

12 See e.g. Pring [1991]. Moving average rules divide the period under study in either buy or sell segments depending on the relative position of a 'short' and a 'long' moving average of prices. A buy signal occurs when the short MA is above the long MA; a sell signal when the short MA is below the long MA. Trading range break rules generate a buy signal when the price level moves above a local maximum (a 'resistance level') and a sell signal when the price moves below a local minimum (a 'support level'). Minima and maxima are computed over the preceding period, say, the previous 200 days. Filter rules produce buy signals when the price level rises x% above its previous low and sell signals when the price falls x% from its previous high.

13 Other studies that show filter rules to be profitable in the foreign exchange market include Dooley and Shafer [1983] and Sweeney [1986]. For the stock market, the evidence is mixed. The early work of Sidney Alexander, Eugene Fama, Marshall Blume, and others is very critical. See e.g. Jensen and Bennington [1970].

14 This particular definition of linearity is critical. Admittedly, there are other definitions.

important example of such a linear process is the martingale. In conclusion, technical analysis only has a chance of being useful if nonlinearities are present in the data.[15]

II The challenge

Nonlinear time series modelling should lead to the construction of better theories that rationalize the new empirical findings. Some interesting efforts are presently underway to model the price-volume relationship. However, it is fair to conclude, as Gallant et al. [1992, p. 202] do, that "existing models .. do not confront the data in its full complexity" and "there seems to be no model with dynamically optimizing, heterogeneous agents" that can jointly account for fat-tailed return distributions, the volume-volatility connection, volatility persistence, and other stylized facts.

Broadly speaking, three avenues are being followed in the literature.[16] All three relax the axiom of 'universal rationality'. The reason is that the axiom quickly leads to the paradoxical and descriptively false prediction that *no* trading is justified by access to private information (Milgrom and Stokey [1982]).

The *first* class of models studies multi-period noisy rational expectations (RE) equilibria. The presence of noise -perhaps caused by non-strategic liquidity traders- is critical but left unexplored. In RE-models, public information usually does not produce trading. However, differences in private information may cause investor disagreement and trading. The *second* class of models is also within the noisy RE-perspective. However, the main focus is on the role of privately informed and strategically uninformed traders. This approach has found application in several market micro-structure studies. The *third* group of models takes naive investors more seriously than the previous two. Behavioral theories employ new assumptions, e.g., positive feedback trading. At a mininum, these models recognize that there are firmly-held differences of opinion among traders (Harris and Raviv [1992]) or that some investors have a distorted view of future cash flows and risk (Shleifer and Summers [1990]). Below, I review elements of each perspective.

Brown and Jennings [1989] rigorously develop the insight that, if spot prices are noisy but rational aggregators of private information, investors can gain from the study of past prices, i.e. from technical analysis. Thus, chartism and market rationality are not always incompatible. It may well be that efficient prices look 'weak-form inefficient' in the sense of Fama. Grundy and McNichols [1989] build a model in which the sequence of past prices can reveal existing private information and motivate trading "even though it appears than no new external

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15 In other words, nonlinearity is a necessary but not a sufficient condition. The precise form of the nonlinearity that allows some technical methods to succeed remains somewhat of a mystery. E.g., standard nonparametric time-series estimators "that can handle a wide variety of nonlinear phenomena" do not produce improved out-of-sample forecasts (Meese and Rose [1990, p. 192]).

16 My discussion ignores trading motives other than private information, e.g. consumption, taxes, or portfolio rebalancing.

information has arrived" (p. 496). Public announcements produce additional trading. Investors disagree on what the news means due to prior private information.[17]

As mentioned, some models of the price-volume relationship are built around the concerns of uninformed but *strategic* liquidity traders (e.g. Admati and Pfleiderer (AP) [1988], and Foster and Viswanathan (FV) [1990]). These theories mirror a structure that originates with Kyle [1985]. Besides (i) non-discretionary liquidity traders, there are (ii) informed traders, and (iii) discretionary liquidity traders. Lastly, there is a risk-neutral market-maker who faces an adverse selection problem. Both the informed and the strategic liquidity traders time their transactions. The market-maker watches the order flow and sets prices so that they reflect fundamentals.

The AP-model predicts that rational traders prefer to cluster, i.e. to transact at the same time of day. Intraday high volume periods should be characterized by high volatility and low trading costs. In the FV model, the information advantage of informed traders diminishes with time. This gives them a reason to speed up their transactions. On the other hand, in response, liquidity traders may delay their trading. FV conclude that, if private information accumulates over weekends, volume should be relatively low on Mondays (compared to other days) but trading costs should be rather high.[18]

The behavioral approach tries to formalize what many find the most likely and intuitive explanation of the data: investor psychology.[19] Important behavioral principles include (i) overconfidence (explaining volume and active portfolio management), (ii) fashions and fads (linked to overreaction), and (iii) bandwagon expectations that extrapolate recent trends in prices.[20] Peters [1991] believes that investor reaction to news occurs in clumps. This behavior rationalizes the leptokurtosis of return distributions. News is never fully digested "until trends are well in place". However, at the trigger point, people react "in a cumulative fashion" (p. 37).

Consistent with the existence of triggers, Donaldson and Kim [1993] find that the rise and fall of the Dow Jones is restrained by support and resistance levels at multiples of 100 (e.g. 3200,

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17 Two more papers within the noisy RE-framework are Holthausen and Verrecchia [1990] and Kim and Verrecchia [1991] Both papers are motivated in part by Beaver's [1968] observation that, for major news announcements, stock returns measure the average change in traders' beliefs due to the news and that volume measures traders' idiosyncratic reactions. Accordingly, Holthausen and Verrecchia identify two effects of news: an informedness effect and a consensus (among agents) effect. They conclude that equilibrium price changes and trading volumes are each influenced by both effects. Kim and Verrecchia suggest that trading volume is proportional to absolute price changes and to differing precisions in the private information of investors. (Shalen [1993] presents a model with similar predictions.) Ziebart [(1990] tests some of the implications of the RE-models.

18 Using data for sixty U.S. companies during 1988, Foster and Viswanathan [1993] find that intraday trading volume is high when returns are most volatile. Contrary to both AP and FV, estimated trading costs are higher at the times of day with high trading volume. In agreement with FV, trading costs are lower and volume is higher on Mondays than on other days.

19 Gilovich [1991] offers a broad survey of the psychology of judgment and decision-making. De Bondt and Thaler [1994] review the relevance of this literature for financial economics. Shiller [1989] and Shleifer and Summers [1989] present interesting summaries of the noise trader approach.

20 Survey and experimental data analyzed in De Bondt [1991, 1993] show that expert economic forecasters actually predict mean reversion in prices. However, naive investors expect trend continuation and behave like positive feedback traders. Frankel and Froot [1990] report that survey predictions of currency movements are more regressive as the forecast horizon lengthens. See also Ito [1990].

3300, etc.). There is unusual news coverage in the financial press as the Dow crosses a new pricing barrier. The anomalous finding is that the Dow closes fewer times, on average, on index values that are close to multiples of 100.

Probably the best-known noise trader model is De Long et. al. [1990]. The theory introduces 'noise trader risk', i.e. risk caused by the unpredictability of naive investors. The interaction between sophisticated and naive traders possibly changes the empirical risk-return tradeoff (Teh [1993]). Other models include Arthur [1991], Brock [1992], Shefrin and Statman [1994], and Vaga [1990]. Brock starts from interactive particle systems probability modelling. His models all share the chaotic property that small input noise produces large shifts in equilibria. Finally, Baker and Iyer [1992] think about financial markets as social networks. Investors receive news through the network and from exogenous sources. (As information transmitters, they are not strategic, e.g. there is no misinformation.) Baker and Iyer show that, even if traders are homogeneous in all respects (e.g. preferences and/or endowments) and if the information flow is random, network configuration affects price volatility and trading volume.

III Conclusion

At least since the 1960s, financial economists routinely made fun of technical analysts. The random walk hypothesis is an important part of academic dogma. Burton Malkiel writes that "chart-reading must share a pedestal with alchemy" and that "the technicians do not help produce yachts for the customers, but they do help generate the trading that provides yachts for the brokers" [1985, p. 142].

Yet, chartism survives and even flourishes. The annual survey of exchange rate forecasting firms run by *Euromoney* found that, in 1988, 18 of 31 firms relied exclusively on chartist methods, 7 firms exclusively on fundamentals, and 6 firms on both (reported by Frankel and Froot [1990, p. 184]. Ten years earlier, in 1978, the survey count was nearly the reverse (Of 23 firms, only 3 relied on charts).

In this paper, I have suggested that the surprising strength (and resurgence) of technical analysis is not without empirical foundation. The globality of the evidence for nonlinear dependence in returns is impressive. This nonlinearity is a necessary but not a sufficient condition for the profitability of technical trading rules. Nevertheless, if we sidestep the thorny issue of what constitutes a proper risk adjustment, several popular trading rules produce "excess" returns. From the viewpoint of finance theory, the new findings are equally challenging. The central question is one of market equilibrium, price-and-volume dynamics, and investor rationality. In other words, even if we accept that technical analysis works in practice, why does it work in theory?

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