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Characterization of Financial Time Series

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Abstract

This paper provides an exhaustive review of the literature on the characterization of financial time series. A *stylized fact* is a term in economics used to refer to empirical findings that are so consistent across markets that they are accepted as truth. Financial time series may be characterized by the following stylized facts. The autocorrelation of returns is largely insignificant. The distribution of returns is non-stationary (clustered volatility) and approximately symmetric with increasingly positive kurtosis as the time interval decreases and has a power law or Pareto-like tail. There are non-linearities in the mean and (especially) the variance of returns. Markets exhibit non-trivial scaling properties. Volatility exhibits positive autocorrelation, long-range dependence of autocorrelation, scaling, has a non-stationary log-normal distribution and exhibits non-linearities. Volume exhibits calendar effects and has a distribution that decays as a power law. Regarding calendar effects, intraday effects exist, the weekend effect seems to have all but disappeared, intramonth effects were found in most countries, the January effect has halved and holiday effects exist in some countries. There is about a 30% chance that stock market returns exhibit long memory, a 50% chance that foreign exchange returns exhibit long memory and an 80% chance that market volatility exhibits long memory. There is little evidence of low-dimensional chaos in financial markets. This note also includes a summary of the important literature on market microstructure and the order book.

1 Introduction

By way of an extensive review of the literature, this paper seeks to characterize financial time series by prescribing stylized facts. A *stylized fact* is a term used in economics to refer to empirical findings that are so consistent (for example, across a wide range of instruments, markets and time periods) that they are accepted as truth. Due to their generality, they are often qualitative.

2 Dependence

The *autocorrelation* (also known as *serial correlation*, *serial dependence* or *mean aversion/mean reversion*) of price changes (and therefore log returns) is largely insignificant, but some small but interesting anomalies exist, as outlined below. In light of the asymptotic validity of the weak form of the efficient market hypothesis, such insignificant-but-non-zero results are not surprising. Figure 1 (page 3) shows average autocorrelations of returns and various non-linear transformations of the returns across 20 financial time series (for details, see Chapter 4, Taylor (2005)).

2.1 Autocorrelation in Returns

Fama (1970) found that 22 out of the 30 stocks of the Dow Jones Industrial Average (DJIA) exhibited positive daily serial correlation. Fama and French (1988) found that autocorrelations of stock return indices (they used portfolios) form a U-shaped pattern across increasing return horizons. The autocorrelations become negative for 2-year returns, reach minimum values for 3–5-year returns, and then move back toward 0.0 for longer return horizons. Lo and MacKinlay (1988) found significant positive serial correlation for weekly and monthly holding-period index returns, but negative autocorrelations for individual securities with weekly data. Ball and Kothari (1989) found negative serial correlation in five-year stock returns. Lo and MacKinlay (1990) found negative autocorrelation in the weekly returns of individual stocks, whilst weekly portfolio returns were strongly positively autocorrelated. Jegadeesh (1990) found highly significant negative serial correlation in monthly individual stock returns and strong positive serial correlation at twelve months. Brock et al. (1992) found positive autocorrelation in DJIA daily returns. Boudoukh et al. (1994) found that for small-firm indices, the spot index's autocorrelation is significantly higher than that of the futures. Zhou (1996) found that high-frequency FX returns exhibit extremely high negative first-order autocorrelation. Longin (1996) found positive autocorrelation for a daily index of stocks. The autocorrelation of weekly stock returns is weakly negative, whilst the autocorrelations of daily, weekly and monthly stock index returns are positive (Campbell et al., 1996). Lo and MacKinlay (1999) found a positive autocorrelation for weekly holding-period market indices returns, but a random walk for monthly. They also found negative serial correlation for individual stocks with weekly data. Cont (2001) found negative autocorrelation on a tick-by-tick basis for both foreign exchange (USD/JPY) and a stock (KLM shares traded on the New York Stock Exchange (NYSE)). He also claims that weekly and monthly autocorrelations exist. The autocorrelation of 1 minute FX returns is negative (Dacorogna et al., 2001). Ahn et al. (2002) looked at daily autocorrelations and found that the indices are positive even though the futures are close to zero. Lewellen (2002) found negative autocorrelation for stock portfolios after a year. Llorente et al. (2002) found that the first-order autocorrelation of daily returns is negative for stocks with large bid–ask spreads (-0.088) and small sizes (-0.076). It is positive but very small for large stocks (0.003) and stocks with small bid–ask spreads (0.01). Bianco and Renò (2006) found negative serial correlation of returns on the Italian stock index futures in periods smaller than 20 minutes. Cerrato and Sarantis (2006) looked at monthly data on black market exchange rates and found evidence of non-linear mean reversion in the real exchange rates of developing and emerging market economies. Lim et al. (2008) examined ten Asian emerging stock markets and discovered that all the returns series exhibit non-linear serial dependence. Serletis and Rosenberg (2009) used daily data on four US stock market indices and concluded that US stock market returns display mean reversion.

In summary, weekly and monthly stock returns are weakly negatively correlated, whilst daily, weekly and monthly index returns are positively correlated. Campbell et al. (1996) (p. 74) point out that this somewhat paradoxical result can mean only one thing: large positive cross-autocorrelations across individual securities across time. High frequency market returns exhibit negative autocorrelation.

2.2 Autocorrelation in Absolute and Squared Returns

In contrast to the lack of dependence in returns, the autocorrelation for the absolute and squared returns is always positive and significant, and decays slowly. In addition, the autocorrelation in the absolute returns is generally higher than the autocorrelation in the corresponding squared returns. See Figure 2 (page 3).

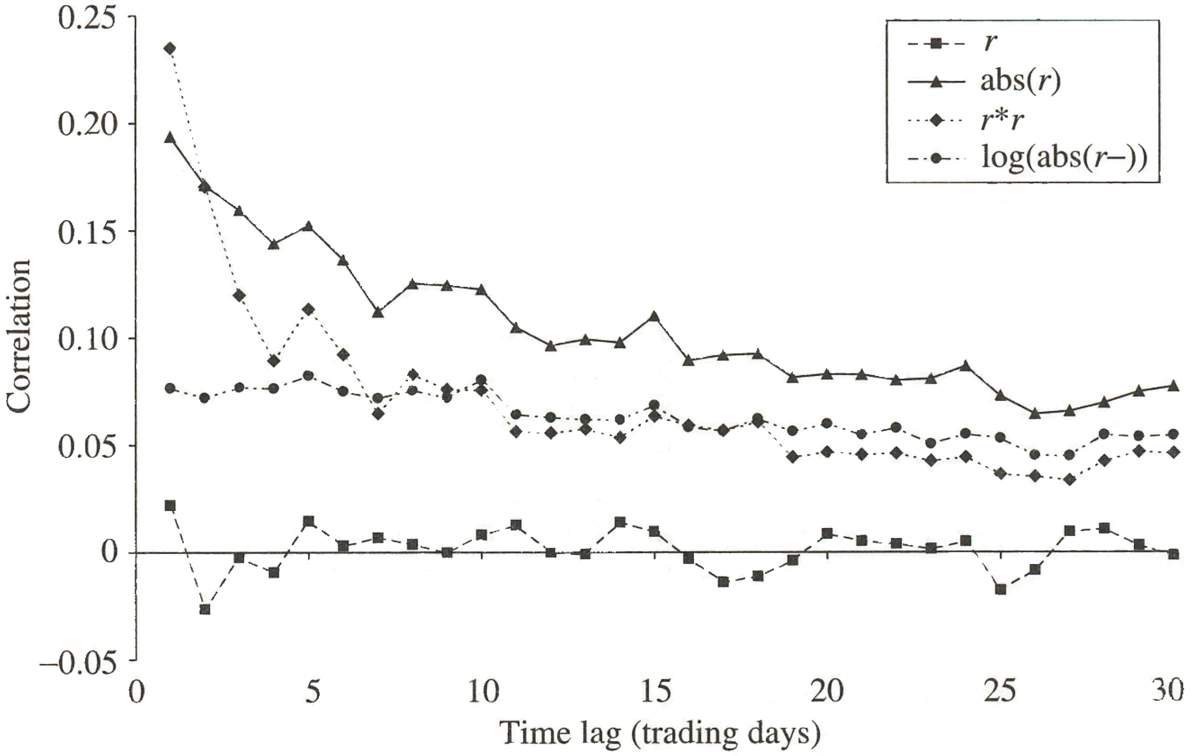

Figure 1: *Average autocorrelations across 20 financial time series (Taylor, 2005)*

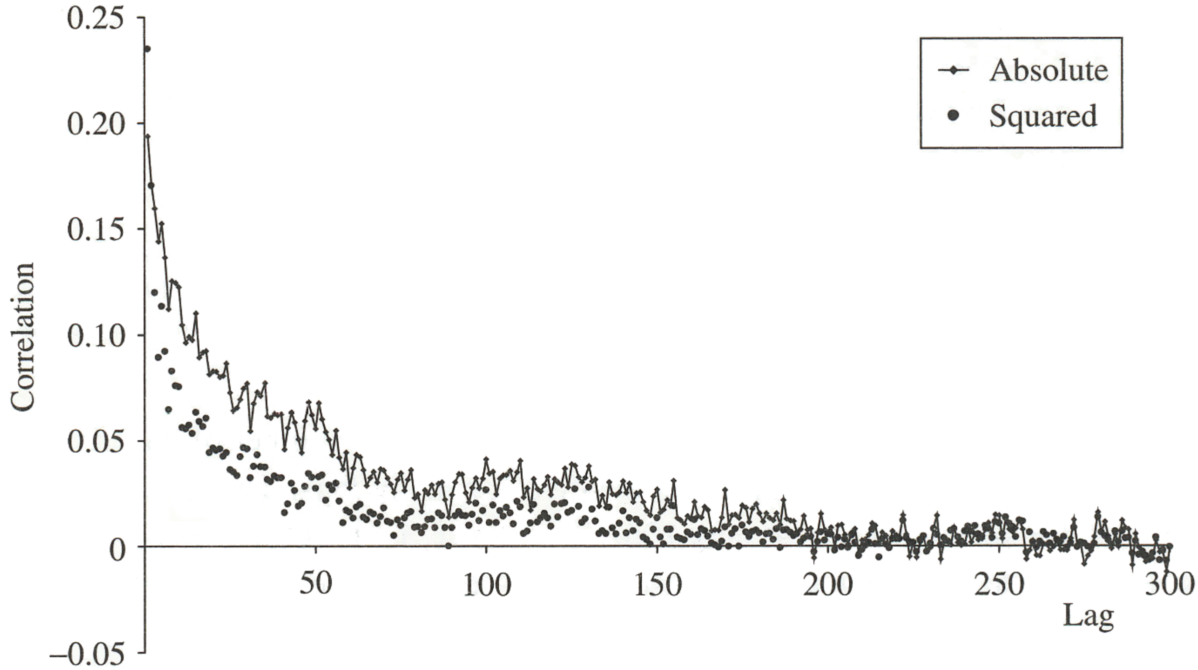

Figure 2: *Autocorrelations of absolute and squared returns; averages across 20 financial time series (Taylor, 2005)*

3 Distribution

Security returns are non-stationary, so I speak here of the asymptotic probability density function (pdf). The distribution of returns is approximately symmetric and has high kurtosis (that is, fat tails and a peaked centre compared with the normal distribution). The distributions are increasingly fat-tailed as data frequency increases (smaller interval sizes). Annual returns are approximately normal. The leptokurtosis was first identified by Mitchell (1915), Mitchell (1921), Olivier (1926), Mills (1927), Osborne (1959), Larson (1960) and Alexander (1961).

Definition 1 *A random process Y is* infinitely divisible *if, for every natural number n, it can be represented as the sum of n independent identically distributed (i.i.d.) random variables*

$$Y = X_1 + X_2 + \cdots + X_n.$$

Definition 2 *Consider the sum of n i.i.d. random variables,*

$$Y = X_1 + X_2 + \cdots + X_n.$$

When the functional form of Y is the same as the functional form of X_i, the stochastic process is said to be stable.

Special cases of stable distributions:

- Gaussian distribution
- Cauchy distribution
- Lévy distribution

Definition 3 *A* power law *relationship between two scalar quantities x and y is any such that the relationship can be written as*

$$y = ax^k$$

where a and k are constants.

Definition 4 *A random variable x with a* Pareto distribution *has a probability density function given by*

$$f(x) = ak^a x^{-(a+1)},\ x \geq k,$$

where a and k are positive constants. The Pareto distribution is a 'power law' distribution.

The *Gaussian distribution*, also called the *normal distribution* or the *bell curve*, is ubiquitous in nature and statistics due to the central limit theorem: every variable that can be modelled as a sum of many small independent variables is approximately normal. The Gaussian distribution is the only stable distribution having all of its moments finite.

The central limit theorem states that the sum of a number of random variables with *finite* variances will tend to a normal distribution as the number of variables grows. A generalization of the central limit theorem states that the sum of a number of random variables with power-law tail distributions decreasing as $1/|x|^{\alpha+1}$ where $0 < \alpha < 2$ (and therefore having infinite variance) will tend to a stable distribution $\mathrm{f}(x; \alpha, 0, c, 0)$ as the number of variables grows, where c is a scale parameter.

Figure 3 (page 5) illustrates the classes of random processes mentioned above, whilst Figure 4 (page 6) shows the distribution of a stock index and how it compares to a Gaussian and a Levy distribution.

According to the survey by Cont (2001), 'the (unconditional) distribution of returns seems to display a power-law or Pareto-like tail, with a tail index which is finite, higher than two and less than five for most data sets studied. In particular this excludes stable laws with infinite variance and the normal distribution. However the precise form of the tails is difficult to determine.'

Given that market log returns are additive, due to the central limit theorem (above), one might expect market log returns above anything but the highest frequency to be approximately normally distributed. This is only the case over the longest of time periods, such as annual returns. One simple explanation (my own) is as follows. Price-influencing events may be normally distributed, but the likelihood of said events being reported in the news increases with the magnitude of the impact of the event. For the latter distribution, one can factor in the tendency for the media to simplify and exaggerate. Multiply the normal distribution by the distribution according to the likelihood/duration/impact of news reports and one has a much fatter-tailed distribution than a Gaussian.

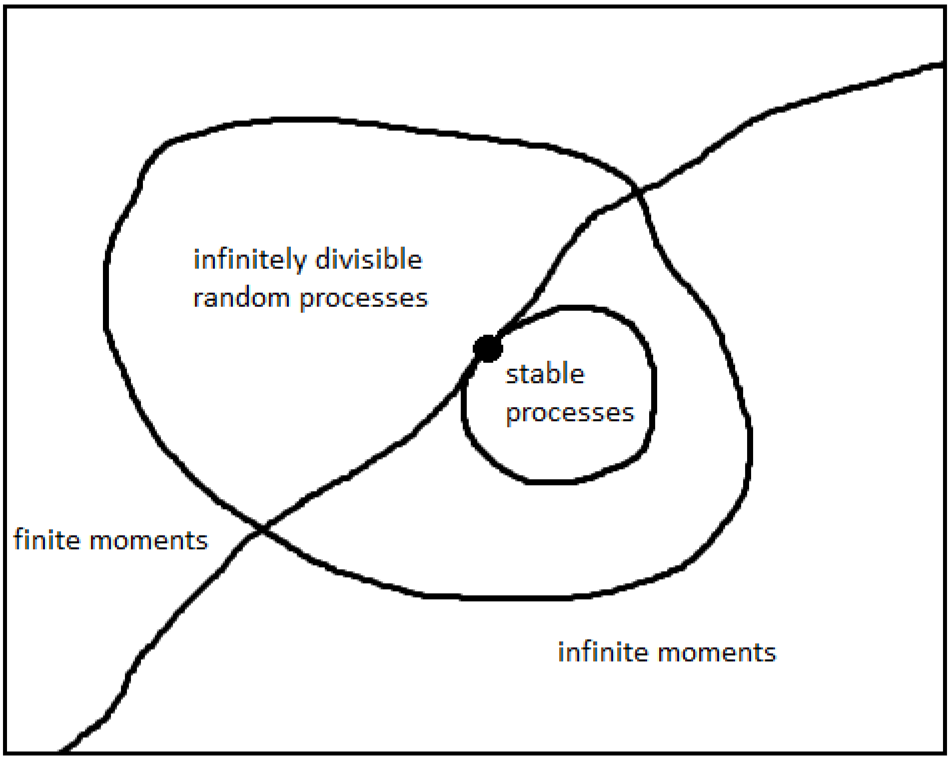

Figure 3: *Illustration scheme of classes of random processes. The solid circle denotes the stable Gaussian process. Adapted from Mantegna and Stanley (2000)*

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4 Heterogeneity

It is a stylized fact that the distributions of financial returns are non-stationary. This has been found empirically since Kendall (1953), Houthakker (1961) and Osborne (1962). Clustered volatility, characterized by autoregressive conditional heteroskedasticity (ARCH) (Engle, 1982) and generalized autoregressive conditional heteroskedasticity (GARCH) (Bollerslev, 1986) models, ensures that the standard deviation of returns is not constant over time. However, in sharp contrast to the findings in the existing literature, Lee et al. (2010) investigated the stationarity of real stock prices for 32 developed and 26 developing countries covering the period January 1999 to May 2007, and with structural breaks and cross-sectional correlations introduced into the model, concluded that real stock price indices are stationary in developed and developing countries.

The nonstationarity has important consequences with regards to option pricing, but is also of interest as the way it is dealt with highlights the different philosophies of various disciplines. Economists speak in terms of a *structural break* (for example, Stock (1994)). This enables their stationary models to continue working, as they can employ model switching. Applied mathematicians and physicists likely prefer dealing with *jump diffusion* processes (see, for example, Cont and Tankov (2004)), as they are comfortable dealing with Brownian motion plus a poisson process. A discretionary trader may explain his losses by claiming that the *markets have changed* (when, more than likely, he was trading randomly all along and his luck changed). Practitioners of machine learning sometimes speak of *concept drift* (for example, Widmer and Kubat (1996)). This is an altogether less emotive term and more realistic approach because it allows for continuous change (which may be fast, slow, cyclical, temporary, etc.) and does not require the assumptions (such as thresholds) that are necessary when dealing with ‘discrete’ changes.

5 Non-Linearity

A time series model may be *non-linear in mean* and/or *non-linear in variance*. ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models are non-linear in variance, but not in mean.

Hsieh (1989) investigated daily changes in five major foreign exchange rates and found no linear correlation, but evidence that indicates the presence of substantial non-linearity in a multiplicative rather than additive form. Scheinkman and LeBaron (1989) found evidence that indicates the presence of non-linear dependence on weekly returns from the Center for Research in Security Prices (CRSP) value-weighted index. Frank and Stengos (1989) ex-

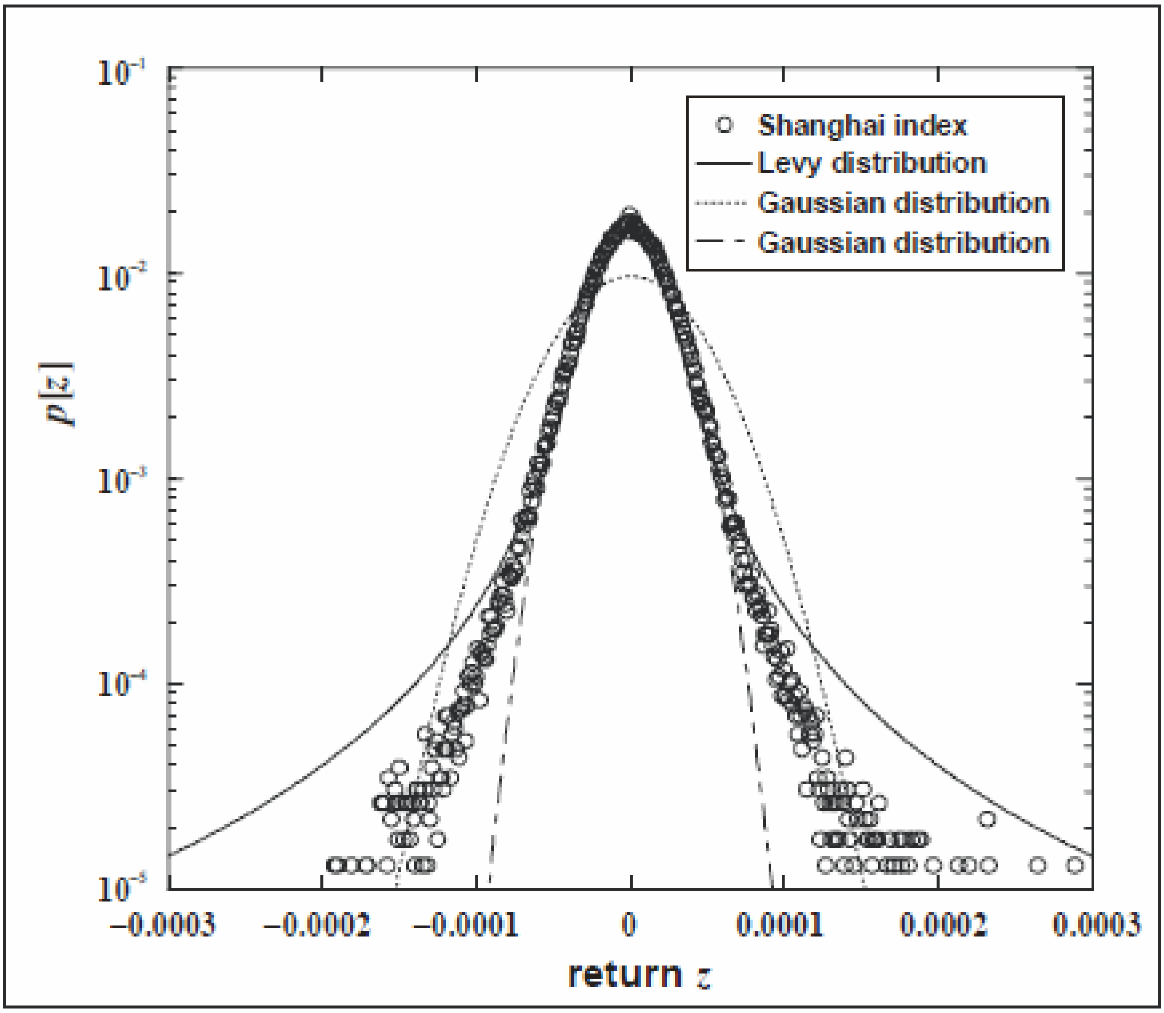

Figure 4: *Probability distribution function of returns for Shanghai market data with $\Delta t = 10$ seconds and $z[t] = \log(\frac{x[t]}{x[t-\Delta t]})$. This plot is compared to a stable symmetric Levy distribution using the value $\alpha = 1.44$ determined from the slope in a log-log plot of the central peak of the pdf as a function of the time increment. The agreement is very good over the main central portion, with deviations for large z. Two attempts to fit a Gaussian are also shown. The wider Gaussian is chosen to have the same standard deviation as the empirical data. However, the peak in the data is much narrower and higher than this Gaussian, and the tails are fatter. The narrower Gaussian is chosen to fit the central portion, however the standard deviation is now too small. It can be seen that the data has tails which are much fatter and furthermore have a non-Gaussian functional dependence. Johnson et al. (2003)*

amined the rates of return on gold and silver and found evidence of a non-linear deterministic data-generating process. Brock et al. (1991) concluded that GARCH models can account for most but not all non-linearity in stock returns and exchange rates. Abhyankar et al. (1995) tested for the presence of non-linear dependence in minute-by-minute real time returns on the FTSE 100 index and found clear evidence of non-linearity. Brooks (1996) tested for non-linearity in 10 daily GBP exchange rates and found irrefutable evidence of non-linearity in many of the series. Abhyankar et al. (1997) found non-linear dependence in the world's four most important stock market indices. Barkoulas and Travlos (1998) tested stock returns in the Athens Stock Exchange, an emerging capital market, the results of which suggest the presence of non-linearities. Ammermanna and Patterson (2003) showed that non-linear serial dependencies play a significant role in the returns for a broad range of financial time series, including returns from six different stock market indices from across the world, as well as the stock returns for the vast majority of individual stocks trading on the Taiwan Stock Exchange. Lim et al. (2008) examined ten Asian emerging stock markets and discovered that all the returns series still contain predictable non-linearities even after removing linear serial correlation from the data.

6 Scaling

Unlike physics or biology, there are no constants or absolute sizes in economics, so there is no characteristic scale in empirical or theoretical economics. For this reason, one might expect to find scaling properties in financial time series. There is no privileged time interval at which financial time series should be polled. Scaling laws describe the absolute size of returns as a function of the time interval at which they are measured. Markets exhibit non-trivial scaling properties. The scaling law is empirically found for a wide range of financial data and time intervals in good approximation. It gives a direct relation between time intervals t and the average volatility measured as a certain power p of the absolute returns observed over these intervals,

$$\{E[|r|^p]\}_{1/p} = c(p)\Delta t^{D(p)} \tag{1}$$

where E is the expectation operator, and $c(p)$ and $D(p)$ are deterministic functions of p. D is called the drift exponent. This form for the left hand side of (1) is chosen in order to obtain, for a Gaussian random walk, a constant drift exponent of 0.5 whatever the choice of p. A typical choice is $p = 1$, which corresponds to absolute returns.

Mandelbrot (1963) found scaling in cotton prices. Müller et al. (1990) analysed several million intra-day FX prices and found scaling in the mean absolute changes of logarithmic prices, although the distributions vary across different time intervals. Mantegna and Stanley (1995) showed that the scaling of the probability distribution of the S&P 500 can be described by a non-Gaussian process. Evertsz (1995) found distributional self-similarity in USD/DEM exchange rate records and the 30 main German stock price records. Guillaume et al. (1997) reported that scaling laws hold for all time series studied and for a wide variety of time intervals—from 10 minutes to 2 months. Fisher et al. (1997) found evidence of a multifractal scaling law in DEM/USD returns. Galluccio et al. (1997) found scaling in currency exchange rates. Gopikrishnan et al. (1999) presented evidence that the distributions of returns retain the same functional form for a range of time scales. Pasquini and Serva (1999) showed that volatility correlations of NYSE daily returns exhibit a multiscale behaviour. Skjeltorp (2000) found scaling in the Norwegian stock market. Gopikrishnan et al. (2000) found that the distribution of stock price fluctuations preserves its functional form for fluctuations on time scales that differ by 3 orders of magnitude, from 1 min up to approximately 10 days. Barndorff-Nielsen and Prause (2001) claim that apparent scaling is largely due to the semi-heavy tailedness of the distributions concerned rather than to real scaling. Gençay et al. (2001) showed that foreign exchange rate volatilities follow different scaling laws at different horizons. Andersen et al. (2001b) analysed high-frequency data on DEM and JPY returns against USD and found remarkably precise scaling laws. Wang and Hui (2001) identified scaling in the Hang Seng Index. Dacorogna et al. (2001) showed that the empirical scaling law for USD/JPY and GBP/USD is indeed a power law for time intervals from 10 minutes to 2 months. Xu and Gençay (2003) presented strong evidence that USD/DEM returns exhibit power-law scaling in the tails. Di Matteo et al. (2003) found different scaling properties in the indices of stock markets at different stages of development. Johnson et al. (2003) list as a stylized fact that the probability distribution function of price changes displays non-trivial scaling properties. Lee and Lee (2007) considered minute data from the Korean stock market index and observed scaling behaviour in the tail parts of the probability distribution of the return and in the autocorrelation function of the absolute return. Du and Ning (2008) found that the Shanghai stock market has (weak) multifractal properties and exhibits scale invariance. Qiu et al. (2008) observed data from the Chinese stock market and found scaling in the time intervals that volatility is above a certain threshold.

7 Volatility

Volatility is the standard deviation of the change in value of a financial instrument and is considered a proxy for risk. In this section I consider the dependence, distribution, heterogeneity, non-linearity and scaling of volatility.

7.1 Dependence

The autocorrelation function of the volatility exhibits long-range dependence and is well described by a power-law decay (Bollerslev and Mikkelsen, 1996; Liu et al., 1999; Andersen et al., 2001a,b).

7.2 Distribution

Studies show that the distribution of volatility is log-normal (Cizeau et al., 1997; Andersen et al., 2001a,b), although Liu et al. (1999) found that the tail of the distribution is better described by a power law.

7.3 Heterogeneity

Volatility clustering is ubiquitous in financial time series returns. Such nonstationarity has been known since Kendall (1953), and is characterized by ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models.

7.4 Non-Linearity

Franses and Van Dijk (1996) found that a non-linear model improves the forecasting of weekly stock market volatilities. Similarly, Díaz et al. (2002) and Maheu and McCurdy (2002) found evidence of non-linearity in FX volatility. Whilst Martens et al. (2004) detailed non-linearities in S&P 500 volatility. ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models are non-linear in variance.

7.5 Scaling

The distribution of the volatility scales for a range of time intervals (Liu et al., 1999; Andersen et al., 2001a,b; Gençay et al., 2001).

8 Volume

Volume refers to the level of trading activity in a market; for example, the number of shares traded during a specific period. Jain and Joh (1988) found that average volume traded shows significant differences across trading hours of the day and across days of the week. Plerou et al. (2000) show that the distribution of trading activity decays as a power law and that it has long-range correlations. Lobato and Velasco (2000) found strong evidence that stock market trading volume exhibits long memory. Gopikrishnan et al. (2000) found that the distribution of number of shares traded displays a power-law decay, and that the time correlations display long-range persistence. Plerou et al. (2001) found that trading activity displays power-law decaying time correlations and the distribution displays asymptotic power-law decay. Chordia et al. (2001) studied NYSE-listed stocks from 1988 to 1998 and found a strong day-of-the-week effect: trading activity is relatively high on Tuesdays and low on Fridays. Plerou et al. (2004) found that the distribution of volume decays as a power law. Statman et al. (2006) found that market-wide share turnover increases in the months following high market returns. Eisler and Kertész (2007) found long memory in both the frequency and the size of consecutive transactions on the NYSE. Qiu et al. (2009) investigated the trading volume of Chinese stocks; they observed long-range autocorrelation, and found that the cumulative distribution is well fitted by a stretched exponential function.

9 Calendar Effects

Calendar effects (sometimes less accurately described as 'seasonal effects') are cyclical anomalies in returns, where the cycle is based on the calendar. This section considers intraday effects, the weekend effect (the Monday effect), intramonth effects, the January effect, holiday effects, the Halloween indicator and the daylight saving anomaly. The most important calendar anomalies are (or at least were) the January effect and the weekend effect.

The following books include sections on calendar effects: Thaler (1992), Siegel (1998), Lofthouse (2001), Damodaran (2003), Constantinides et al. (2003), Singal (2004), Taylor (2005). Relevant papers include Lakonishok and Smidt (1988), Hawawini and Keim (1995), Mills and Coutts (1995), Arsad and Coutts (1997) and Dzhabarov and Ziemba (2010).

Sullivan et al. (2001) highlight the dangers of data mining calendar effects and point out that using the same data set to formulate and test hypotheses introduces data-mining biases that, if not accounted for, invalidate the assumptions underlying classical statistical inference. They show that the significance of calendar trading rules is much weaker when it is assessed in the context of a universe of rules that could plausibly have been evaluated. They are correct to highlight the dangers of datamining, but don't mention the fact that classical statistical inference is already flawed (Atkins and Jarrett, 1979; Minka, 1998; Gabor, 2004). A more useful reality check is to remember that a surprising result requires more evidence, Bayesian reasoning makes this clear:

$$\text{P(hypothesis)} = \text{prior belief} \times \text{strength of evidence.}$$

So, for example, it is quite rational to require more evidence for a lunar effect than a tax-loss selling effect.

Many calendar effects have diminished, disappeared altogether or even reversed since they were discovered.

9.1 Intraday Effects

Intraday effects are best exposed by relaying the results from Lawrence Harris's seminal (but dated) 1986 paper (Harris, 1986).

First 45 minutes of trading

- **Mondays** prices fell
- **Tuesdays–Fridays** prices rose significantly

12.30pm–1.30pm market rallied

2.15pm–3.30pm market fell

the close market rallied

last transaction of the day prices rose

Harris (1986) discovered that '[f]or all firms, significant weekday differences in intraday returns accrue during the first 45 minutes after the market opens. On Monday mornings, prices drop, while on the other weekday mornings, they rise. Otherwise the pattern of intraday returns is similar on all weekdays. Most notable is an increase in prices on the last trade of the day.' Harris (1989) found a day-end price anomaly. A large mean price change was observed on the last daily NYSE transaction.

9.2 Weekend Effect

The *weekend effect* (also known as the *Monday effect*, the *day-of-the-week effect* or the *Monday seasonal*) refers to the tendency of stocks to exhibit relatively large returns on Fridays compared to those on Mondays. This is a particularly puzzling anomaly because, as Monday returns span three days, if anything, one would expect returns on a Monday to be higher than returns for other days of the week due to the longer period and the greater risk. The significance of the weekend effect is shown in Figure 5 (page 10).

The weekend effect was first noticed by Fields (1931). Cross (1973) found that the market tended to rise on Fridays and fall on Mondays. The seminal paper vis-à-vis the weekend effect is 'Stock returns and the weekend effect' published in 1980 by Kenneth R. French (French, 1980). He noted that under the calendar time hypothesis average Monday returns should be three times the expected return for other days of the week, whilst under the trading time hypothesis the expected return is the same for each day of the week. French discovered that neither hypothesis was true, and that although the average return for the other four days of the week was positive, the average for Monday was significantly negative. Gibbons and Hess (1981) found strong and persistent negative returns on Monday for stocks and below-average returns for Treasury bills on Mondays (Treasury bills are a form of US government debt). Keim and Stambaugh (1984) found consistently negative Monday returns (a) for the Standard & Poor's Composite index as early as 1928, (b) for exchange-traded stocks of firms of all sizes, and (c) for actively traded over-the-counter (OTC) stocks. Jaffe and Westerfield (1985) examined the daily stock market returns in the US, the UK, Japan, Canada and Australia and found the weekend effect in each country. Harris (1986) studied weekly and intradaily patterns in stock returns and discovered that on Monday mornings, prices drop, whilst on the other weekday mornings, they rise. Lakonishok and Smidt (1988) studied 90 years of daily data on the DJIA and concluded that the rate of return on Monday was substantially negative (-0.14 per cent). Connolly (1989) examined the robustness of the weekend effect and concluded that it was smaller than previously believed, difficult to profit from and seemed to have disappeared by 1975.

Lakonishok and Maberly (1990) documented the trading patterns of individual and institutional investors. They found that Monday was the day with the lowest trading volume; also that the propensity of individuals to transact on Monday

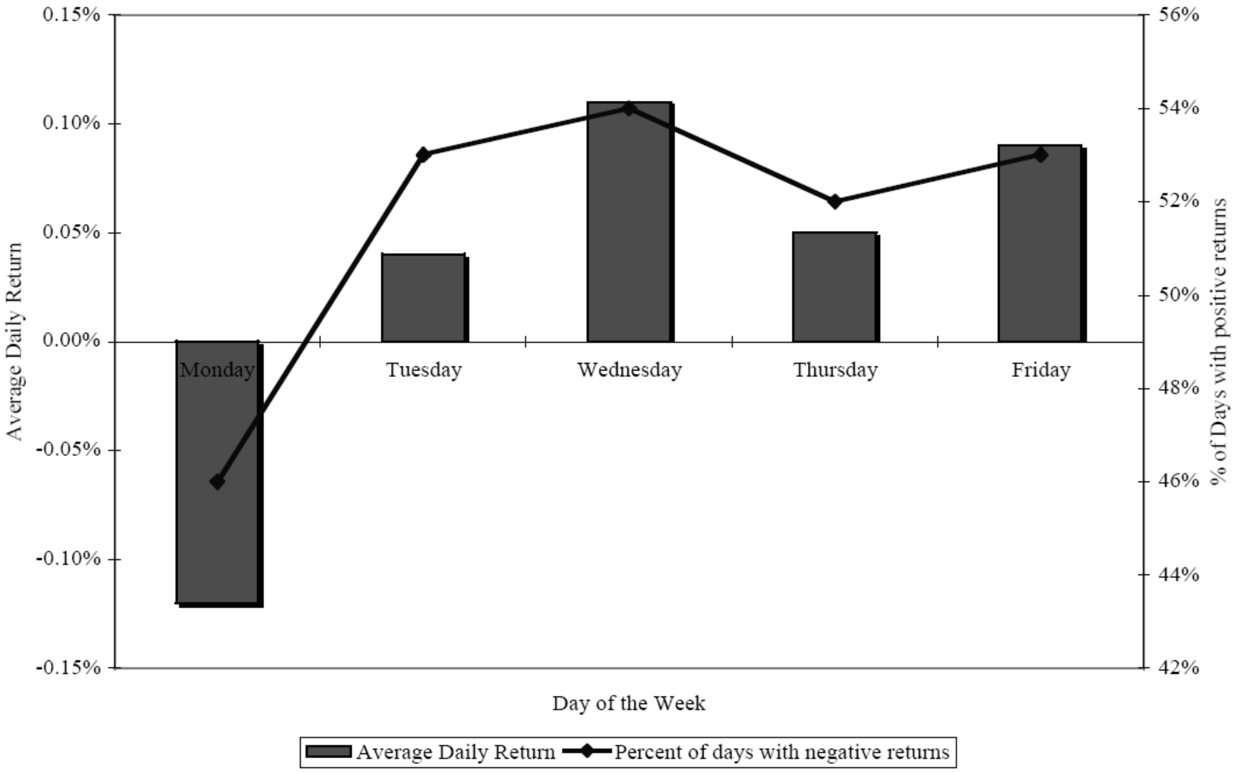

Figure 5: *Returns by day of the week, 1927–2001. Raw data from CRSP. Damodaran (2003)*

was highest relative to other days of the week whilst that of institutions was the lowest. They also found a tendency for individuals to increase the number of sell transactions relative to buy transactions on Mondays, which might explain at least part of the weekend effect. Agrawal and Tandon (1994) examined seasonal patterns in stock markets of eighteen countries. They found a daily seasonal in nearly all the countries, but a weekend effect in only nine countries. The authors also found that the daily seasonal largely disappeared in the 1980s. Abraham and Ikenberry (1994) claimed that the Monday effect is substantially the consequence of information revealed in prior trading sessions, particularly on Fridays. Hawawini and Keim (1995) found that stock returns, in many Western countries, are on average negative on Monday. Kamara (1997) showed that equity derivatives and the institutionalization of equity markets affect the Monday seasonal. Wang et al. (1997) showed that the Monday effect occurred primarily in the last two weeks (fourth and fifth weeks) of the month. In his paper on rational markets Rubinstein (2001) informs us that although the Monday effect is the strongest of the calendar anomalies, it is not large enough to support a profitable trading strategy if one assumes realistic trading costs, and that after 1987 the Monday effect disappeared and even reversed. Steeley (2001) showed that the weekend effect in the UK equity market disappeared during the 1990s. However, when partitioning the data on the basis of market direction they uncovered systematic day-of-the-week effects: negative returns on Mondays and Fridays are significantly different from their mid-week counterparts. Sullivan et al. (2001) highlighted the dangers of data mining. They noted that the single most significant calendar rule is the Monday effect, but warn that ‘the solution to the puzzling abnormal Monday effect actually lies outside the specificity of Mondays and rather has to do with the very large number of rules considered besides the Monday rule.’ Chen and Singal (2003) argued that speculative short sellers cause the weekend effect. Schwert (2003) concluded that the weekend effect seems to have disappeared, or at least substantially attenuated, since it was first documented in 1980. Christophe et al. (2009) examine daily short selling of Nasdaq stocks and found that speculative short selling does not explain an economically meaningful portion of the weekend effect in returns. Keef et al. (2009) examined the temporal dynamics of the international Monday effect in 50 countries, and found a very weak Monday effect that has remained stable over the period 1994 to 2006. Blau et al. (2009) looked at short-sale data for NYSE-listed common stocks and concluded that the weekend effect was not caused by short selling. Lim and Chia (2010) found support for the day-of-the-week effect in the stock markets of Malaysia and Thailand.

9.3 Intramonth Effects

Intramonth effects include the existence of positive returns only in the first half of the month, and more specifically a *turn-of-the-month effect* where the last day of one month and the first three of the next are particularly high. The seminal paper on the intramonth effect is 'A monthly effect in stock returns' by Robert Ariel (Ariel, 1987). He concluded that the mean return for stocks is positive only for days immediately before and during the first half of calendar months, and indistinguishable from zero for days during the last half of the month. Penman (1987) found that the aggregate corporate earnings news arriving at the market during the first half-month of calendar quarters 2 through 4 tends to be good, whereas earnings reports arriving later are more likely to convey bad news. Lakonishok and Smidt (1988) found only mild support for the idea that rates of return are larger in the first half of the month than in the last half. Jaffe and Westerfield (1989) found only weak evidence supporting the monthly effect found by Ariel in four other countries. However, they do find stronger evidence of a 'last day of the month' effect. Ogden (1990) showed that the standardization of payments in the United States at the turn of each calendar month generally induces a surge in stock returns at the turn of each calendar month. Cadsby and Ratner (1992) found that turn-of-month effects are significant in Canada, the UK, Australia, Switzerland and West Germany, but not in Japan, Hong Kong, Italy or France. Hensel and Ziemba (1996) showed that after adjustment for risk, a strategy of being long in the S&P 500 index during the turn-of-the-month period and long in Treasury bills at other times dominates the other strategies they considered, including a 100 per cent allocation to small-capitalization stocks. Kunkel et al. (2003) found a turn-of-the-month effect in 16 out of 19 countries during the period from 1988 to 2000. Nikkinen et al. (2007) suggest that the turn-of-the-month and intramonth anomalies arise from clustered information, namely from important macroeconomic news announcements, which are released systematically at a certain point each month. Dzhabarov and Ziemba (2010) concluded that the turn-of-the-month effect still exists but with a bit of anticipation. Zhao and Yan (2010) found the turn-of-the-month effect in the Chinese stock market.

9.4 January Effect

The *January effect* (also known as the *turn-of-the-year effect* or the *January anomaly*) is arguably now the most important calendar anomaly. The returns on common stocks in January are much higher than in other months, and this phenomenon is due to smaller-capitalization stocks in the early days of the month. Figure 6 below shows how significant the January effect is. Wachtel (1942) identified a December–January seasonal rise. Praetz (1973) showed

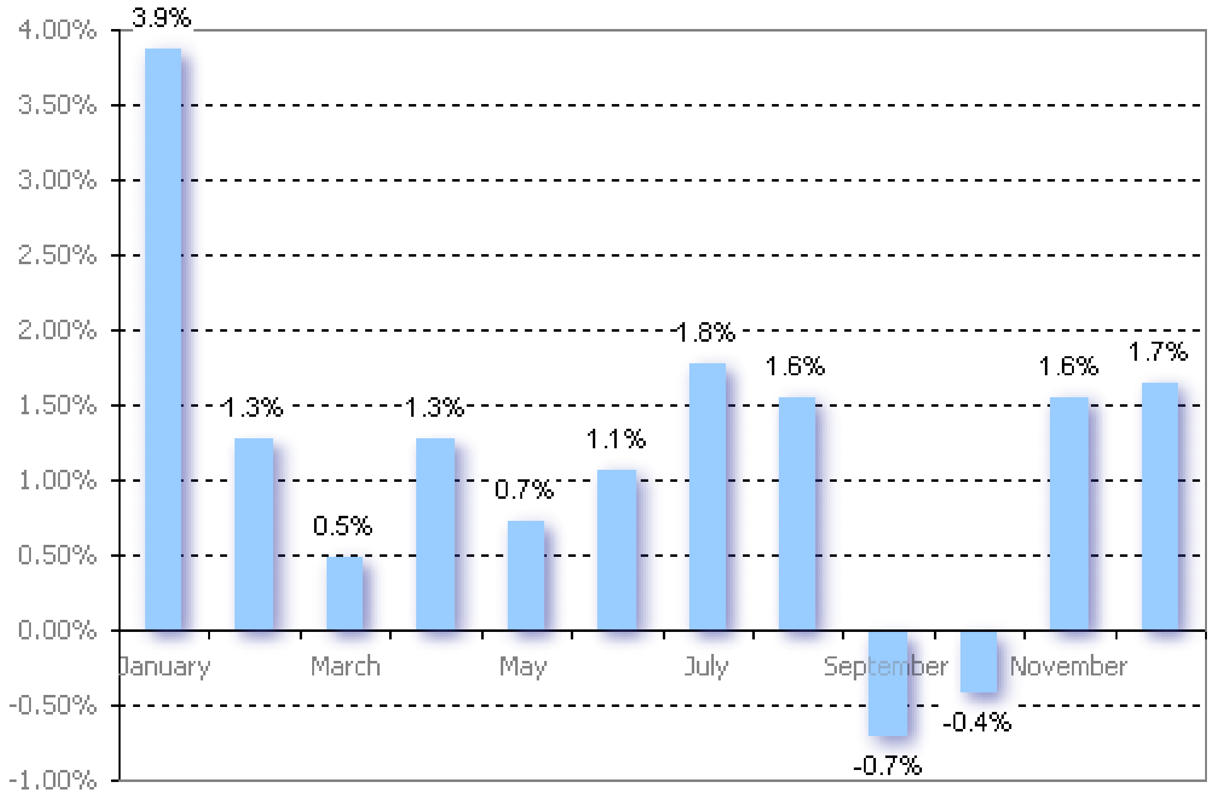

Figure 6: *Returns by month of the year 1927–2001. Raw data from French. Damodaran (2003)*

that Australian return distributions depend upon the month. Officer (1975) found some evidence of seasonality in the Australian capital markets. In what was to become a seminal paper, Rozeff and Kinney (1976) first discovered the January effect in the NYSE. Roll (1983) suggested that the turn-of-the-year effect is due to tax loss selling induced by negative returns over the previous year. Keim (1983) provided evidence that daily abnormal return distributions in January have large means relative to the remaining eleven months, and that the relation between abnormal returns and firm size is always negative and more pronounced in January than in any other month. Reinganum (1983) showed that the exceptionally large returns of small firms during the first few trading days of January appear to be consistent with tax-loss selling, but tax-loss selling cannot explain the entire January seasonal effect. Gultekin and Gultekin (1983) found evidence for the January effect in most of the major industrialized countries they examined. Constantinides (1984) explained that tax trading does not explain the small-firm anomaly but predicts a seasonal pattern in trading volume which maps into a seasonal pattern in stock prices, the January anomaly, only if investors are irrational or ignorant of the price seasonality. Robert A. Haugen and Josef Lakonishok wrote the book *The Incredible January Effect: The Stock Market's Unsolved Mystery* (Haugen and Lakonishok, 1987). The book helped to publicize the January effect to investors and suggested an investment strategy to take advantage of the phenomenon, so likely contributed to the diminishment of the effect. Ritter (1988) showed that the ratio of stock purchases to sales by individual investors explains about half of the turn-of-the year effect. Lakonishok and Smidt (1988) found evidence of persistently high end-of-December returns. Keim (1989) found systematic tendencies for closing prices to be recorded at the bid in December and at the ask in early January.

Bhardwaj and Brooks (1992) found that the January effect is primarily a low share price phenomenon rather than a small firm effect. Agrawal and Tandon (1994) examined seasonal patterns in the stock markets of eighteen countries and found that January returns are large in most countries. Hawawini and Keim (1995) examined the average monthly returns of eighteen market indices by month of the year and found that average returns during January were always positive and generally significantly higher than during the rest of the year (a notable exception was Korea). They also noted that broader and equally-weighted indices, which emphasize smaller stocks, exhibited a stronger January seasonal than narrower or value-weighted indices. Sias and Starks (1997) provide evidence in support of the tax-loss-selling hypothesis (as opposed to the window-dressing hypothesis) as an explanation for the turn-of-the-year effect. Cataldo II and Savage (2000) edited *The January Effect and Other Seasonal Anomalies: A Common Theoretical Framework*, a book that applies John Maynard Keynes' theory of investor liquidity preferences to the examination of the stock market literature on the January effect and other seasonal anomalies. Poterba and Weisbenner (2001) suggested that year-end, tax-motivated trading by individual investors contributes to turn-of-the-year return anomalies. Sullivan et al. (2001) warn of the dangers of data mining calendar effects. Schwert (2003) found that the turn-of-the-year anomaly has halved, but is still reliably positive. Haug and Hirschey (2006) analysed US equity returns and found that abnormally high rates of return on small-capitalization stocks continue to be observed during the month of January. Starks et al. (2006) examined turn-of-the-year return and volume patterns for municipal bond closed-end funds and provide direct evidence supporting the tax-loss selling hypothesis as an explanation of the January effect. Rendon and Ziemba (2007) found that the January effect is still alive in the futures markets. Moller and Zilca (2008) found higher abnormal returns in the first part of January and lower abnormal returns in the second part of January in recent years, but the overall magnitude of the January effect remained unchanged. Dzhabarov and Ziemba (2010) concluded that the January turn-of-the-month effect still exists, but has moved to December. Sun and Tong (2010) argued that the January effect is not due to risk per se, but rather it is due to higher compensation for risk (the risk premium) in the month.

9.5 Holiday Effect

The *holiday effect* refers to the tendency of the market to do well on any day which precedes a holiday. Fields (1934) found that the DJIA showed a high proportion of advances the day before holidays. Lakonishok and Smidt (1988) found that the preholiday rate of return was 23 times larger than the regular daily rate of return, and holidays account for about 50 per cent of the price increase in the DJIA. Ariel (1990) found that on the trading day prior to holidays stocks show high mean returns, averaging nine to fourteen times the mean return of the remaining days of the year. Incredibly, over one-third of the total return accruing to the market over the 1963–1982 period was earned on the eight trading days prior to holidays during each year. Cadsby and Ratner (1992) found that pre-holiday effects were significant in the US, Canada, Japan, Hong Kong and Australia, but not in the UK, Italy, Switzerland, West Germany and France. Liano et al. (1992) examined the pattern of daily returns on the daily value-weighted and the equally weighted return indices of over-the-counter (OTC) stocks during the period 1973–1989 and found evidence of unusually high returns on pre-holiday trading days and unusually low returns on post-holiday trading days. Kim and Park (1994) provided further evidence of the holiday effect in stock returns, which they found in all three of the major stock markets in the US (the NYSE, AMEX and NASDAQ), the UK and Japan. Arsad and Coutts (1997) found evidence of the holiday effect in the FT 30 index. Brockman and Michayluk (1998) investigated the holiday effect for equities traded on the NYSE, AMEX and NASDAQ exchanges during the period 1987–93 and found that pre-holiday returns are significantly higher than non-holiday returns. Vergin and McGinnis (1999) found that in the ten years from 1987 to 1996 the excess holiday returns have disappeared for large firms and have substantially diminished for small firms. A study by Meneu and Pardo (2004) confirmed the existence of a pre-holiday effect in the most traded Spanish stocks. Keef and Roush (2005) found that the pre-holiday effect was strong up to 1987, but greatly diminished after 1987. McGuinness (2005) identified a strong pre-holiday effect in Hong Kong stock returns. Chong et al. (2005) examined the pre-holiday effect in the US, UK and Hong Kong markets, and found that it had declined in all three markets, but only significantly in the US. Lu and Liu (2008) found evidence of a pre-holiday effect and a post-holiday effect in the stock market in China. Marrett and Worthington (2009) found evidence of a pre-holiday effect in the Australian stock market. Dzhabarov and Ziemba (2010) concluded that the holiday effect still exists to some extent three days before the holiday, but has diminished greatly over the 1990s and 2000s.

9.6 Halloween Indicator

Bouman and Jacobsen (2002) revealed that a trading strategy of tactical asset allocation based on the old saying 'sell in May and go away' generated abnormal returns in comparison with stock market indices in most countries in their study. Dzhabarov and Ziemba (2010) showed that the 'sell in May and go away' strategy beats a buy-and-hold strategy.

9.7 Daylight Saving Anomaly

Kamstra et al. (2000) found a daylight saving anomaly. Daylight-saving weekends are typically followed by large negative returns on financial market indices (roughly 200 to 500 per cent of the regular weekend effect), and they argue that the effect could be a direct result of changes in sleep patterns.

10 Long Memory

In 1906, Harold Edwin Hurst, a young English civil servant, came to Cairo, Egypt, which was then under British rule. As a hydrological consultant, Hurst's problem was to predict how much the Nile flooded from year to year. He developed a test for long-range dependence and found significant long-term correlations among fluctuations in the Nile's outflows and described these correlations in terms of power laws. This statistic is known as the 'rescaled range', 'range over standard deviation' or 'R/S' statistic. From 1951 to 1956, Hurst, then in his seventies, published a series of papers describing his findings (Hurst, 1951). I run the world's only website dedicated to long-range dependence.[1] The definition of long memory below is taken from Beran (1994) (p. 42).

Definition 5 *If $\rho(k)$ is the correlation at lag k, let X_t be a stationary process for which the following holds. There exists a real number $\alpha \in (0,1)$ and a constant $c_p > 0$ such that*

$$\lim_{k\to\infty} \frac{\rho(k)}{c_\rho k^{-\alpha}} = 1. \tag{2}$$

Then X_t is called a stationary process with long memory or long-range dependence or strong dependence, or a stationary process with slowly decaying or long-range correlations. The parameter $H = 1 - \frac{\alpha}{2}$ will also be used instead of α. In terms of this parameter, long memory occurs for $\frac{1}{2} < H < 1$. Knowing the covariances (or correlations and variance) is equivalent to knowing the spectral density f. Therefore, long-range dependence can also be defined by imposing a condition on the spectral density. If $f(\lambda)$ is the spectral density, let X_t be a stationary process for which the following holds: there exists a real number $\beta \in (0,1)$ and a constant $c_f > 0$ such that

$$\lim_{\lambda\to 0} \frac{f(\lambda)}{c_f\,|\lambda|^{-\beta}} = 1. \tag{3}$$

Then X_t is called a stationary process with long memory or long-range dependence or strong dependence.

10.1 Returns

Mandelbrot (1972) applied R/S analysis to financial returns. Greene and Fielitz (1977) claimed that many daily stock return series are characterized by long-term dependence. Aydogan and Booth (1988) concluded that there was no significant evidence for long-term memory in common stock returns.

[1] `http://www.long-memory.com`

Lo (1991) modified the R/S statistic to ensure that it is robust to short-range dependence and found little evidence of long-term memory in historical US stock market returns. Cheung (1993) found evidence of long memory in foreign exchange rates. Goetzmann (1993) considered three centuries of stock market prices. R/S tests provided some evidence that the detrended London Stock Exchange and NYSE prices may exhibit long-term memory. Cheung and Lai (1993) examined the long memory behaviour in gold returns during the post-Bretton Woods period and found that the long memory behaviour in gold returns is rather unstable. They concluded, '[w]hen only few observations corresponding to major political events in the Middle East, together with the Hunts event, in late 1979 are omitted, little evidence of long memory can be found.' Mills (1993) found little evidence of long memory in daily UK stock returns. Embrechts (1994) claims that the Hurst coefficient for JPY/USD returns indicates a memory effect. Embrechts et al. (1994) applied rescaled range analysis to US Fed Fund rates, US Treasury notes, CHF/USD exchange rates and the Japanese stock market (TOPIX) and claimed that it shows that most financial markets follow a biased random walk. Bhar (1994) tested for long-term memory in the JPY/USD exchange rate using Lo's methodology and found no evidence of long-term memory. Moody and Wu (1995) performed rescaled range and Hurst exponent analysis on tick-by-tick interbank foreign exchange rates, and found that they are mean-reverting. Nawrocki (1995) considered the CRSP monthly value-weighted index and the S&P 500 daily index, and found that the Hurst exponent and the Lo-modified R/S statistic indicate that there is persistent finite memory. Tschernig (1995) found evidence for weak long memory in the changes of DEM/USD spot rates and the CHF/USD spot rates; in contrast, there was no evidence for long memory in the DEM/CHF spot rate changes. Chow et al. (1996) found evidence that consistently revealed the absence of long-term dependence in 22 international equity market indices. Moody and Wu (1996) improve Lo's R/S statistic and conclude that the DEM/USD series is mildly trending on time scales of 10 to 100 ticks. Peters (1996) applied R/S analysis and concluded that most of the capital markets are characterized by long memory processes. Lux (1996) analysed German stock market data and found no evidence for (positive or negative) long-term dependence in the returns series. Barkoulas and Baum (1996) applied the spectral regression method and found no evidence of long memory in either aggregate or sectoral stock indices, but evidence of long memory in 5, intermediate memory in 3 and no fractal structure in 22 of the 30 DJIA companies. Overall findings did not offer convincing evidence against the martingale model. Using the spectral regression method, Barkoulas and Baum (1997) found significant evidence of long memory in the 3- and 6-month returns (yield changes) on Eurocurrency deposits denominated by JPY (Euroyen). Hiemstra and Jones (1997) applied the modified rescaled range test to the return series of 1,952 common stocks and their results indicated that long memory is not a widespread characteristic of those stocks. Lobato and Savin (1998) found no evidence of long memory in daily stock returns. Willinger et al. (1999) found empirical evidence of long-range dependence in stock price returns, but the evidence was not absolutely conclusive. Huang and Yang (1999) applied the modified R/S technique to intraday data and found the phenomenon of long-term memory in both NYSE and NASDAQ indices. Baum et al. (1999) reject the hypothesis of long memory in real exchange rates in the post-Bretton Woods era.

Using the spectral regression method, Barkoulas et al. (2000) found significant and robust evidence of positive long-term persistence in the Greek stock market. Chen (2000) calculated the classical rescaled range statistic of Hurst for seven Asia-Pacific countries' stock indices and concluded that all the index returns have long memory. Crato and Ray (2000) found no evidence for long memory in futures' returns. Weron and Przybyłowicz (2000) found that electricity price returns are strongly mean-reverting. Zhuang et al. (2000) investigated British stock returns and found little or no evidence of long-range dependence. Sadique and Silvapulle (2001) examined the presence of long memory in weekly stock returns of seven countries, namely Japan, Korea, New Zealand, Malaysia, Singapore, the USA and Australia. They found evidence for long-term dependence in four countries: Korea, Malaysia, Singapore and New Zealand. Cheung and Lai (2001) found long memory in JPY-based real exchange rates. Nath (2001) found indications of long-term memory in the Indian stock market using R/S analysis, but suggested that a more rigid analysis, such as Lo's modified R/S statistic, should be used. Panas (2001) found long memory in the Athens Stock Exchange. Cavalcante and Assaf (2002) found little evidence of long memory in the returns of the Brazilian Stock Market. Nath and Reddy (2002) used R/S analysis and found long-term memory in the USD/INR exchange rate, although the variance ratio test clearly implied that there exists only short-term memory. Henry (2002) investigated long range dependence in nine international stock index returns. They found evidence of long memory in four of them, the German, Japanese, South Korean and Taiwanese markets, but not for the markets of the UK, USA, Hong Kong, Singapore and Australia. Tolvi (2003a) found long memory in Finnish stock market return data. Using a monthly data set consisting of stock market indices of 16 OECD countries, Tolvi (2003b) found statistically significant long memory for three countries: Denmark, Finland and Ireland, which are all small markets. In a paper that examines and compares the behaviour of four tests for fractional integration in daily observations of silver prices, de Peretti (2003) concluded that one must use at least a bilateral bootstrap test to detect long-range dependence in time series, and deduced that silver prices do not exhibit long memory. Beine and Laurent (2003) investigated the major exchange rates and found no evidence of long memory in the conditional mean. Limam (2003) analysed stock index returns in 14 markets and concluded that long memory tends to be associated with thin markets. Sapio (2004) used spectral analysis and found long memory in day-ahead electricity prices. Cajueiro and Tabak (2004) found that the markets of Hong Kong, Singapore and China exhibit long-range dependence. Naively, Cajueiro and Tabak (2005) state that the presence of long-range dependence in asset returns seems to be a stylized fact. They studied the individual stocks in the Brazilian stock market and found evidence that firm-specific variables can explain, at least partially, the long-range dependence phenomena. Grau-Carles (2005) applied four tests for long memory to two major daily stock indices, the S&P 500 and the DJIA, two samples from each. There was no evidence of long memory in the returns. Oh et al. (2006) studied the long-term memory in diverse stock market indices and foreign exchange rates using detrended fluctuation analysis. For all daily and high-frequency market data studied, no significant long-term memory was detected in the return series. Elder and Serletis (2007) found no evidence of long memory in the DJIA. Serletis and Rosenberg (2009) used daily data on four US stock market indices and concluded that US stock market returns display anti-persistence.

10.2 Volatility

Absolute returns and squared returns are proxies for volatility. Taylor (1986) was the first to notice the apparent stylized fact that the absolute values of stock returns tended to have very slowly decaying autocorrelations. Dacorogna et al. (1993) modelled foreign exchange volatility and were surprised to find that the positive autocorrelation of absolute price changes declined hyperbolically rather than exponentially as a function of the lag. Crato and de Lima (1994) found long memory in the conditional variance of the returns of US stock indices. Bollerslev and Mikkelsen (1996) found long memory in the volatility of the S&P 500. Ding and Granger (1996) looked at the S&P 500, the Nikkei, DEM/USD and individual stock returns for Chevron (the US-based energy company) and Ajinomoto (a Japanese food company) and found long memory in the volatility of all five series. Long memory is usually strongest for absolute returns, but for the exchange rate, long memory was strongest for absolute returns taken to the power of $\frac{1}{4}$. Granger and Ding (1996) remind us of the long memory found in absolute returns from a daily stock market index and explain that the $I(d)$ model is not the only one available that produces long memory properties. Andersen and Bollerslev (1997) inspected a one-year time series of five-minute USD/DEM exchange rates and found long memory in the volatility. Breidt et al. (1998) found long memory in the volatility of daily market index data. Lobato and Savin (1998) found strong evidence of long memory in squared stock returns. Comte and Renault (1998) found long memory in the volatility of options on CAC 40 of the Paris Stock Exchange. The long memory phenomenon was stronger when they considered absolute values (or squared values) of the differenced volatility. Granger and Hyung (1999) showed that S&P 500 absolute stock returns are more likely to show the 'long memory' property because of the presence of breaks in the series rather than an $I(d)$ process. Gallant et al. (1999) model long memory in the volatility of IBM stock returns. Granger et al. (2000) found long memory in absolute returns of daily data for individual shares, stock price indices, residuals of the CAPM model, commodity prices and interest rates. Andersen et al. (2001b) found long memory in exchange rate volatility. Ding et al. (1993) found long memory in power transformations of the absolute returns in the S&P 500. Diebold and Inoue (2001) make the point that long memory and regime switching can be easily confused. Kirman and Teyssière (2002) estimated the fractional degree of integration for the absolute returns for the following currency pairs: DEM/FRF, GBP/FRF, GBP/USD, USD/CHF, USD/DEM, USD/FRF, USD/JPY. All exhibited long memory in the volatility. Giraitis et al. (2003) found long memory in the squared returns of GBP/USD exchange rate data. Granger and Hyung (2004) analysed the S&P 500 and demonstrated that absolute stock returns may show the long memory property because of the presence of neglected breaks, rather than because it really is an $I(d)$ process. Ohanissian et al. (2008) tested intraday USD/DEM and USD/JPY data and concluded that the long memory property in exchange rate volatility is generated by a true long memory process.

10.3 Volume

Lobato and Velasco (2000) analysed the trading volume for the 30 stocks in the DJIA index and concluded that there is strong evidence that stock market trading volume exhibits long memory. Eisler and Kertész (2007) found long memory in both the frequency and the size of consecutive transactions on the NYSE.

10.4 Other

Müller and Sgier (1992) found short- and long-term memory in intra-day bid–ask spreads in the foreign exchange market. In their intra-daily foreign exchange markets review paper, Guillaume et al. (1997) state that intra-day studies confirm the presence of short- and long-term memories for volatility, the spread, the volatility ratio and the directional change frequency. Using trades and quotes data from liquid French stocks, Bouchaud et al. (2004) discovered that the sign of the trades shows surprisingly long-range (power-law) correlations, at least up to 15,000 trades (two trading days). They found long-range correlated market orders and mean reverting limit orders. Lillo and Farmer (2004) made use of a data set from the London Stock Exchange and demonstrated that the signs of order flow, order size and liquidity are all long memory processes. The persistence in order signs is compensated for by anti-correlated fluctuations in transaction size and liquidity. Qiu et al. (2008) observed data from the Chinese stock market and found long memory in the time intervals that volatility is above a certain threshold.

11 Chaos

Chaos has a precise meaning within the world of physics and non-linear mathematics, but applications of 'chaos theory' in other domains (in management, for example) are generally bogus. Mathematical definitions of chaos vary, what follows is an informal one. *Chaos* exists when a deterministic dynamical system is sensitive to initial conditions and gives rise to effectively unpredictable long-term behaviour. Note that high dimensional chaos is indistinguishable from a stochastic process, we're interested in whether markets exhibit low-dimensional chaos.

Savit (1988) wrote an introduction to chaos in market prices. Frank and Stengos (1989) examined gold and silver returns and found that the correlation dimension is between 6 and 7 while the Kolmogorov entropy is about 0.2 for both assets. Peters (1991) claimed to have found chaos in the financial markets. Brock et al. (1991) concluded that the evidence for the presence of deterministic low-dimensional chaotic generators in economic and financial data is not very strong. Blank (1991) analysed the futures prices for the S&P 500 index and soybeans. All of their results were consistent with those of markets with underlying generating systems characterized by deterministic chaos (they give necessary, but not sufficient, conditions to prove the existence of deterministic chaos). In an excellent paper, Hsieh (1991) found no evidence of low complexity chaotic behaviour in stock returns. Willey (1992) tested the daily prices of the S&P 100 and the NASDAQ-100. Deterministic chaos was rejected by two of three recently developed empirical tests. Decoster et al. (1992) searched for evidence of chaos in commodity futures (silver, copper, sugar and coffee) prices and found evidence of non-linear structure. Evidence for the presence of chaos was provided, but the authors note that further research is needed before they can confirm or reject the discovery of chaos. Mayfield and Mizrach (1992) estimated the dimension of the S&P 500 (sampled at approximately 20-second intervals) and concluded that the data are either of low dimension with high entropy or non-linear but of high dimension. Yang and Brorsen (1993) found evidence of non-linearity in several futures markets, which was consistent with deterministic chaos in about half of the cases. Abhyankar et al. (1995) tested for the presence of chaos in the FTSE 100 index using a six month sample of about 60,000 minute-by-minute returns and found little to support the view that the process is chaotic at any frequency. Sewell et al. (1996) examined weekly changes for the period 1980 to 1994 in six major stock indices (the US, Korea, Taiwan, Japan, Singapore and Hong Kong) and the World Index as well as the corresponding foreign exchange rates between the US and the other five countries. They concluded that '[t]hese results do not prove the existence of chaos in these markets but are consistent with its existence in some cases.' Abhyankar et al. (1997) tested the world's four most important stock market indices: the S&P 500, the DAX, the Nikkei 225 and the FTSE 100 index and found no evidence of low-dimensional chaotic processes. Serletis and Gogas (1997) tested for deterministic chaos in seven East European black market exchange rates and concluded that there is evidence consistent with a chaotic non-linear generation process in only two out of seven series. Barkoulas and Travlos (1998) investigated the existence of a deterministic non-linear structure in the stock returns of the Athens Stock Exchange (an emerging capital market) and found no strong evidence of chaos. In a working paper, Wei and Leuthold (1998) looked at six agricultural futures markets—corn, soybeans, wheat, hogs, coffee and sugar—and found that five of them (all except sugar) were chaotic processes. Gao and Wang (1999) examined the daily prices of four futures contracts (S&P 500, JPY, DEM and Eurodollar) and found no evidence of deterministic chaos.

Andreou et al. (2000) examined four major currencies against the Greek drachma (GRD) and found evidence of chaos in two out of four. Panas and Ninni (2000) found strong evidence of chaos in daily oil products for the Rotterdam and Mediterranean petroleum markets. Adrangi et al. (2001) tested for the presence of low-dimensional chaotic structure in crude oil, heating oil and unleaded gasoline futures prices from the early 1980s and found no evidence of chaos. Antoniou and Vorlow (2005) investigated the 'compass rose' patterns revealed in phase portraits (delay plots) of FTSE 100 stock returns and found a strong non-linear and possibly deterministic signature in the data-generating processes. Cecen and Ugur (2005) looked at stock market data and exchange rate returns and concluded that there is little evidence in favour of low dimensional chaos in financial time series and explain that non-linear stochastic time dependence seems to account for much of the temporal dependence in these series. Wang and Fu (2007) analysed the Shanghai stock index and claim to prove that the stock market in China is a chaotic system. Zhao (2009) used the GARCH model and chaos methods together to study the non-linear characteristics of the Shanghai Composite index and the Shenzhen Component index and concluded that China's stock markets show some degrees of chaotic behaviour.

12 Market Microstructure

Market microstructure is a branch of economics and finance concerned with the details of how exchange occurs in markets, most commonly financial markets. Market microstructure research typically examines the ways in which the working process of a market affects trading costs, prices, volume and trading behaviour.

Garman (1976) used a collection of market agents to model both 'dealership' and 'auction' markets. Morse and Ushman (1983) examined the effect of information announcements on the bid–ask spreads. They found no significant changes in bid–ask spreads surrounding quarterly earnings announcements, but significant increases in the size of bid–ask spreads are found on the day of large price changes.

Amihud et al. (1990) studied the impact of the stock market microstructure on return volatility and on the value discovery process in the Milan stock exchange; the primary trading mechanism employed by this exchange is a call market, which is usually preceded and followed by trading in a continuous market. They found that the opening transaction in the continuous market had the highest volatility, and that opening the market with the call transaction seemed to produce relatively lower volatility. Reinganum (1990) investigated the influence of market microstructure on liquidity premiums. Premiums of a competitive, multiple-dealership market (NASDAQ) were contrasted with those of a monopolistic, specialist system (NYSE). The NASDAQ appeared to have a liquidity advantage over the NYSE for small firms but not for large companies. In Bossaerts and Hillion (1991), four continental European currencies with respect to the French franc were examined, and the bid–ask spread in the spot and forward foreign exchange markets when some traders have superior information about government intervention was investigated. Larger bid–ask spreads on Fridays were documented. Reliable evidence of asymmetric bid–ask spreads for all days of the week, albeit more pronounced on Fridays, were presented. Lease et al. (1991) investigated the importance of bid–ask spread-induced biases on event date returns as exemplified by seasoned equity offerings by NYSE listed firms. They document significant negative return biases on the offering day. Buy-sell order flow imbalance was prominent around the offering and induces a relatively large spread bias. Allen and Gorton (1992) explain that buyers wish to avoid trading with informed investors, will usually be able to choose the time at which they trade, and so will tend to cluster. So when liquidity buyers are not clustering, purchases are more likely to be by an informed trader than sales so the price movement resulting from a purchase is larger than for a sale. As a result, profitable manipulation by uninformed investors may occur; and the authors present a model where the specialist takes account of the possibility of manipulation in equilibrium. Dubofsky (1992) proposed a market microstructure explanation of the positive abnormal returns found on ex-stock distribution days. The abnormal returns are argued to be the result of NYSE Rule 118 and AMEX Rule 132, which dictate how open limit orders to buy and sell stock are handled on ex-days. Loughran (1993) demonstrated that the relatively poor performance of small NASDAQ securities relative to the performance of similarly-sized NYSE securities during the 1973–1988 period was largely due to initial public offerings (IPOs), rather than market microstructure differences (on average, IPOs underperform during the six calendar years after going public). Huang and Stoll (1994) developed a two-equation econometric model of quote revisions and transaction returns and used it to identify the relative importance of different microstructure theories and to make predictions. Microstructure variables and lagged stock index futures returns had in-sample and out-of-sample predictive power based on data observed at five-minute intervals. The most striking microstructure implication of the model, confirmed by the empirical results, specified that the expected quote return is positively related to the deviation between the transaction price and the quote midpoint while the expected transaction return is negatively related to the same variable.

Wang et al. (1995) examined the Real Estate Investment Trust (REIT) market microstructure and its relationship to stock returns. When compared with the general stock market, REIT stocks tend to have a lower level of institutional investor participation and are followed by fewer security analysts. Also, REIT stocks that have a higher percentage of institutional investors or are followed by more security analysts tend to perform better than other REIT stocks. Park (1995) examined the impact of bid–ask bounce on variations in stock returns following large price changes. By using the average of the bid–ask prices in the sample selection process, the previously reported price reversal on the day following the events (day +1) disappears. However, for a short-run period after day +1, systematic abnormal return patterns are still observed (but the profits from a contrarian investment strategy designed to exploit the patterns would not cover transaction costs). Maureen O'Hara wrote *Market Microstructure Theory* (O'Hara, 1995), which provides a comprehensive guide to the theoretical work. Brennan and Subrahmanyam (1996) investigated the empirical relation between monthly stock returns and measures of illiquidity obtained from intraday data. They found a significant return premium associated with both the fixed and variable elements of the cost of transacting. The relation between the premium and the variable cost was concave, which is consistent with clientele effects caused by small traders concentrating in the less liquid stocks. However, the relation between the premium and the estimated fixed cost component was convex. Campbell et al. (1996) contains a chapter on market microstructure which covers nonsynchronous trading, the bid–ask spread and modelling transactions data. Hasbrouck (1996) provided an overview of the various approaches to modelling microstructure time series. Spulber (1996) considered market microstructure and intermediation. Amihud et al. (1997) showed that improvements in market microstructure are valuable. Specifically, they found that stocks that were transferred to a more efficient trading method in the Tel Aviv Stock Exchange enjoyed significant and permanent price increases. Spulber (1999) wrote *Market Microstructure: Intermediaries and the Theory of the Firm*, which presents a theory of the firm based on its economic role as an intermediary between customers and suppliers. He applies the term 'market microstructure' generically to refer to the operation of markets for all types of goods and services. MacKinnon and Nemiroff (1999) examined the effect of the move to decimalization by the Toronto Stock Exchange and found an unambiguous gain to investors. Effective spreads decreased significantly, yet price impact was unaffected, thus reducing transaction costs, and there was an increase in trading activity.

Madhavan (2000) reviewed the theoretical, empirical and experimental literature on market microstructure relating to (a) price formation, (b) market structure and design, (c) transparency and (d) applications to other areas of finance. Kauffman and Wang (2001) studied the dynamics of an instance of dynamic pricing—group-buying discounts—used by MobShop.com, whose products' selling prices drop as more buyers place their orders. They found a positive *participation externality effect*, a *price drop effect* and a significant *ending effect*. Muscarella and Piwowar (2001) studied a sample of Paris Bourse stocks that were transferred between call trading and continuous trading. They found that frequently-traded stocks that are transferred from call trading to continuous trading experience, on average, liquidity improvements that are positively associated with price appreciation; and infrequently-traded stocks that are transferred from continuous trading to call trading experience price and liquidity declines. Cheung and Chinn (2001) reported findings from a survey of United States foreign exchange traders. They found that (a) in recent years electronically-brokered transactions have risen substantially, mostly at the expense of traditional brokers; (b) the market norm is an important determinant of interbank bid–ask spread and the most widely-cited reason for deviating from the conventional bid–ask spread is a thin/hectic market; (c) half or more of market respondents believe that large players dominate in the GBP/USD and USD/CHF markets; and (d) exchange rate predictability is viewed as fairly low (surprisingly, there is little variation in the proportion of traders who hold this view over the various horizons—from intraday to over six months). Lyons (2001) published *The Microstructure Approach to Exchange Rates*, a book that focuses on the economics of financial information and how microstructure tools help to clarify the types of information most relevant to exchange rates. Hasbrouck (2002) provided an overview of econometric approaches to characterizing the random-walk component in single- and multiple-price settings. Larry Harris published *Trading and Exchanges: Market Microstructure for Practitioners* (Harris, 2002), an excellent book about trading, the people who trade securities and contracts, the marketplaces where they trade and the rules that govern trading. Dominguez (2003) explored whether aspects of market microstructure influence the effectiveness of central bank intervention. Her results indicated that some traders typically know that the Fed is intervening at least one hour prior to the Reuters' report that a central bank is intervening, and the effects of interventions generally persist, at least to the end of the day. There was evidence of mean reversion in returns subsequent to Fed interventions particularly in the USD/DEM market, suggesting some initial overreaction by the market. Also, the evidence suggested that the timing of intervention operations matters—interventions that occur during heavy trading volume, that are closely timed to scheduled macro announcements, and that are coordinated with another central bank are the most likely to have large effects.

In an excellent review paper, Biais et al. (2005) surveyed the literature analysing the price formation and trading process, and the consequences of market organization for price discovery and welfare. Aït-Sahalia et al. (2005) considered the question of how often to sample a continuous-time process in the presence of market microstructure noise, and their answer is: model the noise and sample as often as possible. Hansen and Lunde (2006) analysed the properties of market microstructure noise and its influence on empirical measures of volatility, and examined a simple bias correction of the realized variance. An empirical analysis of the 30 stocks that comprise the DJIA revealed that market microstructure noise is (a) time-dependent and (b) correlated with increments in the efficient price. The results were established for both transaction data and quotation data and were found to hold for intraday returns that are based on both calendar-time sampling and tick-time sampling. Hasbrouck (2006) published *Empirical Market Microstructure: The Institutions, Economics, and Econometrics of Securities Trading*, the first integrated introduction to the most important models of empirical market microstructure. In *Information and Learning in Markets: The Impact of Market Microstructure* Vives (2008) shows that the microstructure of a market is the crucial factor in the informational efficiency of prices. In a PhD thesis, Thurlin (2009) wrote four essays on market microstructure, which cover price discovery, market transparency, informed trading and the effect of macroeconomic data.

13 Order Book

An *order book* is a compiled list of orders (prices at which traders are willing to buy or sell) received that a trading venue (e.g. a stock exchange) uses to record the interest of buyers and sellers in a particular financial instrument.

Bollerslev and Domowitz (1993) used computer simulations to study the effects of varying the length of an electronic order book. They state that the appearance and increasing persistence of serial correlation in the variance of transactions price returns is traced to the existence and length of the electronic book, as is the degree of non-normality in transactions returns. Whilst increases in the serial correlation of the market bid–ask spread as the book lengthens is isolated as one possible transmission mechanism of serial dependence in the variance of transactions prices. Hamao and Hasbrouck (1995) investigated the behaviour of intraday trades and quotes for individual stocks on the Tokyo Stock Exchange. They found that when orders that would otherwise walk through the limit order book are converted into limit orders, execution is delayed, but some orders execute (at least in part) at more favourable prices; an order that is held with an indicative quote has a larger cumulative price impact than one that is immediately executed in full; and after a market order is executed the quote hit by the market order generally tends to continue to move in the same direction (this is due in part to order autocorrelation and in part to the cancellation of limit orders). Biais et al. (1995) analysed the history of the order book for the 40 stocks in the CAC 40 and found evidence of information effects in the order process. Harris and Hasbrouck (1996) examined NYSE SuperDOT market and limit orders. Their results suggest that the limit order placement strategies most commonly used by NYSE SuperDOT traders do in fact perform best; limit orders placed at or better than the prevailing quote perform better than do market orders, even after imputing a penalty for unexecuted orders and after taking into account market order price improvement; and unconditional order submission strategies that use SuperDOT to offer liquidity in competition with the specialist do not appear to be profitable. Using data from the Helsinki Stock Exchange, Hedvall et al. (1997) studied the limit order book. Although the order flow was found to be quite symmetric in general, they identified clear asymmetries for various trade categories suggesting differences between the order submission of buyers and sellers using a limit order book. Jarnecic and McInish (1997) calculated the option value of the limit order book for four snapshots each day (1100hrs, 1200hrs, 1430hrs and 1558hrs) for thirty firms listed on the Australian Stock Exchange (ASX) (the value of bid and ask limit orders to other market participants can be considered analogous to put and call option prices respectively). They found that the option value of the limit order book is stable from day to day with changes in value due to changes in spreads offsetting those due to changes in depth; the option value of the limit order book is lowest at 1100hrs when the relatively higher bid–ask sizes do not offset the wider spreads and the option value of the limit order book increases throughout the trading day; and approximately 65% of the option value on the bid (ask) side is at the best bid (ask). Coppejans and Domowitz (1998) used durations (the time between transactions) to compare the relative importance of information sets in limit order book trading. Kavajecz (1999) investigated a database of 144 NYSE-listed securities and found that specialists' quotes may reflect only the limit order book on the side (or sides) of the market where they believe there is a chance of informed trading. Brown et al. (1999) used stocks on the ASX to estimate and examine certain characteristics of the order flow through an electronic open limit order book. They found that the proportion of informed orders is less than 10%, informed traders choose smaller orders than uninformed traders, there are U-shaped intraday patterns in order arrival and the information content of the order flow appears to follow this pattern across the day.

Al-Suhaibani and Kryzanowski (2000) analysed the order book, and order flow and execution on the Saudi stock market and described the microstructure. Bisière and Kamionka (2000) studied the flow of orders to buy and sell Alcatel shares at the Paris Bourse. Their model offers evidence of information and liquidity effects, as put forward by market microstructure theories. Maslov and Mills (2001) studied high-frequency NASDAQ Level II order book data and found that a large imbalance in the number of limit orders placed at bid and ask sides of the book was shown to lead to a predictable short-term price change (which is in accord with the law of supply and demand). Challet and Stinchcombe (2001) reported on a statistical analysis of the Island ECN (NASDAQ) order book, providing static (the size and lifetime probability distributions, the average shape of the orders distribution and market impact functions) and dynamic properties of the system. They then analysed them from a physicist's viewpoint and identify the fundamental dynamical processes. Coppejans and Domowitz (2002) evidenced that the information gleaned from the limit order book substantially affects the timing of trades, order submissions and cancellations. Declerck (2002) considered the trading costs in the limit order book market of the Paris Bourse and graph some interesting results concerning the spread. She also found that the conditional probability of the reversal of the order flow appears constant at 26%. Bouchaud et al. (2002) investigated several statistical properties of the order book of three liquid stocks of the Paris Bourse. They found that incoming limit order prices follow a power law around the current price with a diverging mean and also described the shape of the average order book. Daníelsson and Payne (2002) considered dynamic trading patterns in limit order markets, primarily foreign exchange and money markets. Clear feedback was observed between liquidity, volatility and volume. Zovko and Farmer (2002) defined the relative limit price as the difference between the limit price and the best price available. Using a data set of roughly two million orders from the London Stock Exchange, they demonstrated that the unconditional cumulative distribution of relative limit prices decays roughly as a power law with exponent approximately -1.5. They discovered that time series of relative limit prices show interesting temporal structure, characterized by an autocorrelation function that asymptotically decays as $C(\tau) \sim \tau^{-0.4}$. They also found that relative limit price levels are positively correlated with and are led by price volatility, and note that this feedback may potentially contribute to clustered volatility. Bates et al. (2003) used order flow data coupled with order book data in an evolutionary reinforcement learning algorithm to automate FX trading. Their preliminary results showed that using order flow and order book data is usually superior to trading on technical signals alone. Potters and Bouchaud (2003) analysed order book data from the NASDAQ. They (a) found that the statistics of incoming limit order prices revealed a very slowly decaying tail, (b) described the shape of the average order book, and (c) found that the lifetime of a given order increases as one moves away from the bid–ask. They also determine the 'price impact' function using French and British stocks, and found a logarithmic, rather than a power-law, dependence of the price response on the volume; and concluded that the 'weak time dependence of the response function shows that the impact is, surprisingly, quasi-permanent, and suggests that trading itself is interpreted by the market as new information.' Hall et al. (2003) used limit order book data from the SEATS system of the ASX. They showed that the state of the order book as well as the observed trading process had a significant impact on the bivariate buy and sell intensity, and thus influenced traders' decisions when to trade and on which side of the market. Ranaldo (2004) analysed order and transaction data from the Swiss Stock Exchange (SWX). His results showed that patient traders become more aggressive when their own side (the opposite side) of the book is thicker (thinner), the spread wider, and the temporary volatility increases. He also found that the buy and the sell sides of the book affect the order submission differently. Using data provided by the ASX, Cao et al. (2004) assessed the informational content of an open limit order book and found that the order book beyond the first step provides 30% of the information and provides additional power in explaining future short-term returns. Hall and Hautsch (2004) looked at limit order book data from the ASX. They showed that buy-sell pressure is particularly influenced by recent market and limit orders and the current depth in the ask and bid queue; they found evidence for the hypothesis that traders use order book information in order to infer from the price setting behaviour of market participants; and they state that their results indicate that buy-sell pressure is clearly predictable and is a significant determinant of trade-to-trade returns and volatility. Using trades and quotes data for liquid stocks on the Paris stock market, Bouchaud et al. (2004) found that market orders exhibited persistence, whilst limit orders were mean reverting; with the interplay between the two processes resulting in traded prices following a random walk. Lillo and Farmer (2004) made use of a data set from the London Stock Exchange and demonstrated that the signs of order flow, order size and liquidity are all long memory processes. The persistence in order signs is compensated for by anti-correlated fluctuations in transaction size and liquidity. Kavajecz and Odders-White (2004) considered data for limit order books for NYSE stocks and showed that the limit order book depth manifests itself in the price (reconciling technical analysis with market efficiency). Pascual and Veredas (2004) studied limit order book data from the Spanish stock exchange. They found that most of the explanatory power of the book concentrates on the best quotes, although the book beyond the best quotes also matters in explaining the aggressiveness of traders. They also deduced that liquidity providers benefit more from an increased degree of pre-trade transparency than liquidity consumers, and that no piece of book information matters in explaining the timing of orders.

Harris and Panchapagesan (2005) examined SuperDOT limit orders in the TORQ database for the NYSE. They found that the limit order book is informative about future price movements; that specialists use this information in ways that favour them (and sometimes the floor community) over the limit order traders; that the results are more evident for active stocks where the competition between specialists and limit order traders is more intense; and they found strong evidence that specialists in lower-priced stocks are less likely to initiate such actions because of the large relative tick size. Weber and Rosenow (2005) studied the Island ECN order book. They calculated the average price impact of market orders and also used the order book to match market orders with limit orders to calculate the 'virtual price impact'. It turns out that the virtual price impact function is convex and increases much faster than the concave price impact function for market orders. This difference can be explained by the strong anticorrelation between returns and limit order flow; the anticorrelation leads to an additional influx of limit orders as a reaction to price changes, which reduces the price impact of market orders. Using order book data from the ASX, Hall and Hautsch (2006) found that market depth, the queued volume, the bid–ask spread, recent volatility, as well as recent changes in both the order flow and the price play an important role in explaining the determinants of order aggressiveness. In short, order book information plays the dominant role in explaining order aggressiveness. Using data from the ASX, Cao et al. (2009) found that the order book is moderately informative—its contribution to price discovery is approximately 22%. The remaining 78% is from the best bid and ask prices on the book and the last transaction price. Furthermore, the authors found that order imbalances between the demand and supply schedules along the book are significantly related to future short-term returns, even after controlling for the autocorrelations in return, the inside spread and the trade imbalance. Roşu (2009) presents a model of an order-driven market, where the driving force is not asymmetric information, but waiting costs and competition among liquidity providers. The author makes a number of empirical predictions.

14 Conclusion

The literature on the characterization of financial time series may be distilled into the following stylized facts.

Dependence Autocorrelation in returns is largely insignificant, except at high frequencies when it becomes negative.

Distribution Approximately symmetric, increasingly positive kurtosis as the time interval decreases and a power-law or Pareto-like tail.

Heterogeneity Non-stationary (clustered volatility).

Non-linearity Non-linearities in mean and (especially) variance.

Scaling Markets exhibit non-trivial scaling properties.

Volatility Volatility exhibits positive autocorrelation, long-range dependence of autocorrelation, scaling, has a non-stationary log-normal distribution and exhibits non-linearities.

Volume Distribution decays as a power law, also calendar effects.

Calendar effects Intraday effects exist, the weekend effect seems to have all but disappeared, intramonth effects were found in most countries, the January effect has halved, and holiday effects exist in some countries.

Long memory There is about a 30% chance that stock market returns exhibit long memory, a 50% chance that foreign exchange returns exhibit long memory and an 80% chance that market volatility exhibits long memory.

Chaos There is little evidence of low-dimensional chaos in financial markets.

References

Abhyankar, A., Copeland, L. S. and Wong, W. (1995), Nonlinear dynamics in real-time equity market indices: Evidence from the United Kingdom, *The Economic Journal* **105**(431), 864–880.

Abhyankar, A., Copeland, L. S. and Wong, W. (1997), Uncovering nonlinear structure in real-time stock-market indexes: The S&P 500, the DAX, the Nikkei 225, and the FTSE-100, *Journal of Business & Economic Statistics* **15**(1), 1–14.

Abraham, A. and Ikenberry, D. L. (1994), The individual investor and the weekend effect, *The Journal of Financial and Quantitative Analysis* **29**(2), 263–277.

Adrangi, B., Chatrath, A., Dhanda, K. K. and Raffiee, K. (2001), Chaos in oil prices? Evidence from futures markets, *Energy Economics* **23**(4), 405–425.

Agrawal, A. and Tandon, K. (1994), Anomalies or illusions? Evidence from stock markets in eighteen countries, *Journal of International Money and Finance* **13**(1), 83–106.

Ahn, D.-H., Boudoukh, J., Richardson, M. and Whitelaw, R. F. (2002), Partial adjustment or stale prices? Implications from stock index and futures return autocorrelations, *The Review of Financial Studies* **15**(2), 655–689.

Aït-Sahalia, Y., Mykland, P. A. and Zhang, L. (2005), How often to sample a continuous-time process in the presence of market microstructure noise, *The Review of Financial Studies* **18**(2), 351–416.

Al-Suhaibani, M. and Kryzanowski, L. (2000), An exploratory analysis of the order book, and order flow and execution on the Saudi stock market, *Journal of Banking & Finance* **24**(8), 1323–1357.

Alexander, S. S. (1961), Price movements in speculative markets: Trends or random walks, *Industrial Management Review* **2**(2), 7–26.

Allen, F. and Gorton, G. (1992), Stock price manipulation, market microstructure and asymmetric information, *European Economic Review* **36**(2–3), 624–630.

Amihud, Y., Mendelson, H. and Lauterbach, B. (1997), Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange, *Journal of Financial Economics* **45**(3), 365–390.

Amihud, Y., Mendelson, H. and Murgia, M. (1990), Stock market microstructure and return volatility: Evidence from Italy, *Journal of Banking & Finance* **14**(2–3), 423–440.

Ammermanna, P. A. and Patterson, D. M. (2003), The cross-sectional and cross-temporal universality of nonlinear serial dependencies: evidence from world stock indices and the Taiwan Stock Exchange, *Pacific-Basin Finance Journal* **11**(2), 175–195.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Ebens, H. (2001a), The distribution of realized stock return volatility, *Journal of Financial Economics* **61**(1), 43–76.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2001b), The distribution of realized exchange rate volatility, *Journal of the American Statistical Association* **96**(453), 42–55.

Andersen, T. G. and Bollerslev, T. (1997), Heterogeneous information arrivals and return volatility dynamics: Uncovering the long-run in high frequency returns, *The Journal of Finance* **52**(3), 975–1005.

Andreou, A. S., Pavlides, G. and Karytinos, A. (2000), Nonlinear time-series analysis of the Greek exchange-rate market, *International Journal of Bifurcation and Chaos* **10**(7), 1729–1758.

Antoniou, A. and Vorlow, C. E. (2005), Price clustering and discreteness: Is there chaos behind the noise?, *Physica A* **348**, 389–403.

Ariel, R. A. (1987), A monthly effect in stock returns, *Journal of Financial Economics* **18**(1), 161–174.

Ariel, R. A. (1990), High stock returns before holidays: Existence and evidence on possible causes, *The Journal of Finance* **45**(5), 1611–1626.

Arsad, Z. and Coutts, J. A. (1997), Security price anomalies in the London International Stock Exchange: A 60 year perspective, *Applied Financial Economics* **7**(5), 455–464.

Atkins, L. and Jarrett, D. (1979), The Significance of 'Significance Tests', *in* J. Irvine, I. Miles and J. Evans (eds.), *Demystifying social statistics*, Pluto Press, London, Chapter 8, pp.87–109.

Aydogan, K. and Booth, G. G. (1988), Are there long cycles in common stock returns?, *Southern Economic Journal* **55**(1), 141–149.

Ball, R. and Kothari, S. P. (1989), Nonstationary expected returns: Implications for tests of market efficiency and serial correlation in returns, *Journal of Financial Economics* **25**(1), 51–74.

Barkoulas, J. and Travlos, N. (1998), Chaos in an emerging capital market? The case of the Athens Stock Exchange, *Applied Financial Economics* **8**(3), 231–243.

Barkoulas, J. T., Baum, C. F. and Travlos, N. (2000), Long memory in the Greek stock market, *Applied Financial Economics* **10**(2), 177–184.

Barkoulas, J. T. and Baum, C. F. (1996), Long-term dependence in stock returns, *Economics Letters* **53**(3), 253–259.

Barkoulas, J. T. and Baum, C. F. (1997), Long memory and forecasting in euroyen deposit rates, *Financial Engineering and the Japanese Markets* **4**(3), 189–201.

Barndorff-Nielsen, O. E. and Prause, K. (2001), Apparent scaling, *Finance and Stochastics* **5**(1), 103–113.

Bates, R. G., Dempster, M. A. H. and Romahi, Y. S. (2003), Evolutionary reinforcement learning in FX order book and order flow analysis, *in 2003 IEEE International Conference on Computational Intelligence for Financial Engineering. Proceedings*, IEEE, Piscataway, NJ, pp.355–362.

Baum, C. F., Barkoulas, J. T. and Caglayan, M. (1999), Long memory or structural breaks: Can either explain nonstationary real exchange rates under the current float?, *Journal of International Financial Markets, Institutions & Money* **9**(4), 359–376.

Beine, M. and Laurent, S. (2003), Central bank interventions and jumps in double long memory models of daily exchange rates, *Journal of Empirical Finance* **10**(5), 641–660.

Beran, J. (1994), *Statistics for Long-Memory Processes*, Vol. 61 of *Monographs on Statistics and Applied Probability*, Chapman & Hall/CRC, Boca Raton.

Bhar, R. (1994), Testing for long-term memory in yen/dollar exchange rate, *Asia-Pacific Financial Markets* **1**(2), 101–109.

Bhardwaj, R. K. and Brooks, L. D. (1992), The January anomaly: Effects of low share price, transaction costs, and bid-ask bias, *The Journal of Finance* **47**(2), 553–575.

Biais, B., Glosten, L. and Spatt, C. (2005), Market microstructure: A survey of microfoundations, empirical results, and policy implications, *Journal of Financial Markets* **8**(2), 217–264.

Biais, B., Hillion, P. and Spatt, C. (1995), An empirical analysis of the limit order book and the order flow in the Paris Bourse, *The Journal of Finance* **50**(5), 1655–1689.

Bianco, S. and Renò, R. (2006), Dynamics of intraday serial correlation in the Italian futures market, *The Journal of Futures Markets* **26**(1), 61–84.

Bisière, C. and Kamionka, T. (2000), Timing of Orders, Orders Aggressiveness and the Order Book at the Paris Bourse, *Annales D'Économie et de Statistique* **60**.

Blank, S. C. (1991), "Chaos" in futures markets? A nonlinear dynamical analysis, *The Journal of Futures Markets* **11**(6), 711–728.

Blau, B. M., Ness, B. F. V. and Ness, R. A. V. (2009), Short selling and the weekend effect for NYSE securities, *Financial Management* **38**(3), 603–630.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* **31**(3), 307–327.

Bollerslev, T. and Domowitz, I. (1993), Some effects of restricting the electronic order book in an automated trade execution system, *in* D. Friedman and J. Rust (eds.), *The Double Auction Market: Institutions, Theories, and Evidence*, Vol. XIV of *Santa Fe Institute Studies in the Sciences of Complexity*, Santa Fe Institute, Westview Press, Boulder, CO, pp.221–252.

Bollerslev, T. and Mikkelsen, H. O. (1996), Modeling and pricing long memory in stock market volatility, *Journal of Econometrics* **73**(1), 151–184.

Bossaerts, P. and Hillion, P. (1991), Market microstructure effects of government intervention in the foreign exchange market, *The Review of Financial Studies* **4**(3), 513–541.

Bouchaud, J.-P., Gefen, Y., Potters, M. and Wyart, M. (2004), Fluctuations and response in financial markets: The subtle nature of 'random' price changes, *Quantitative Finance* **4**(2), 176–190.

Bouchaud, J.-P., Mézard, M. and Potters, M. (2002), Statistical properties of stock order books: Empirical results and models, *Quantitative Finance* **2**(4), 251–256.

Boudoukh, J., Richardson, M. P. and Whitelaw, R. F. (1994), A tale of three schools: Insights on autocorrelations of short-horizon stock returns, *The Review of Financial Studies* **7**(3), 539–573.

Bouman, S. and Jacobsen, B. (2002), The Halloween indicator, "sell in May and go away": Another puzzle, *The American Economic Review* **92**(5), 1618–1635.

Breidt, F. J., Crato, N. and de Lima, P. (1998), The detection and estimation of long memory in stochastic volatility, *Journal of Econometrics* **83**(1–2), 325–348.

Brennan, M. J. and Subrahmanyam, A. (1996), Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* **41**(3), 441–464.

Brock, W. A., Hsieh, D. A. and LeBaron, B. (1991), *Nonlinear Dynamics, Chaos, and Instability: Statistical Theory and Economic Evidence*, The MIT Press, Cambridge, MA.

Brock, W., Lakonishok, J. and LeBaron, B. (1992), Simple technical trading rules and the stochastic properties of stock returns, *The Journal of Finance* **47**(5), 1731–1764.

Brockman, P. and Michayluk, D. (1998), The persistent holiday effect: Additional evidence, *Applied Economics Letters* **5**(4), 205–209.

Brooks, C. (1996), Testing for non-linearity in daily sterling exchange rates, *Applied Financial Economics* **6**(4), 307–317.

Brown, P., Thomson, N. and Walsh, D. (1999), Characteristics of the order flow through an electronic open limit order book, *Journal of International Financial Markets, Institutions & Money* **9**(4), 335–357.

Cadsby, C. B. and Ratner, M. (1992), Turn-of-month and pre-holiday effects on stock returns: Some international evidence, *Journal of Banking & Finance* **16**(3), 497–509.

Cajueiro, D. O. and Tabak, B. M. (2004), Evidence of long range dependence in Asian equity markets: The role of liquidity and market restrictions, *Physica A* **342**(3–4), 656–664.

Cajueiro, D. O. and Tabak, B. M. (2005), Possible causes of long-range dependence in the Brazilian stock market, *Physica A* **345**(3–4), 635–645.

Campbell, J. Y., Lo, A. W. and Mackinlay, A. C. (1996), *The Econometrics of Financial Markets*, Princeton University Press, Princeton, NJ.

Cao, C., Hansch, O. and Wang, X. (2004), The informational content of an open limit order book, 31st EFA Annual Meeting - Maastricht, 18-21 August 2004 and Sixty Fifth Annual Meeting of the American Finance Association, Philadelphia, PA January 7-9, 2005.

Cao, C., Hansch, O. and Wang, X. (2009), The information content of an open limit-order book, *Journal of Futures Markets* **29**(1), 16–41.

Cataldo II, A. J. and Savage, A. A. (eds.) (2000), *The January Effect and Other Seasonal Anomalies: A Common Theoretical Framework*, Vol. 9 of *Studies in Managerial and Financial Accounting*, JAI Press.

Cavalcante, J. and Assaf, A. (2002), Long-range dependence in the returns and volatility of the Brazilian stock market, Stock Market Manuscript, Rio de Janeiro.

Cecen, A. and Ugur, A. (2005), On testing for nonlinear dependence and chaos in financial time series data, *in 2005 IEEE International Conference on Systems, Man and Cybernetics, Vol. 1*, IEEE, pp.203–208.

Cerrato, M. and Sarantis, N. (2006), Nonlinear mean reversion in real exchange rates: Evidence from developing and emerging market economies, *Economics Bulletin* **6**(7), 1–14.

Challet, D. and Stinchcombe, R. (2001), Analyzing and modeling $1 + 1d$ markets, *Physica A* **300**(1–2), 285–299.

Chen, H. and Singal, V. (2003), Role of speculative short sales in price formation: The case of the weekend effect, *The Journal of Finance* **58**(2), 685–706.

Chen, S.-H. (2000), Lecture 7: Rescale range analysis and the Hurst exponent, Financial Economics (I), Department of Economics, National Chengchi University.

Cheung, Y.-W. (1993), Long memory in foreign-exchange rates, *Journal of Business & Economic Statistics* **11**(1), 93–101.

Cheung, Y.-W. and Chinn, M. D. (2001), Currency traders and exchange rate dynamics: A survey of the US market, *Journal of International Money and Finance* **20**(4), 439–471.

Cheung, Y.-W. and Lai, K. S. (1993), Do gold market returns have long memory?, *The Financial Review* **28**(2), 181–202.

Cheung, Y.-W. and Lai, K. S. (2001), Long memory and nonlinear mean reversion in Japanese yen-based real exchange rates, *Journal of International Money and Finance* **20**(1), 115–132.

Chong, R., Hudson, R., Keasey, K. and Littler, K. (2005), Pre-holiday effects: International evidence on the decline and reversal of a stock market anomaly, *Journal of International Money and Finance* **24**(8), 1226–1236.

Chordia, T., Roll, R. and Subrahmanyam, A. (2001), Market liquidity and trading activity, *The Journal of Finance* **56**(2), 501–530.

Chow, K. V., Pan, M.-S. and Sakano, R. (1996), On the long-term or short-term dependence in stock prices: Evidence from international stock markets, *Review of Quantitative Finance and Accounting* **6**(2), 181–194.

Christophe, S. E., Ferri, M. G. and Angel, J. J. (2009), Short selling and the weekend effect in Nasdaq stock returns, *The Financial Review* **44**(1), 31–57.

Cizeau, P., Liu, Y., Meyer, M., Peng, C.-K. and Stanley, H. E. (1997), Volatility distribution in the S&P500 stock index, *Physica A* **245**(3–4), 441–445.

Comte, F. and Renault, E. (1998), Long memory in continuous-time stochastic volatility models, *Mathematical Finance* **8**(4), 291–323.

Connolly, R. A. (1989), An examination of the robustness of the weekend effect, *The Journal of Financial and Quantitative Analysis* **24**(2), 133–169.

Constantinides, G. M. (1984), Optimal stock trading with personal taxes: Implications for prices and the abnormal January returns, *Journal of Financial Economics* **13**(1), 65–89.

Constantinides, G. M., Harris, M. and Stulz, R. M. (eds.) (2003), *Handbook of the Economics of Finance*, Elsevier North-Holland, Amsterdam.

Cont, R. (2001), Empirical properties of asset returns: Stylized facts and statistical issues, *Quantitative Finance* **1**(2), 223–236.

Cont, R. and Tankov, P. (2004), *Financial Modelling With Jump Processes*, Chapman & Hall/CRC Financial Mathematics Series, Chapman & Hall/CRC, Boca Raton.

Coppejans, M. and Domowitz, I. (1998), Stock and flow information as inputs to limit order book trading activity, Working paper, presented at the "Symposium on Microstructure and High Frequency Data" in Paris, December 1998.

Coppejans, M. and Domowitz, I. (2002), An empirical analysis of trades, orders, and cancellations in a limit order market, Working Paper, Duke University.

Crato, N. and de Lima, P. J. F. (1994), Long-range dependence in the conditional variance of stock returns, *Economics Letters* **45**(3), 281–285.

Crato, N. and Ray, B. K. (2000), Memory in returns and volatilities of futures' contracts, *The Journal of Futures Markets* **20**(6), 525–543.

Cross, F. (1973), The behavior of stock prices on Fridays and Mondays, *Financial Analysts Journal* **29**(6), 67–69.

Dacorogna, M. M., Gençay, R., Müller, U., Olsen, R. B. and Pictet, O. V. (2001), *An Introduction to High-Frequency Finance*, Academic Press, San Diego, CA.

Dacorogna, M. M., Müller, U. A., Nagler, R. J., Olsen, R. B. and Pictet, O. V. (1993), A geographical model for the daily and weekly seasonal volatility in the foreign exchange market, *Journal of International Money and Finance* **12**(4), 413–438.

Damodaran, A. (2003), *Investment Philosophies: Successful Strategies and the Investors Who Made Them Work*, Wiley, Hoboken, NJ.

Daníelsson, J. and Payne, R. (2002), Measuring and explaining liquidity on an electronic limit order book: evidence from Reuters D2000-2, *in Risk Measurement and Systemic Risk: Proceedings of the Third Joint Central Bank Research Conference*, Bank for International Settlements, Basel, pp.161–165.

de Peretti, C. (2003), Bilateral bootstrap tests for long memory: An application to the silver market, *Computational Economics* **22**(2–3), 187–212.

Declerck, F. (2002), Trading costs on a limit order book market: Evidence from the Paris Bourse, *Banque et Marché* **57**, 31–45.

Decoster, G. P., Labys, W. C. and Mitchell, D. W. (1992), Evidence of chaos in commodity futures prices, *The Journal of Futures Markets* **12**(3), 291–305.

Di Matteo, T., Aste, T. and Dacorogna, M. M. (2003), Scaling behaviors in differently developed markets, *Physica A* **324**(1–2), 183–188.

Díaz, A. F., Grau-Carles, P. and Mangas, L. E. (2002), Nonlinearities in the exchange rates returns and volatility, *Physica A* **316**(1–4), 469–482.

Diebold, F. X. and Inoue, A. (2001), Long memory and regime switching, *Journal of Econometrics* **105**(1), 131–159.

Ding, Z., Granger, C. W. J. and Engle, R. F. (1993), A long memory property of stock market returns and a new model, *Journal of Empirical Finance* **1**(1), 83–106.

Ding, Z. and Granger, C. W. J. (1996), Modeling volatility persistence of speculative returns: A new approach, *Journal of Econometrics* **73**(1), 185–215.

Dominguez, K. M. E. (2003), The market microstructure of central bank intervention, *Journal of International Economics* **59**(1), 25–45.

Du, G. and Ning, X. (2008), Multifractal properties of Chinese stock market in Shanghai, *Physica A* **387**(1), 261–269.

Dubofsky, D. A. (1992), A market microstructure explanation of ex-day abnormal returns, *Financial Management* **21**(4), 32–43.

Dzhabarov, C. and Ziemba, W. T. (2010), Do seasonal anomalies still work?, *The Journal of Portfolio Management* **36**(3), 93–104.

Eisler, Z. and Kertész, J. (2007), Liquidity and the multiscaling properties of the volume traded on the stock market, *EPL (Europhysics Letters)* **77**(2), 28001 p1–p5.

Elder, J. and Serletis, A. (2007), On fractional integrating dynamics in the US stock market, *Chaos, Solitons & Fractals* **34**(3), 777–781.

Embrechts, M. (1994), Basic concepts of nonlinear dynamics and chaos theory, *in* G. J. Deboeck (ed.), *Trading on the Edge: Neural, Genetic, and Fuzzy Systems for Chaotic Financial Markets*, Wiley, New York, Chapter 15, pp.265–279.

Embrechts, M., Cader, M. and Deboeck, G. J. (1994), Nonlinear dimensions of foreign exchange, stock, and bond markets, *in* G. J. Deboeck (ed.), *Trading on the Edge: Neural, Genetic, and Fuzzy Systems for Chaotic Financial Markets*, Wiley, New York, Chapter 17, pp.297–313.

Engle, R. F. (1982), Autoregressive conditional heteroscedasticity with estimates of variance of United Kingdom inflation, *Econometrica* **50**(4), 987–1008.

Evertsz, C. J. (1995), Fractal geometry of financial time series, *Fractals* **3**(3), 609–616.

Fama, E. F. (1970), Efficient capital markets: A review of theory and empirical work, *The Journal of Finance* **25**(2), 383–417.

Fama, E. F. and French, K. R. (1988), Permanent and temporary components of stock prices, *Journal of Political Economy* **96**(2), 246–273.

Fields, M. J. (1931), Stock prices: A problem in verification, *The Journal of Business of the University of Chicago* **4**(4), 415–418.

Fields, M. J. (1934), Security prices and stock exchange holidays in relation to short selling, *The Journal of Business of the University of Chicago* **7**(4), 328–338.

Fisher, A., Calvet, L. and Mandelbrot, B. (1997), Multifractality of Deutschemark / US dollar exchange rates, Discussion Paper 1166, Cowles Foundation.

Frank, M. and Stengos, T. (1989), Measuring the strangeness of gold and silver rates of return, *The Review of Economic Studies* **56**(4), 553–567.

Franses, P. H. and Van Dijk, D. (1996), Forecasting stock market volatility using (non-linear) GARCH models, *Journal of Forecasting* **15**(3), 229–235.

French, K. R. (1980), Stock returns and the weekend effect, *Journal of Financial Economics* **8**(1), 55–69.

Gabor, G. (2004), Classical statistics: Smoke and mirrors, Department of Mathematics and Statistics, Dalhousie University, Halifax, NS.

Gallant, A. R., Hsu, C.-T. and Tauchen, G. (1999), Using daily range data to calibrate volatility diffusions and extract the forward integrated variance, *The Review of Economics and Statistics* **81**(4), 617–631.

Galluccio, S., Caldarelli, G., Marsili, M. and Zhang, Y.-C. (1997), Scaling in currency exchange, *Physica A* **245**(3–4), 423–436.

Gao, A. H. and Wang, G. H. K. (1999), Modeling nonlinear dynamics of daily futures price changes, *The Journal of Futures Markets* **19**(3), 325–351.

Garman, M. B. (1976), Market microstructure, *Journal of Financial Economics* **3**(3), 257–275.

Gençay, R., Selçuk, F. and Whitcher, B. (2001), Scaling properties of foreign exchange volatility, *Physica A* **289**(1–2), 249–266.

Gibbons, M. R. and Hess, P. (1981), Day of the week effects and asset returns, *The Journal of Business* **54**(4), 579–596.

Giraitis, L., Kokoszka, P., Leipus, R. and Teyssière, G. (2003), Rescaled variance and related tests for long memory in volatility and levels, *Journal of Econometrics* **112**(2), 265–294.

Goetzmann, W. N. (1993), Patterns in three centuries of stock market prices, *The Journal of Business* **66**(2), 249–270.

Gopikrishnan, P., Plerou, V., Amaral, L. A. N., Meyer, M. and Stanley, H. E. (1999), Scaling of the distribution of fluctuations of financial market indices, *Physical Review E* **60**(5), 5305–5316.

Gopikrishnan, P., Plerou, V., Liu, Y., Amaral, L. A. N., Gabaix, X. and Stanley, H. E. (2000), Scaling and correlation in financial time series, *Physica A* **287**(3–4), 362–373.

Granger, C. W. J. and Ding, Z. (1996), Varieties of long memory models, *Journal of Econometrics* **73**(1), 61–77.

Granger, C. W. J. and Hyung, N. (1999), Occasional structural breaks and long memory, Discussion paper 99-14, University of California, San Diego, San Diego.

Granger, C. W. J. and Hyung, N. (2004), Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns, *Journal of Empirical Finance* **11**(3), 399–421.

Granger, C. W. J., Spear, S. and Ding, Z. (2000), Stylized facts on the temporal and distributional properties of absolute returns: An update, *in* W.-S. Chan, W. K. Li and H. Tong (eds.), *Proceedings of the Hong Kong International Workshop on Statistics and Finance: An Interface*, Imperial College Press, London, pp.97–120.

Grau-Carles, P. (2005), Tests of long memory: A bootstrap approach, *Computational Economics* **25**(1–2), 103–113.

Greene, M. T. and Fielitz, B. D. (1977), Long-term dependence in common stock returns, *Journal of Financial Economics* **4**(3), 339–349.

Guillaume, D. M., Dacorogna, M. M., Davé, R. R., Müuller, U. A., Olsen, R. B. and Pictet, O. V. (1997), From the bird's eye to the microscope: A survey of new stylized facts of the intra-daily foreign exchange markets, *Finance and Stochastics* **1**(2), 95–129.

Gultekin, M. N. and Gultekin, N. B. (1983), Stock market seasonality: International evidence, *Journal of Financial Economics* **12**(4), 469–481.

Hall, A. D. and Hautsch, N. (2004), A continuous-time measurement of the buy-sell pressure in a limit order book market, Discussion paper 04-07, University of Copenhagen, Copenhagen.

Hall, A. D. and Hautsch, N. (2006), Order aggressiveness and order book dynamics, *Empirical Economics* **30**(4), 973–1005.

Hall, A., Hautsch, N. and McCulloch, J. (2003), Estimating the intensity of buy and sell arrivals in a limit order book market, *in New Frontiers in Financial Volatility Modelling*, Università degli Studi di Firenze, pp.1–35.

Hamao, Y. and Hasbrouck, J. (1995), Securities trading in the absence of dealers: Trades and quotes on the tokyo stock exchange, *The Review of Financial Studies* **8**(3), 849–878.

Hansen, P. R. and Lunde, A. (2006), Realized variance and market microstructure noise, *Journal of Business & Economic Statistics* **24**(2), 127–161.

Harris, L. (1986), A transaction data study of weekly and intradaily patterns in stock returns, *Journal of Financial Economics* **16**(1), 99–117.

Harris, L. (1989), A day-end transaction price anomaly, *The Journal of Financial and Quantitative Analysis* **24**(1), 29–45.

Harris, L. (2002), *Trading and Exchanges: Market Microstructure for Practitioners*, Financial Management Association Survey and Synthesis Series, Oxford University Press, New York.

Harris, L. E. and Panchapagesan, V. (2005), The information content of the limit order book: Evidence from NYSE specialist trading decisions, *Journal of Financial Markets* **8**(1), 25–67.

Harris, L. and Hasbrouck, J. (1996), Market vs. Limit orders: The SuperDOT evidence on order submission strategy, *The Journal of Financial and Quantitative Analysis* **31**(2), 213–231.

Hasbrouck, J. (1996), Modeling market microstructure time series, *in* G. S. Maddala and C. R. Rao (eds.), *Handbook of Statistics 14: Statistical Methods in Finance*, North-Holland, Amsterdam, Chapter 22, pp.647–692.

Hasbrouck, J. (2002), Stalking the "efficient price" in market microstructure specifications: An overview, *Journal of Financial Markets* **5**(3), 329–339.

Hasbrouck, J. (2006), *Empirical Market Microstructure: The Institutions, Economics, and Econometrics of Securities Trading*, Oxford University Press, New York.

Haug, M. and Hirschey, M. (2006), The January effect, *Financial Analysts Journal* **62**(5), 78–88.

Haugen, R. A. and Lakonishok, J. (1987), *The Incredible January Effect: The Stock Market's Unsolved Mystery*, Dow Jones-Irwin, Homewood, IL.

Hawawini, G. and Keim, D. B. (1995), On the predictability of common stock returns: World-wide evidence, *in* R. A. Jarrow, V. Maksimovic and W. T. Ziemba (eds.), *Handbooks in Operations Research and Management Science, Volume 9, Finance*, North Holland, Amsterdam, Chapter 17, pp.497–544.

Hedvall, K., Niemeyer, J. and Rosenqvist, G. (1997), Do buyers and sellers behave similarly in a limit order book? A high-frequency data examination of the Finnish stock exchange, *Journal of Empirical Finance* **4**(2–3), 279–293.

Henry, Ó. T. (2002), Long memory in stock returns: Some international evidence, *Applied Financial Economics* **12**(10), 725–729.

Hensel, C. R. and Ziemba, W. T. (1996), Investment results from exploiting turn-of-the-month effects (digest summary), *The Journal of Portfolio Management* **22**(3), 17–23.

Hiemstra, C. and Jones, J. D. (1997), Another look at long memory in common stock returns, *Journal of Empirical Finance* **4**(4), 373–401.

Houthakker, H. S. (1961), Systematic and random elements in short-term price movements, *The American Economic Review* **51**(2), 164–172.

Hsieh, D. A. (1989), Testing for nonlinear dependence in daily foreign exchange rates, *The Journal of Business* **62**(3), 339–368.

Hsieh, D. A. (1991), Chaos and nonlinear dynamics: Application to financial markets, *The Journal of Finance* **46**(5), 1839–1877.

Huang, B.-N. and Yang, C. W. (1999), An examination of long-term memory using the intraday stock returns, Technical Report 99–03, Clarion University of Pennsylvania, Clarion.

Huang, R. D. and Stoll, H. R. (1994), Market microstructure and stock return predictions, *The Review of Financial Studies* **7**(1), 179–213.

Hurst, H. E. (1951), Long-term storage capacity of reservoirs, *Transactions of the American Society of Civil Engineers* **116**, 770–799, 800–808.

Jaffe, J. and Westerfield, R. (1985), The week-end effect in common stock returns: The international evidence, *The Journal of Finance* **40**(2), 433–454.

Jaffe, J. and Westerfield, R. (1989), Is there a monthly effect in stock market returns? : Evidence from foreign countries, *Journal of Banking & Finance* **13**(2), 237–244.

Jain, P. C. and Joh, G.-H. (1988), The dependence between hourly prices and trading volume, *The Journal of Financial and Quantitative Analysis* **23**(3), 269–283.

Jarnecic, E. and McInish, T. H. (1997), An empirical investigation of the option value of the limit order book on the Australian Stock Exchange, Working paper, University of Sydney.

Jegadeesh, N. (1990), Evidence of predictable behavior of security returns, *The Journal of Finance* **45**(3), 881–898.

Johnson, N. F., Jefferies, P. and Hui, P. M. (2003), *Financial Market Complexity: What Physics Can Tell Us about Market Behaviour*, Oxford University Press, Oxford.

Kamara, A. (1997), New evidence on the Monday seasonal in stock returns, *The Journal of Business* **70**(1), 63–84.

Kamstra, M. J., Kramer, L. A. and Levi, M. D. (2000), Losing sleep at the market: The daylight saving anomaly, *The American Economic Review* **90**(4), 1005–1011.

Kauffman, R. J. and Wang, B. (2001), New buyers' arrival under dynamic pricing market microstructure: The case of group-buying discounts on the Internet, *Journal of Management Information Systems* **18**(2), 157–188.

Kavajecz, K. A. (1999), A specialist's quoted depth and the limit order book, *The Journal of Finance* **54**(2), 747–771.

Kavajecz, K. A. and Odders-White, E. R. (2004), Technical analysis and liquidity provision, *The Review of Financial Studies* **17**(4), 1043–1071.

Keef, S. P. and Roush, M. L. (2005), Day-of-the-week effects in the pre-holiday returns of the Standard & Poor's 500 stock index, *Applied Financial Economics* **15**(2), 107–119.

Keef, S. P., Khaled, M. and Zhu, H. (2009), The dynamics of the Monday effect in international stock indices, *International Review of Financial Analysis* **18**(3), 125–133.

Keim, D. B. (1983), Size-related anomalies and stock return seasonality: Further empirical evidence, *Journal of Financial Economics* **12**(1), 13–32.

Keim, D. B. (1989), Trading patterns, bid-ask spreads, and estimated security returns: The case of common stocks at calendar turning points, *Journal of Financial Economics* **25**(1), 75–97.

Keim, D. B. and Stambaugh, R. F. (1984), A further investigation of the weekend effect in stock returns, *The Journal of Finance* **39**(3), 819–835.

Kendall, M. G. (1953), The analysis of economic time-series—Part I: Prices, *Journal of the Royal Statistical Society. Series A (General)* **116**(1), 11–25.

Kim, C.-W. and Park, J. (1994), Holiday effects and stock returns: Further evidence, *The Journal of Financial and Quantitative Analysis* **29**(1), 145–157.

Kirman, A. and Teyssière, G. (2002), Microeconomic models for long memory in the volatility of financial time series, *Studies in Nonlinear Dynamics and Econometrics* **5**(4), 281–302.

Kunkel, R. A., Compton, W. S. and Beyer, S. (2003), The turn-of-the-month effect still lives: The international evidence, *International Review of Financial Analysis* **12**(2), 207–221.

Lakonishok, J. and Maberly, E. (1990), The weekend effect: Trading patterns of individual and institutional investors, *The Journal of Finance* **45**(1), 231–243.

Lakonishok, J. and Smidt, S. (1988), Are seasonal anomalies real? A ninety-year perspective, *The Review of Financial Studies* **1**(4), 403–425.

Larson, A. B. (1960), Measurement of a random process in futures prices, *Food Research Institute Studies* **1**(3), 313–24.

Lease, R. C., Masulis, R. W. and Page, J. R. (1991), An investigation of market microstructure impacts on event study returns, *The Journal of Finance* **46**(4), 1523–1536.

Lee, C.-C., Lee, J.-D. and Lee, C.-C. (2010), Stock prices and the efficient market hypothesis: Evidence from a panel stationary test with structural breaks, *Japan and the World Economy* **22**(1), 49–58.

Lee, K. E. and Lee, J. W. (2007), Scaling and multiscaling properties in the korean stock market, *Journal of the Korean Physical Society* **50**(1), 178–181.

Lewellen, J. (2002), Momentum and autocorrelation in stock returns, *The Review of Financial Studies* **15**(2), 533–563.

Liano, K., Marchand, P. H. and Huang, G.-C. (1992), The holiday effect in stock returns: Evidence from the OTC market, *Review of Financial Economics* **2**(1), 45–54.

Lillo, F. and Farmer, J. D. (2004), The long memory of the efficient market, *Studies in Nonlinear Dynamics and Econometrics* **8**(3), 1–33.

Lim, K.-P., Brooks, R. D. and Hinich, M. J. (2008), Nonlinear serial dependence and the weak-form efficiency of Asian emerging stock markets, *Journal of International Financial Markets, Institutions and Money* **18**(5), 527–544.

Lim, S. Y. and Chia, R. C.-J. (2010), Stock market calendar anomalies: Evidence from ASEAN-5 stock markets, *Economics Bulletin* **30**(2), 1005–1014.

Limam, I. (2003), Is long memory a property of thin stock markets? International evidence using arab countries, *Review of Middle East Economics and Finance* **1**(3), 251–266.

Liu, Y., Gopikrishnan, P., Cizeau, P., Meyer, M., Peng, C.-K. and Stanley, H. E. (1999), Statistical properties of the volatility of price fluctuations, *Physical Review E* **60**(2), 1390–1400.

Llorente, G., Michaely, R., Saar, G. and Wang, J. (2002), Dynamic volume-return relation of individual stocks, *The Review of Financial Studies* **15**(4), 1005–1047.

Lo, A. W. (1991), Long-term memory in stock market prices, *Econometrica* **59**(5), 1279–1313.

Lo, A. W. and MacKinlay, A. C. (1988), Stock market prices do not follow random walks: Evidence from a simple specification test, *The Review of Financial Studies* **1**(1), 41–66.

Lo, A. W. and MacKinlay, A. C. (1990), When are contrarian profits due to stock market overreaction?, *The Review of Financial Studies* **3**(2), 175–205.

Lo, A. W. and MacKinlay, A. C. (1999), *A Non-Random Walk Down Wall Street*, Princeton University Press, Princeton, NJ.

Lobato, I. N. and Savin, N. E. (1998), Real and spurious long-memory properties of stock-market data, *Journal of Business & Economic Statistics* **16**(3), 261–268.

Lobato, I. N. and Velasco, C. (2000), Long memory in stock-market trading volume, *Journal of Business & Economic Statistics* **18**(4), 410–427.

Lofthouse, S. (2001), *Investment Management*, second edition, Wiley, Chichester.

Longin, F. M. (1996), The asymptotic distribution of extreme stock market returns, *The Journal of Business* **69**(3), 383–408.

Loughran, T. (1993), NYSE vs NASDAQ returns: Market microstructure or the poor performance of initial public offerings?, *Journal of Financial Economics* **33**(2), 241–260.

Lu, L. and Liu, S. (2008), Are there holiday effect in China's stock market?, *Journal of Financial Research* **2**.

Lux, T. (1996), Long-term stochastic dependence in financial prices: Evidence from the German stock market, *Applied Economics Letters* **3**(11), 701–706.

Lyons, R. K. (2001), *The Microstructure Approach to Exchange Rates*, The MIT Press, Cambridge, MA.

MacKinnon, G. and Nemiroff, H. (1999), Liquidity and tick size: does decimalization matter?, *Journal of Financial Research* **22**(3), 287–299.

Madhavan, A. (2000), Market microstructure: A survey, *Journal of Financial Markets* **3**(3), 205–258.

Maheu, J. M. and McCurdy, T. H. (2002), Nonlinear features of realized FX volatility, *The Review of Economics and Statistics* **84**(4), 668–681.

Mandelbrot, B. (1963), The variation of certain speculative prices, *The Journal of Business* **36**(4), 394–419.

Mandelbrot, B. B. (1972), Statistical methodology for non-periodic cycles: From the covariance to R/S analysis, *Annals of Economic and Social Measurement* **1**, 259–290.

Mantegna, R. N. and Stanley, H. E. (1995), Scaling behaviour in the dynamics of an economic index, *Nature* **376**(6535), 46–49.

Mantegna, R. N. and Stanley, H. E. (2000), *An Introduction to Econophysics: Correlations and Complexity in Finance*, Cambridge University Press.

Marrett, G. J. and Worthington, A. C. (2009), An empirical note on the holiday effect in the Australian stock market, 1996–2006, *Applied Economics Letters* **16**(17), 1769–1772.

Martens, M., van Dijk, D. and de Pooter, M. (2004), Modeling and forecasting S&P 500 volatility: Long memory, structural breaks and nonlinearity, Tinbergen Institute Discussion Paper, TI 2004-067/4.

Maslov, S. and Mills, M. (2001), Price fluctuations from the order book perspective—empirical facts and a simple model, *Physica A* **299**(1–2), 234–246.

Mayfield, E. S. and Mizrach, B. (1992), On determining the dimension of real-time stock-price data, *Journal of Business & Economic Statistics* **10**(3), 367–374.

McGuinness, P. B. (2005), A re-examination of the holiday effect in stock returns: The case of Hong Kong, *Applied Financial Economics* **15**(16), 1107–1123.

Meneu, V. and Pardo, A. (2004), Pre-holiday effect, large trades and small investor behaviour, *Journal of Empirical Finance* **11**(2), 231–246.

Mills, F. C. (1927), *The Behavior of Prices*, National Bureau of Economic Research, New York.

Mills, T. C. (1993), Is there long-term memory in UK stock returns?, *Applied Financial Economics* **3**(4), 303–306.

Mills, T. C. and Coutts, J. A. (1995), Calendar effects in the London Stock Exchange FT-SE indices, *The European Journal of Finance* **1**(1), 79–94.

Minka, T. P. (1998), Pathologies of orthodox statistics, MIT Media Lab note, revised 2001.

Mitchell, W. C. (1915), The making and using of index numbers, *Bulletin of the US Bureau of Labor Statistics* **173**.

Mitchell, W. C. (1921), The making and using of index numbers, *Bulletin of the US Bureau of Labor Statistics* **284**.

Moller, N. and Zilca, S. (2008), The evolution of the January effect, *Journal of Banking & Finance* **32**(3), 447–457.

Moody, J. and Wu, L. (1995), Price behavior and Hurst exponents of tick-by-tick interbank foreign exchange rates, *in Proceedings of the IEEE/IAFE 1995 Computational Intelligence for Financial Engineering*, IEEE Service Center, pp.26–30.

Moody, J. and Wu, L. (1996), Improved estimates for the rescaled range and Hurst exponents, *in* A.-P. N. Refenes, Y. Abu-Mostafa, J. Moody and A. Weigend (eds.), *Neural Networks in Financial Engineering: Proceedings of the Third International Conference on Neural Networks in the Capital Markets London, England 11-13 October 95*, World Scientific, London, pp.537–553.

Morse, D. and Ushman, N. (1983), The effect of information announcements on the market microstructure, *The Accounting Review* **58**(2), 247–258.

Müller, U. A., Dacorogna, M. M., Olsen, R. B., Pictet, O. V., Schwarz, M. and Morgenegg, C. (1990), Statistical study of foreign exchange rates, empirical evidence of a price change scaling law, and intraday analysis, *Journal of Banking & Finance* **14**(6), 1189–1208.

Müller, U. A. and Sgier, R. G. (1992), Statistical analysis of intra-day bid-ask spreads in the foreign exchange market, Unpublished manuscript, Olsen & Associates, Zürich.

Muscarella, C. J. and Piwowar, M. S. (2001), Market microstructure and securities values: Evidence from the Paris Bourse, *Journal of Financial Markets* **4**(3), 209–229.

Nath, G. C. (2001), Long memory and Indian stock market – an empirical evidence, National Stock Exchange of India Ltd., Mumbai.

Nath, G. C. and Reddy, Y. V. (2002), Long memory in rupee-dollar exchange rate – an empirical study, Capital Market Conference 2002, Indian Institute of Capital Markets.

Nawrocki, D. (1995), R/S analysis and long term dependence in stock market indices, *Managerial Finance* **21**(7), 78–91.

Nikkinen, J., Sahlström, P. and Äijö, J. (2007), Turn-of-the-month and intramonth effects: Explanation from the important macroeconomic news announcements, *Journal of Futures Markets* **27**(2), 105–126.

Officer, R. R. (1975), Seasonality in Australian capital markets: Market efficiency and empirical issues, *Journal of Financial Economics* **2**(1), 29–51.

Ogden, J. P. (1990), Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and January effects, *The Journal of Finance* **45**(4), 1259–1272.

Oh, G., Um, C.-J. and Kim, S. (2006), Long-term memory and volatility clustering in daily and high-frequency price changes, arXiv:physics/0601174.

Ohanissian, A., Russell, J. R. and Tsay, R. S. (2008), True or spurious long memory? A new test, *Journal of Business & Economic Statistics* **26**(2), 161–175.

O'Hara, M. (1995), *Market Microstructure Theory*, Blackwell Publishing, Malden, MA.

Olivier, M. (1926), Les Nombres Indices de la Variation des Prix, PhD thesis, University of Paris, Paris.

Osborne, M. F. M. (1959), Brownian motion in the stock market, *Operations Research* **7**(2), 145–73.

Osborne, M. F. M. (1962), Periodic structure in the Brownian motion of stock prices, *Operations Research* **10**(3), 345–379.

Panas, E. (2001), Estimating fractal dimension using stable distributions and exploring long memory through ARFIMA models in the Athens Stock Exchange, *Applied Financial Economics* **11**(4), 395–402.

Panas, E. and Ninni, V. (2000), Are oil markets chaotic? A non-linear dynamic analysis, *Energy Economics* **22**(5), 549–568.

Park, J. (1995), A market microstructure explanation for predictable variations in stock returns following large price changes, *The Journal of Financial and Quantitative Analysis* **30**(2), 241–256.

Pascual, R. and Veredas, D. (2004), What pieces of limit order book information do are informative? An empirical analysis of a pure order-driven market, Working paper FIN-04-003, NYU Stern School of Business, New York.

Pasquini, M. and Serva, M. (1999), Multiscale behaviour of volatility autocorrelations in a financial market, *Economics Letters* **65**(3), 275–279.

Penman, S. H. (1987), The distribution of earnings news over time and seasonalities in aggregate stock returns, *Journal of Financial Economics* **18**(2), 199–228.

Peters, E. E. (1991), *Chaos and Order in the Capital Markets: A New View of Cycles, Prices, and Market Volatility*, Wiley, Somerset, NJ.

Peters, E. E. (1996), *Chaos and Order in the Capital Markets: A New View of Cycles, Prices, and Market Volatility*, second edition, Wiley, New York.

Plerou, V., Gopikrishnan, P., Amaral, L. A. N., Gabaix, X. and Stanley, H. E. (2000), Economic fluctuations and anomalous diffusion, *Physical Review E* **62**(3), R3023–R3026.

Plerou, V., Gopikrishnan, P., Gabaix, X., Amaral, L. A. N. and Stanley, H. E. (2001), Price fluctuations, market activity and trading volume, *Quantitative Finance* **1**(2), 262–269.

Plerou, V., Gopikrishnan, P., Gabaix, X. and Stanley, H. E. (2004), On the origin of power-law fluctuations in stock prices, *Quantitative Finance* **4**(1), C11–C15.

Poterba, J. M. and Weisbenner, S. J. (2001), Capital gains tax rules, tax-loss trading, and turn-of-the-year returns, *The Journal of Finance* **56**(1), 353–368.

Potters, M. and Bouchaud, J.-P. (2003), More statistical properties of order books and price impact, *Physica A* **324**(1–2), 133–140.

Praetz, P. D. (1973), A spectral analysis of Australian share prices, *Australian Economic Papers* **12**(20), 70–78.

Qiu, T., Guo, L. and Chen, G. (2008), Scaling and memory effect in volatility return interval of the Chinese stock market, *Physica A* **387**(27), 6812–6818.

Qiu, T., Zhong, L. X., Chen, G. and Wu, X. R. (2009), Statistical properties of trading volume of Chinese stocks, *Physica A* **388**(12), 2427–2434.

Ranaldo, A. (2004), Order aggressiveness in limit order book markets, *Journal of Financial Markets* **7**(1), 53–74.

Reinganum, M. R. (1983), The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects, *Journal of Financial Economics* **12**(1), 89–104.

Reinganum, M. R. (1990), Market microstructure and asset pricing: An empirical investigation of NYSE and NASDAQ securities, *Journal of Financial Economics* **28**(1–2), 127–147.

Rendon, J. and Ziemba, W. T. (2007), Is the January effect still alive in the futures markets?, *Financial Markets and Portfolio Management* **21**(3), 381–396.

Ritter, J. R. (1988), The buying and selling behavior of individual investors at the turn of the year, *The Journal of Finance* **43**(3), 701–717.

Roll (1983), Vas ist das? The turn-of-the-year effect and the return premia of small firms, *The Journal of Portfolio Management* **9**(2), 18–28.

Roşu, I. (2009), A dynamic model of the limit order book, *The Review of Financial Studies* **22**(11), 4601–4641.

Rozeff, M. S. and Kinney, Jr, W. R. (1976), Capital market seasonality: The case of stock returns, *Journal of Financial Economics* **3**(4), 379–402.

Rubinstein, M. (2001), Rational markets: Yes or no? The affirmative case, *Financial Analysts Journal* **57**(3), 15–29.

Sadique, S. and Silvapulle, P. (2001), Long-term memory in stock market returns: International evidence, *International Journal of Finance & Economics* **6**(1), 59–67.

Sapio, S. (2004), Market design, bidding rules, and long memory in electricity prices, *Revue d'Economie Industrielle* **107**, 151–170.

Savit, R. (1988), When random is not random: An introduction to chaos in market prices, *The Journal of Futures Markets* **8**(3), 271–290.

Scheinkman, J. A. and LeBaron, B. (1989), Nonlinear dynamics and stock returns, *The Journal of Business* **62**(3), 311–337.

Schwert, G. W. (2003), Anomalies and market efficiency, *in* G. M. Constantinides, M. Harris and R. M. Stulz (eds.), *Handbook of the Economics of Finance: Volume 1B, Financial Markets and Asset Pricing*, Vol. 21 of *Handbooks in Economics*, Elsevier North-Holland, Amsterdam, Chapter 15, pp.937–972.

Serletis, A. and Gogas, P. (1997), Chaos in East European black market exchange rates, *Research in Economics* **51**(4), 359–385.

Serletis, A. and Rosenberg, A. A. (2009), Mean reversion in the US stock market, *Chaos, Solitons & Fractals* **40**(4), 2007–2015.

Sewell, S. P., Stansell, S. R., Lee, I. and Below, S. D. (1996), Using chaos measures to examine international capital market integration, *Applied Financial Economics* **6**(2), 91–101.

Sias, R. W. and Starks, L. T. (1997), Institutions and individuals at the turn-of-the-year, *The Journal of Finance* **52**(4), 1543–1562.

Siegel, J. J. (1998), *Stocks for the Long Run*, second edition, McGraw-Hill, New York.

Singal, V. (2004), *Beyond the Random Walk: A Guide to Stock Market Anomalies and Low-Risk Investing*, Oxford University Press, New York.

Skjeltorp, J. A. (2000), Scaling in the Norwegian stock market, *Physica A* **283**(3–4), 486–528.

Spulber, D. F. (1996), Market microstructure and intermediation, *The Journal of Economic Perspectives* **10**(3), 135–152.

Spulber, D. F. (1999), *Market Microstructure: Intermediaries and the Theory of the Firm*, Cambridge University Press, Cambridge.

Starks, L. T., Yong, L. and Zheng, L. (2006), Tax-loss selling and the January effect: Evidence from municipal bond closed-end funds, *The Journal of Finance* **61**(6), 3049–3067.

Statman, M., Thorley, S. and Vorkink, K. (2006), Investor overconfidence and trading volume, *The Review of Financial Studies* **19**(4), 1531–1565.

Steeley, J. M. (2001), A note on information seasonality and the disappearance of the weekend effect in the UK stock market, *Journal of Banking & Finance* **25**(10), 1941–1956.

Stock, J. H. (1994), Unit roots, structural breaks and trends, *in* R. F. Engle and D. L. McFadden (eds.), *Handbook of Econometrics. Volume 4*, Vol. 2 of *Handbooks in Economics*, Elsevier North Holland, Amsterdam, Chapter 46, pp.2740–2843.

Sullivan, R., Timmermann, A. and White, H. (2001), Dangers of data mining: The case of calendar effects in stock returns, *Journal of Econometrics* **105**(1), 249–286.

Sun, Q. and Tong, W. H. S. (2010), Risk and the January effect, *Journal of Banking & Finance* **34**(5), 965–974.

Taylor, S. J. (1986), *Modelling Financial Time Series*, Wiley, Chichester.

Taylor, S. J. (2005), *Asset Price Dynamics, Volatility, and Prediction*, Princeton University Press, Princeton, NJ.

Thaler, R. H. (1992), *The Winner's Curse: Paradoxes and Anomalies of Economic Life*, Princeton University Press, Princeton, NJ.

Thurlin, A. (2009), Essays on Market Microstructure: Price Discovery and Informed Trading, PhD thesis, Hanken School of Economics, Helsinki.

Tolvi, J. (2003a), Long memory in a small stock market, *Economics Bulletin* **7**(3), 1–13.

Tolvi, J. (2003b), Long memory and outliers in stock market returns, *Applied Financial Economics* **13**(7), 495–502.

Tschernig, R. (1995), Long memory in foreign exchange rates revisited, *Journal of International Financial Markets, Institutions & Money* **5**(2/3), 53–78.

Vergin, R. C. and McGinnis, J. (1999), Revisiting the Holiday Effect: Is it on holiday?, *Applied Financial Economics* **9**(5), 477–482.

Vives, X. (2008), *Information and Learning in Markets: The Impact of Market Microstructure*, Princeton University Press.

Wachtel, S. B. (1942), Certain observations on seasonal movements in stock prices, *The Journal of Business of the University of Chicago* **15**(2), 184–193.

Wang, B. H. and Hui, P. M. (2001), The distribution and scaling of fluctuations for Hang Seng index in Hong Kong stock market, *The European Physical Journal B* **20**(4), 573–579.

Wang, K., Erickson, J., Gau, G. and Chan, S. H. (1995), Market microstructure and real estate returns, *Real Estate Economics* **23**(1), 85–100.

Wang, K., Li, Y. and Erickson, J. (1997), A new look at the Monday effect, *The Journal of Finance* **52**(5), 2171–2186.

Wang, Z. and Fu, C. (2007), A chaos and fractal theory based nonlinear dynamical model for China stock market, *Journal of Communication and Computer* **4**(8), 1–5.

Weber, P. and Rosenow, B. (2005), Order book approach to price impact, *Quantitative Finance* **5**(4), 357–364.

Wei, A. and Leuthold, R. M. (1998), Long agricultural futures prices: ARCH, long memory, or chaos processes?, OFOR Paper 98-03, University of Illinois at Urbana-Champaign, Urbana.

Weron, R. and Przybyłowicz, B. (2000), Hurst analysis of electricity price dynamics, *Physica A* **283**(3–4), 462–468.

Widmer, G. and Kubat, M. (1996), Learning in the presence of concept drift and hidden contexts, *Machine Learning* **23**(1), 69–101.

Willey, T. (1992), Testing for nonlinear dependence in daily stock indices, *Journal of Economics and Business* **44**(1), 63–76.

Willinger, W., Taqqu, M. S. and Teverovsky, V. (1999), Stock market prices and long-range dependence, *Finance and Stochastics* **3**(1), 1–13.

Xu, Z. and Gençay, R. (2003), Scaling, self-similarity and multifractality in FX markets, *Physica A* **323**, 578–590.

Yang, S.-R. and Brorsen, B. W. (1993), Nonlinear dynamics of daily futures prices: Conditional heteroskedasticity or chaos?, *The Journal of Futures Markets* **13**(2), 175–191.

Zhao, H. (2009), A comparative study on GARCH effect and chaos in China's stock markets, *in* Q. Luo and H. Tan (eds.), *2009 International Conference on Test and Measurement (ITCM 2009). Volume 2*, IEEE, Piscataway, NJ, pp.386–389.

Zhao, J. and Yan, X. (2010), An empirical study on turn-of-the-month effect and its causes in Chinese stock market, *South China Journal of Economics* **2**.

Zhou, B. (1996), High-frequency data and volatility in foreign-exchange rates, *Journal of Business & Economic Statistics* **14**(1), 45–52.

Zhuang, Y., Green, C. J. and Maggioni, P. (2000), The great rebound, the great crash, and persistence in British stock prices, Technical Report 00/11, Loughborough University, Loughborough.

Zovko, I. and Farmer, J. D. (2002), The power of patience: A behavioural regularity in limit-order placement, *Quantitative Finance* **2**(5), 387–392.