ExploRing Persistence in Financial Time Series

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1 Introduction

If financial time series exhibits persistence or long-memory, then their unconditional probability distribution may not be normal. This has important implications for many areas in finance, especially asset pricing, option pricing, portfolio allocation and risk management. Furthermore, if the random walk does not apply, a wide range of results obtained by quantitative analysis may be inappropriate. The capital asset pricing model, the Black-Scholes option pricing formula, the concept of risk as standard deviation or volatility, and the use of Sharpe, Treynor, and other performance measures are not consistent with nonnormal distributions. Unfortunately, nonnormality is common among distributions of financial time series according to observations from empirical studies of financial series.

Strict assumptions have to be imposed on the returns of the financial asset to yield an explicit formula for practical applications. For example, in one of the strictest forms, we have to assert that the returns are statistically independent through time and identical across time for a cross-section of returns. Under the assumptions, we can derive a simple and yet elegant relationship between risk and return, as in the case of the security market line. These assumptions can be relaxed, and skewness as well as excess kurtosis can be easily accommodated using other distributions. For example, we can be more flexible in the specification of the distribution function using log-normal or stable class such as Pareto-Levy or stable Paretian distributions (e.g. Cauchy and Bernoulli), of which the normal distribution is a special case.

Models that take into account the asymmetric and fatter tails empirical distribution have been used to model financial time series behaviour. Recent studies concentrated on models that assume returns are drawn from a fat-tailed distribution with finite higher moments. These include t-distribution, mix-normal or conditionally normal. Closed-form expressions that give meaningful relationship are rare and in most cases, the results are not easy to manipulate mathematically or empirically implemented. Furthermore, once nonlinearity is introduced, the possibility is infinite. It becomes difficult analytically and intuitively. In most cases, the mode of analysing and solving the problem is computational.

However, observations suggest that many aspects of financial behaviour may be nonlinear, Attitudes towards risk and expected return are evidently nonlinear, contrary to what unconditional CAPM and other linear models suggest. Derivatives pricing is also inherently nonlinear. Therefore, it is naturally to model such behaviour using nonlinear models.

Once we abandon the random walk hypothesis and without more specific theoretical structure, it is difficult to infer much about phenomena that spans a significant portion of the entire dataset. One area that can yield important insights and addresses some of the violations is long range dependence or the phenomena of persistence in time series. In this chapter, our efforts are focused on exploring persistence in financial time series.

A time series persists in the sense that observations in the past are correlated with observations in the distant future and the relationship may be nontrivial. In the frequency domain, this is characterised by high power at low frequencies, especially near the origin. Detection of long range dependence or persistence has importance implications for short-term trading and long range investment strategies. Transaction costs are not negligible for tactical asset allocation based on short-term strategies and long-horizon predictability may be a more genuine and appropriate form of exploiting profit opportunities. Allocation decisions will be sensitive to the time horizon and may be dependent on the degree of long-term memory.

Empirically, most results of the study of long-memory are focused on financial markets from the developed economies. Here, we look at the stock indices and exchange rates of markets in Asia. We have obtained results on indices and currencies of 10 countries using XploRe.

2 Hurst and Fractional Integration

2.1 Hurst Constant

The Hurst constant H is an index of dependence and lies between 0 and 1 (Hurst 1951). For $0 < H < 0.5$, the series is said to exhibit antipersistence. For $0.5 < H < 1$, the series is said to possess long-memory or persistence. For $H = 0.5$, the series is said to be independent. Although the early work of Hurst was to address the problem of setting a level of discharge such that the reservoir would never overflow or fall below an undesirable level, recent applications have used the Hurst to analyse the fluctuations in financial markets.

In financial markets, H has been interpreted as an indicator of range of dependence, of irregularity and of nervousness (Hall, Härdle, Kleinow, and Schmidt 1999). A higher H signals a less erratic or more regular behaviour; a lower H reveals a more nervous behaviour. For example, May (1999) has used the Hurst constant to generate buy-sell signals for financial time series. His strategy employs the H constant to gauge the stability of the time series. A large Hurst constant signals greater stability and persistence of uptrend, over at least short periods of time. Trade in the financial instruments is said to be subject to less nervousness and enjoys more stability. When H falls below a certain level, it signals that the market is nervous and a sell-signal is given.

2.2 Fractional Integration

A long-memory time series is fractionally integrated of degree d, denoted by $I(d)$, if d is related to the Hurst constant by the equality $d = H - 0.5$. If $d > 0.5$ $(H > 1)$, the series is nonstationary. In case $0 < d < 0.5$, then the series is stationary. The non-integer parameter d is also known as the difference parameter. Notice that if a series is nonstationary, one can obtain a $I(d)$ series with d in the range of $(-0.5, 0.5)$ by differencing the original series until stationary is induced. When $d = 0$, the series is an $I(0)$ process and said to have no long-memory.

3 Tests for $I(0)$ against fractional alternatives

A common feature of the first three tests is the use of the heteroskedastic and autocorrelation consistent (HAC) estimator of the variance (Newey and West 1987) for normalisation. The lag-length Q is a user-chosen number.

(i) Lo's robust rescaled range test (Lo 1991)): lo

(ii) KPSS test (Kwiatkowski, Phillips, Schmidt, and Shin 1992): KPSS

(iii) GKL test (Giraitis, Kokoszka and Leipus 1998): rvlm

The fourth is a nonparametric test

(iv) Lobrob Test (Lobato and Robinson 1998): lobrob
This test is nonparametric in the sense that the test is constructed using the approximation of the spectrum. The bandwidth can be an user-chosen number but Lobato and Robinson (1998) has suggested a plausible m for empirical applications.

4 Semiparametric Estimation of Difference Parameter d

These estimators are semiparametric estimators. The estimators involve the unknown parameter of interest d, in the parametric relation

$$(1-L)^d y_t = x_t \qquad t = 1, 2, \ldots ,$$

where L is the lag operator. The spectra density $f_y(\lambda)$ is estimated nonparametrically imposing the condition that $0 < fy(0) < \infty$, with mild regularity assumptions in a neighbourhood of zero frequency, and its behaviour away from zero is unrestricted. The three estimators of interest are:

(i) GPH (Geweke, and Porter-Hudak 1983)

(ii) Average Periodogram (Robinson 1994)

(iii) Semiparametric Gaussian (Robinson 1995)

Further discussions can be found in Chapter ??. We shall use the default bandwidth for estimation given by the quantlets. Further discussions regarding bandwidth selection can be found in Delgado and Robinson (1996).

5 ExploRing the Data

5.1 Typical Spectral Shape

Figures 1 and 2 are plots of the periodogram and spectral density for the returns computed from DBS50 index. We can see that as frequency approaches zero, the spectral density estimate displayed in Figure 2 increases rapidly. Granger (1966) has observed that this is a "typical spectral shape" of many observed economic time series. Figures 3 and 4 are plots of the periodogram and spectral density for the first difference of the returns computed from DBS50 index. Taking the first difference of the series, we now observe that the spectral density estimate is zero at zero frequency and it increases with f. These results are consistent with $0 < f_y(0) < \infty$, and $(1-L)^d y_t = x_t$.

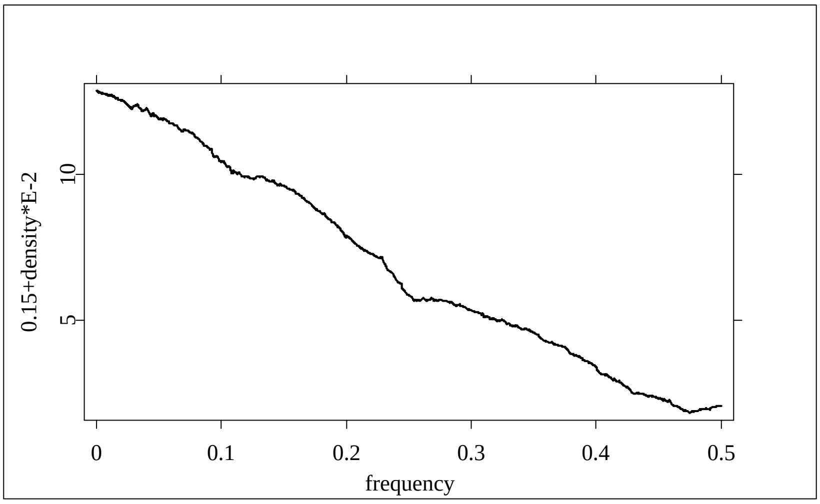

Figure 1: Spectral density for the returns computed from DBS50 index

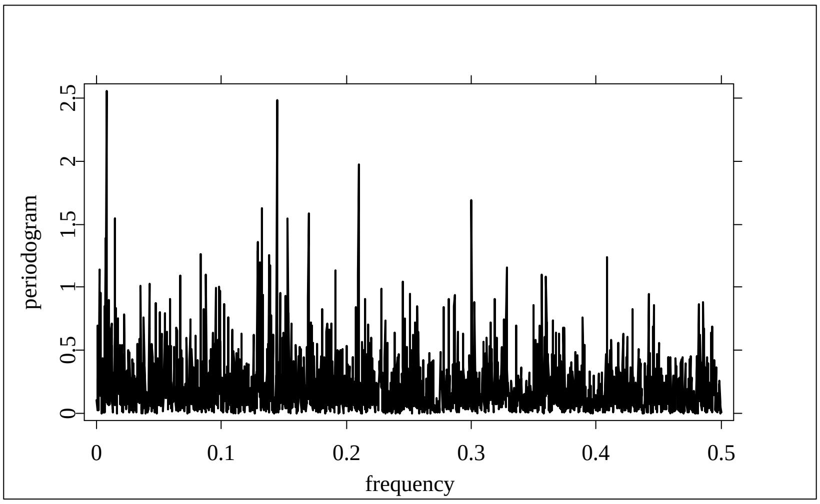

Figure 2: Periodogram for the returns computed from DBS50 index

5.2 Typical Distribution: Mean, Variance, Skewness and Kurtosis

We use the command `descriptive` to obtain the summary statistics of DBS50 returns. We observe that the returns distribution is a "typical thicker-tail and asymmetric" distribution of many observed financial time series (Campbell, Lo, and Mackinlay 1997, Chapter 7). The daily return has extremely high sample kurtosis of 50. This is a clear sign of thicker tails or leptokurtic. The skewness estimate is -1.87. If one believes in the finite higher moments, then using fat-tailed distributions are consistent with the empirical observation. Figure 5 plots the histogram and Figure 6 will give an idea of the degree of deviation from normal distribution.

```
Contents of desc

[ 1,] " "
[ 2,] "========================================================="
[ 3,] " Variable z"
[ 4,] "========================================================="
```

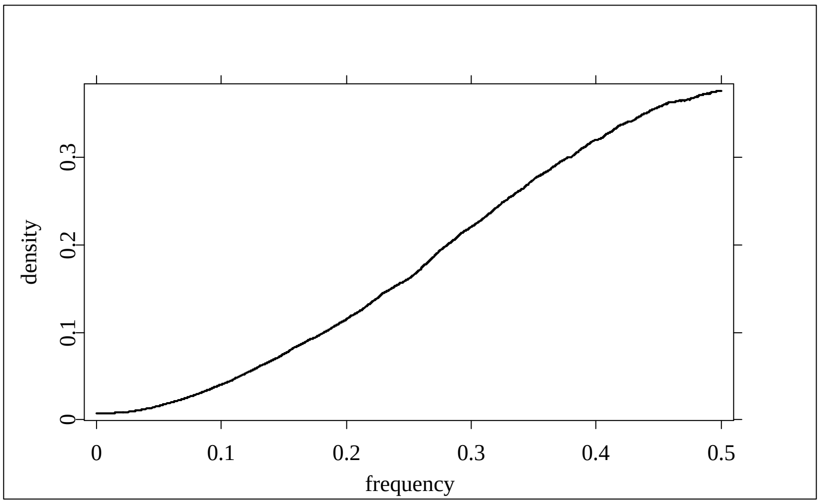

Figure 3: Spectral density for the first difference of the returns computed from DBS50 index

```
[ 5,] " "
[ 6,] " Mean            0.0104578"
[ 7,] " Std.Error        0.589856     Variance          0.34793"
[ 8,] " "
[ 9,] " Minimum          -12.0418     Maximum           6.37548"
[10,] " Range             18.4172"
[11,] " "
[12,] " Lowest cases                  Highest cases "
[13,] "       1935:      -12.0418            4688:      3.45313"
[14,] "       1934:      -6.11557            4509:      3.91006"
[15,] "       1937:      -5.96022            4498:      4.03957"
[16,] "       1469:      -4.72795            1936:      6.26283"
[17,] "       2430:      -4.27287            2684:      6.37548"
[18,] " "
[19,] " Median           0.004296"
[20,] " 25% Quartile    -0.239372     75% Quartile     0.272342"
[21,] " "
[22,] " Skewness         -1.87137     Kurtosis          50.9346"
[23,] " "
[24,] " Observations                   4740"
```

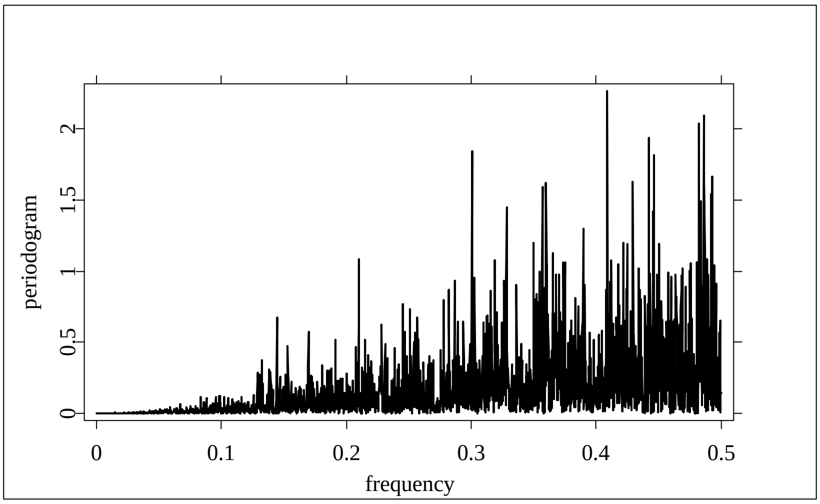

Figure 4: Periodogram for the first difference of the returns computed from DBS50 index

```
[25,] " Distinct observations          4705"
[26,] " "
[27,] " Total number of {-Inf,Inf,NaN}    0"
[28,] " "
[29,] "=================================================="
[30,] " "
```

6 The Data

The daily data on equity and currency are supplied by Bloomberg. These are the data watched by investors on a real time basis. Asset allocation and buy/sell recommendations/decisions for fund managers are sometimes based on reports that rely on these data. The return data are calculated from 1975 to 1998 for ten markets and nine currencies against the USD. The ten markets are Singapore (DBS50), Hong Kong (HSI), Malaysia (KLCI), Japan (NKY), Philippines (PCOMP), Indonesia (JCI), South Korea (KOSPI), Thailand (SET), Taiwan

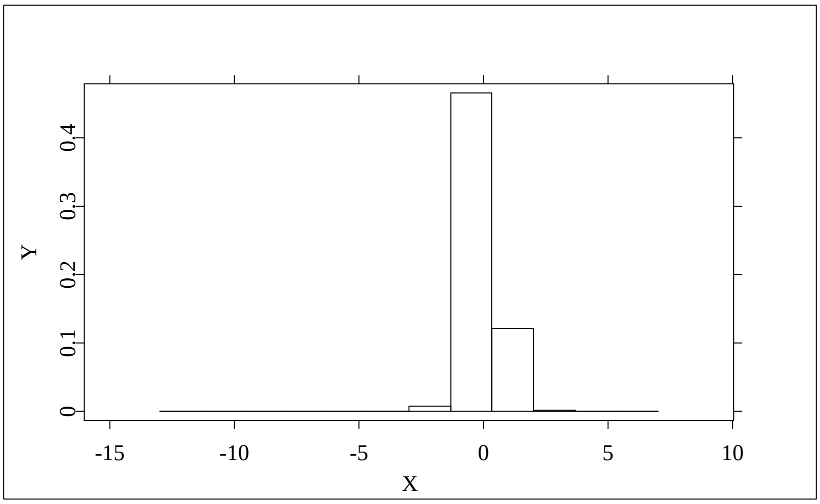

Figure 5: Histogram of returns of DBS50

(TWSE) and USA (INDU). The nine currencies against USD are SGD, HKD, MYR, JPY, PHP, IDR, KRW, THB and TWD.

7 The Quantlets

The followings are the quantlets for producing the results in next section. Each quantlet is just an example and is executed using the data for each country.

Quantlet 1:

```
library("times")
x=read("dbs50.dat")
nobs=4740
x=x[1:nobs]
spec(x)
pgram(x)

library("times")
```

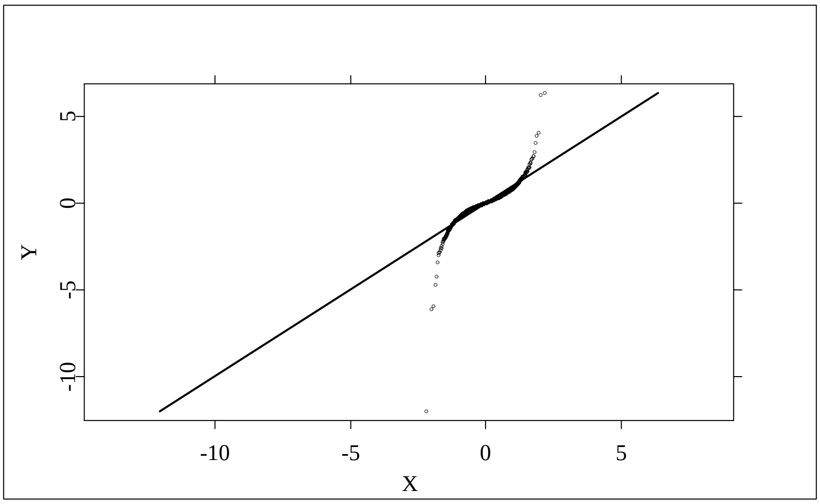

Figure 6: Comparison with Normal distribution of returns of DBS50

```
x=read("dbs50.dat")
nobs=4740
x=x[1:nobs]
y=tdiff(x)
spec(y)
pgram(y)
```

aslm01.xpl

Quantlet 2:

```
library("stats")
x=read("dbs50.dat")
nobs=4740
output("dbs50sum.out","reset")
x=x[1:nobs]
descriptive(x,"z")
library("plot")
setsize(480,320)
plothist(x)
```

```
gr=grqqn(x)
plot(gr)

library("smoother")
h=(max(x)-min(x))*0.05
fh=denest(x,h,"qua")
fh=setmask(fh,"line")
library("plot")
plotdisplay2=createdisplay(1,1)
show(plotdisplay2,1,1,fh)
tl="Density Estimate"
xl="Return"
yl="density fh"
setgopt(plotdisplay2,1,1,"title",tl,"xlabel",xl,"ylabel",yl)
output("dbs50sum.out","close")
```

aslm02.xpl

Quantlet 3:

```
library("times")
x=read("dbs50.dat")
nobs=4740
output("dbs50x.out","reset")
x=x[1:nobs]
y=x
l=lo(y)
k1=kpss(y)
k=rvlm(y)
t=lobrob(y)
g=gph(y)
d=robwhittle(y)
dd=roblm(y)
h=hurst(y,50)
l
k1
k
t
g
d
dd
```

```
h
output("dbs50x.out","close")
```

aslm03.xpl

8 The Results

8.1 Equities

	DBS50	HSI	KLCI	NKY	PCOMP	JCI	KOPSI	SET	TWSE	INDU
lo statistics										
Q = 5	1.28	1.12	1.65	2.16	1.4	1.62	2.15	1.85	1.56	1.26
Q =10	1.25	1.1	1.63	2.17	1.36	1.62	2.18	1.77	1.69	1.29
Q =25	1.16	1.07	1.53	2.1	1.23	1.5	2.02	1.63	1.71	1.31
Q =50	1.08	1.09	1.4	2.04	1.17	1.42	1.89	1.59	1.69	1.29
KPSS statistics										
Order = 1	0.16	0.05	0.29	1.33	0.29	0.3	0.81	0.87	0.03	0.14
Order = 2	0.12	0.04	0.23	1.46	0.2	0.18	0.7	0.58	0.11	0.15
Order = 3	0.1	0.04	0.2	1.36	0.16	0.15	0.59	0.48	0.11	0.15
V/S statistics										
Constant										
Order = 1	0.06	0.05	0.09	0.14	0.07	0.26	0.09	0.06	0.01	0.03
Order = 2	0.04	0.04	0.07	0.16	0.05	0.16	0.08	0.04	0.06	0.03
Order = 3	0.04	0.04	0.06	0.16	0.04	0.13	0.07	0.03	0.06	0.03
Trend										
Order = 1	0.05	0.05	0.08	0.3	0.08	0.28	0.26	0.18	0.01	0.06
Order = 2	0.03	0.04	0.06	0.33	0.06	0.17	0.23	0.18	0.06	0.06
Order = 3	0.03	0.04	0.05	0.31	0.04	0.14	0.19	0.18	0.06	0.07
Bandwidth	630	916	767	874	313	326	490	330	697	1190
lobrob Test	-3.16	-1.24	-1.61	0.27	-2.9	-1.43	-4.58	-3.47	0.82	1.95
d: gph	-0.09	-0.12	0.07	0.12	-0.03	0.08	0.05	0.02	0.07	-0.06
Bandwidth	1185	1174	1352	946	747	946	1025	700	1713	1522
d: lmrob	0.05	0.04	0.04	-0.01	0.04	0.12	-0.005	0.1	-0.11	-0.03
Bandwidth	593	587	676	473	374	473	512	350	857	761
d: lmrob	0.09	0.04	0.05	0.01	0.04	0.01	0.08	0.1	-0.02	-0.02
Bandwidth	296	293	338	237	187	237	256	175	428	381
d: lmrob	0.06	-0.03	0.08	0.07	0.16	0.07	0.11	0.09	0.06	-0.006
Bandwidth	1185	1174	1352	946	747	946	1025	700	1713	1522
d: robwhittle	0.01	0.02	0.01	-0.03	0.05	0.18	-0.1	0.07	-0.26	-0.03
Bandwidth	593	587	676	473	374	473	512	350	857	761
d: robwhittle	0.09	0.09	0.04	-0.04	-0.012	-0.05	0.07	0.09	-0.1	-0.04
Bandwidth	296	293	338	237	187	237	256	175	428	381
d: robwhittle	0.06	-0.01	0.04	0.12	0.16	0.03	0.08	0.12	0.08	-0.03
Hurst	0.35	0.35	0.34	0.3	0.25	0.42	0.16	0.27	0.53	0.34

8.2 Exchange

	SGD	HKD	MYR	YEN	PHP	IDR	KRW	THB	TWD
lo statistics									
Q = 5	1.72	2.48	1.53	1.42	1.43	1.85	1.88	2.03	2.48
Q =10	1.74	2.37	1.63	1.38	1.57	1.73	1.89	1.99	2.34
Q =25	1.63	2.27	1.56	1.28	1.53	1.63	1.63	1.8	2
Q =50	1.6	2.3	1.46	1.23	1.45	1.49	1.49	1.67	1.87
KPSS statistics									
Order = 1	0.19	0.9	0.23	0.12	0.17	0.34	0.15	0.11	1.71
Order = 2	0.22	1.04	0.26	0.1	0.27	0.27	0.19	0.12	1.42
Order = 3	0.19	0.98	0.22	0.08	0.26	0.23	0.13	0.09	1.05
V/S statistics									
Constant									
Order = 1	0.18	0.17	0.08	0.09	0.04	0.1	0.09	0.09	0.16
Order = 2	0.21	0.2	0.09	0.07	0.07	0.08	0.11	0.1	0.14
Order = 3	0.18	0.2	0.07	0.06	0.07	0.07	0.08	0.07	0.11
Trend									
Order = 1	0.18	0.23	0.08	0.09	0.084	0.18	0.1	0.09	0.61
Order = 2	0.21	0.27	0.09	0.08	0.133	0.14	0.13	0.1	0.5
Order = 3	0.18	0.25	0.07	0.06	0.132	0.12	0.09	0.08	0.37
Bandwidth	884	635	1281	1278	347	397	427	869	840
lobrob Test	-0.71	-3.75	0.93	-3.26	2.73	-1.53	-12.16	-3.97	-8.55
d: gph	-0.07	0.09	0.1	0.05	0.23	0.3	-0.08	0.01	0.04
Bandwidth	1135	1135	1526	1523	455	456	1111	1142	900
d: lmrob	0.01	0.12	-0.005	0.04	-0.07	0.04	-0.11	0.05	0.09
Bandwidth	567	568	763	761	227	228	556	571	450
d: lmrob	0.04	0.07	-0.04	0.06	-0.07	0.1	0.18	0.08	0.12
Bandwidth	284	284	381	381	114	114	278	286	225
d: lmrob	0.09	0.03	0.12	0.1	0.09	0.11	0.34	0.11	0.15
Bandwidth	1135	1135	1526	1523	455	456	1111	1142	900
d: robwhittle	-0.02	0.12	0.04	0.01	-0.07	-0.006	-0.48	0.03	0.07
Bandwidth	567	568	763	761	227	228	556	571	450
d: robwhittle	0.02	0.11	-0.23	0.04	-0.27	0.11	0.17	0.1	0.09
Bandwidth	284	284	381	381	114	114	278	286	225
d: robwhittle	0.11	0.03	0.07	0.11	0.1	0.029	0.3	0.14	0.15
Hurst	0.25	0.38	0.46	0.26	0.3	0.33	0.51	-	0.43

Recent studies suggest that long-memory is present in absolute returns and square of returns. We have not reported the results for absolute and squared returns. The results here seem to suggest that some returns series exhibit long-memory characteristics. The returns calculated from the indices Nikkei, KOSPI, and SET exhibit persistence characteristics according to the first three tests. The nonparametric test lobrob seems to suggest that DBS50, JCI, KOSPI, SET and INDU also possess long-memory.

For the exchange rates, it is not surprising that most exchange rates exhibit persistence as most countries manage their currencies either in the form of managed float, pegging or some form of capital control. What is surprising though, is the non-detection of persistence in MYR and IDR, which was expected to exhibit persistence. The deliberate intervention in the market and managed depreciation over the years, especially for Ruppiah, did not show up as persistence in the series.

9 Practical Considerations

Previous studies of long-memory and fractional integration in time series are numerous. Barkoulas, Baum, and Oguz (1999a), Barkoulas, Baum, and Oguz (1999b) studied the long run dynamics of long term interest rates and currencies. Recent studies of stock prices include Cheung and Lai (1995), Lee and Robinson (1996), Andersson and Nydahl (1998). Batten, Ellis, and Hogan (1999) worked with credit spreads of bonds. Wilson and Okunev (1999) searched for long term co-dependence between stock and property markets. While the results on the level of returns are mixed, but there is general consensus that the unconditional distribution is non-normal and there is long-memory in squared and absolute returns. The followings are some issues. Though not mutually exclusive, they are separated by headings for easier discussions:

9.1 Risk and Volatility

Standard deviation is a statistical measure of variability and it has been called the measure of investment risk in the finance literature. Balzer (1995) argues that standard deviation is a measure of uncertainty and it is only a candidate, among many others, for a risk measure. Markowitz (1959) and Murtagh (1995) both found that portfolio selection based on semi-variance tend to produce better performance than those based on variance.

A normal distribution is completely characterised by its first two statistical moments, namely, the mean and standard deviation. However, once nonlinearity is introduced, investment returns distribution is likely to become markedly skewed away from a normal distribution. In such cases, higher order moments such as skewness and kurtosis are required to specify the distribution. Standard deviation, in such a context, is far less meaningful measure of investment risk and not likely to be a good proxy for risk. While recent developments are interested in the conditional volatility and long memory in squared and absolute returns, most practitioners continue to think in terms of unconditional variance and continue to work with unconditional Gaussian distribution in financial applications. Recent publications are drawing attention to the issue of distribution characteristics of market returns, especially in emerging markets , which cannot be summarized by a normal distribution (Bekaert et al. 1998).

9.2 Estimating and Forecasting of Asset Prices

Earlier perception was that deseasonalised time series could be viewed as consisting of two components, namely, a stationary component and a non-stationary component. It is perhaps more appropriate to think of the series consisting of both a long and a short memory components. A semiparametric estimate d can be the first step in building a parametric time series model as there is no restriction of the spectral density away from the origin. Fractional ARIMA, or ARFIMA, can be use for forecasting although the debates on the relative merits of using this class of models are still inconclusive (Hauser, Pötscher, and Reschenhofer 1999), (Andersson 1998). Lower risk bounds and properties of confidence sets of so called ill-posed problems associated with long-memory parameters are also discussed in Potscher (1999). The paper casts doubts on the used on statistical tests in some semiparametric models on the ground that a priori assumptions regarding the set of feasible data generating processes have to be imposed to achieve uniform convergence of the estimator.

9.3 Portfolio Allocation Strategy

The results of Porterba and Summers (1988) and Fama and French (1988) provided the evidence that stock prices are not truly random walk. Based on these observations, Samuelson (1992) has deduced on some rational basis that it is appropriate to have more equity exposure with long investment horizon than short horizon. Optimal portfolio choice under processes other than white noise can also suggest lightening up on stocks when they have risen above trend and loading up when they have fallen behind trend. This coincides with the conventional wisdom that long-horizon investors can tolerate more risk and thereby garner higher mean returns. As one grows older, one should have less holding of equities and more assets with lower variance than equities. This argues for "market timing" asset allocation policy and against the use of "strategic" policy by buying and holding as implied by the random walk model.

Then there is the secondary issue of short-term versus long-horizon tactical asset allocation. Persistence or a more stable market calls for buying and holding after market dips. This would likely to be a mid to long-horizon strategy in a market trending upwards. In a market that exhibits antipersistence, asset prices tend to reverse its trend in the short term thus creating short-term trading opportunities. It is unclear, taking transaction costs into account, whether trading the assets would yield higher risk adjusted returns. This is an area of research that may be of interest to practitioners.

9.4 Diversification and Fractional Cointegration

If assets are not close substitutes for each other, one can reduce risk by holding such substitutable assets in the portfolio. However, if the assets exhibit long-term relationship (e.g., to be co-integrated over the long-term), then there may be little gain in terms of risk reduction by holding such assets jointly in the portfolio. The finding of fractional cointegration implies the existence of long-term co-dependence, thus reducing the attractiveness of diversification strategy as a risk reduction technique. Furthermore, portfolio diversification decisions in the case of strategic asset allocation may become extremely sensitive to the investment horizon if long-memory is present. As Cheung and Lai (1995) and Wilson and Okunev (1999) have noted, there may be diversification benefits in the short and medium term, but not if the assets are held together over the long term if long-memory is presence.

9.5 MMAR and FIGARCH

The recently developed MMAR (multifractal model of asset returns) of Mandelbrot, Fisher and Calvet (1997) and FIGARCH process of Baillie, Bollerslev, and Mikkelsen (1996) incorporate long-memory and thick-tailed unconditional distribution. These models account for most observed empirical characteristics of financial time series, which show up as long tails relative to the Gaussian distribution and long-memory in the volatility (absolute return). The MMAR also incorporates scale-consistency, in the sense that a well-defined scaling rule relates return over different sampling intervals.

10 Conclusion

Besides those issues discussed above, the implications for deviation from Gaussian and white-noise process are not fully understood yet for the pricing of the underlying instruments and the implications for derivatives will be challenging to derive. The discussions in this chapter are not meant to be exhaustive on the issues surrounding long-memory or persistence in financial time series, with the related problems of deviation from normality, and different time interval. We have no doubt that the literature addressing these issues will continue to grow and alternative models will be suggested.

In this chapter, We concentrated on searching for long-memory in Asian financial time series. As in previous studies, we found mix evidence of long-memory in Asia stock indices and exchange rates. Finally, we have not adequately dealt with the issue of bandwidth selection in this study and it is likely that the conclusion is sensitive to the choice of bandwidth. Some automatic selection of bandwidth will be desirable and future research should be conducted.

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