Long Memory in the Gulf States' Foreign Currency Markets

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Abstract :

Spectral regression analyses, using both the Geweke, Porter-Hudak (GPH) and Hurvich and Deo (HD) methods are applied to detect the long-range dependence in Gulf States' foreign exchange markets. The estimators based on the OPH method indicate that the Balirain Dinar/ Pound, the Oman Rial (both for Euro and Pound), and the Qatar Riyal/Euro fall in the long memory interval with the 95% confidence level. However, based on the optimal estimators of the HD plug-in method, one can not confirm the GPH results. Accordingly, based on the optimal HD estimators, all of which fall in —0.5 < $\hat{d}_{bd} \leq$ *0.50, we conclude that these exchange rates series are stationary and ergodic, hence, the exchange rates at level are non-stationary.*

Keywords: Long memory, exchange rates, Gulf States, Optimal Periodogramic ordinate.

1 Introduction

The efficient market hypothesis (EMH) is a common assumption in traditional financial economics. In its weak form EMH implies that the changes in financial time series (e.g., equity prices, interest rates, exchange rates) are white noise processes consisting of independent, identically distributed random variables[1]. These assumptions imply that the time series at level follow random walks.

A time series that follows a random walk process has two important properties. First, the series has long memory in the sense that the effects of distant shocks are strongly felt at present. Second, the first difference of the series is a white noise, short memory process (Engle and Granger, 1991).

Understanding whether exchange rates are short or long memory series has important policy implications. First, accurate forecasting of a long-memory process is more challenging because the shocks of distant past have prominent effect in present. Second, establishing that shocks to an exchange rate persist would give the Central Bank's authorities an incentive to intervene in the currency markets. These interventions would aim at steering the nominal exchange rate toward its long-run equilibrium path, in absence of which, the nominal rate would diverge away from the equilibrium rate.

Additionally, the long-memory property of an exchange rate could affect its volatility which is an important determinant of riskiness of direct foreign and portfolio investment opportunities. Moreover, it is well-known that the ever-present political, economic, and financial shocks are important factors in country risk analysis (Erb,et *al.*, 1996) that influence the strength or weakness of a currency, thus ultimately determining the potential profits of foreign investments.

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[1]Noise refers to the power spectra, or what is the same thing, squared magnitude of the Fourier transform of a time series. Noises follow a power law in the form of $f^{ß}$, where f is frequency and ß is a constant. White noise has a spectral exponent of ß= 0.

In this study, I would explore the nature of several currency markets in the Gulf states by examining the memory properties of the exchange rate series.

To understand the memory property of a Gaussian process, we examine the autocorrelation function or the spectral density of the series. If a series exhibits long-range dependence or “biased random walk”, there is persistent temporal dependence between distant observations. In the time domain, this is characterized by auto-correlation function that decays hyperbolically. In the frequency domain, this is characterized by high power at low frequencies, especially near the origin.

A broader definition of the long memory processes requires that the autocovariances are not summable or that the spectral density is unbounded.

There are many empirical works that test for the presence of long memory in the financial and economic time series. These studies include, for example, Soofi(1998) and Cheung (1993). Cheung first applied the ARFIMA model to foreign exchange rate series. In this study, using the weekly changes of US-Dollar spot rate of the British Pound, the Deutsche Mark, the Swiss Franc, the French Franc and the Japanese Yen for the period from January 1974 to December 1989, Cheung finds the statistical evidence for long memory using various estimation techniques. Soofi (1998) tests for the presence of long-memory in the black market exchange rates of a number of oil producing countries.

In empirical modeling of long memory processes the autoregressive fractionally integrated moving average (ARFIMA) model that was proposed by Hosking(1981) and Granger and Joyeux(1980) is used. Many of the empirical studies of long range dependence are based on the estimation method by Geweke and Porter-Hudak (1983) (GPH). However, developments in optimal estimation of the long-memory parameter have brought the statistical properties of the estimators in sharper focus (see plug-in method of Hurvich and

Deo,1999). Accordingly, in this study I use both methods of estimating the memory property of the exchange rates.

The paper is arranged as follows. In section 2, two methods for testing the long-memory property of a time series are presented. First, we proceed with a short discussion of GPH method and then examine the plug-in method based on the work of Hurvich and Deo(1999) to estimate the differencing parameter of the ARFIMA model. In the third section, we discuss the data used here and present the empirical results of the study. The final section gives the conclusions.

2 Methodologies

In this section I would discuss both the GPH and UD methods. See a general survey on ARFIMA estimation methods by Bhansali and Kokoszka(2002).

2.1 Spectral regression test

Consider a time series $X = \{x_t\}_{t=1}^{N}$. It is said to be integrated of order *d*, signified as *I(d)*, if it has a stationary, invertible autoregressive moving average (ARMA) representation after applying differencing operator $(1 - L)^d$, where *L* is the backward lag operator. The series is fractionally integrated when *d* is not an integer.

A time series $X = \{x_t\}$ follows a fractionally integrated autoregressive moving average (ARFIMA) process if

$$A(L)(1-L)^d x_t = B(L)\varepsilon_t \qquad (1)$$

Where $\varepsilon_t \sim iid(0, \sigma^2)$, $A(L) = 1 - a_1 L - \dots - a_p L^p$; $B(L) = 1 - b_1 L - \dots - b_q L^q$; all roots of *A(L)* and *B(L)* are outside of unit circle, and $(1 - L)^d$ *d* is the fractional differencing operator defined by

$$(1 - L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(k+1)\Gamma(-d)}, \qquad (2)$$

with Γ(.) being the gamma function. Model (1) extends the standard ARIMA model to all real values of *d*. For $0 \le d < 0.5$, the autocorrelations of X decay at a hyperbolic rate that is proportional to $k^{(2d-1)}$ for large *k*, as compared to a faster, geometric decaying rate of a stationary ARMA process.

According to the GPH method, given the periodogram $I(\omega_j)$ of variable X one can estimate *d* by:

$$\ln(I(\omega_j)) = c - d\ln(4\sin^2(\omega_j/2)) + n_j \qquad (j=1,\ldots,m) \qquad (3)$$

where $\omega_j = \frac{2\pi j}{N}$ for $(j = 1,\ldots m)$ denote the harmonic ordinates, $c = \log C - \theta$, θ

is Euler's constant $\theta = 0.5772\ldots$ and $n_j = \log\{(4\sin^2(\omega_j/2))^d I(\omega_j)/C\} + \theta$

And C is the constant assumed by Geweke and Porter-Hudak(1983) to approximate the spectral density $f(.)$ by $C\,(4\sin^2(./2))^{-d}$ in only a neighborhood of zero frequency, so an asymptotic theory will require that *m* tend to infinity more slowly than *N*.

Note that selection of a large sample size leads to estimator's sensitivity to short memory, and an inadequate sample size will result in an imprecise estimation. As suggested by GPH (1983), one should use *m* observations, where $m\ g(N) < N$.

The critical values for the GPH test are non-standard, and critical evaluation of estimated *d* requires computation of empirical values[2]. The choice of $m = T^{\mu}$, where GPH suggests using 0.5, 0.55, and 0.6, based on the simulation studies. These choices, however, yield suboptimal convergence rate, see Hurvich, Deo, and Brodsky(1998).

Robinson(1995) in addressing this problem proposed a Gaussian semiparametric estimator (GSE). Since GSE is defined implicitly, derivation of a formula for asymptotically optimal *m* is rather problematic. Moreover, the estimation method rests on a theory of optimal selection of *m* yielding a formula which includes both *m* and *d*. To deal with this problem Delgado and Robinson (1996) proposed an iterative method of estimating *d* and *m* in alternating cycles.

To resolve some of these problems, Hurvich and Deo (1999) proposed a plug-in method of selecting *m* as follows. Let X consists of *N*

[2] For the quantiles of Monto Carlo distribution of GPH standardized t-statistics which are based on $GPHT = \frac{\hat{d} - d}{SD(\hat{d})}$ where d is estimate of *d*, and ***SD(d)*** is the asymptotic standard error of $\hat{d}$, see Soofi(1998).

observations such that $\{x_i\}_{i=1}^{N}$ are both normal and stationary. Hurvich and Deo(1999) suggests using $\hat{C}$ to construct estimators of $\hat{d}_m$ where,

$$\hat{m} = \hat{C} N^{4/5}. \quad (4)$$

is consistently estimated by

$$\hat{C} = \left(\frac{27}{128_{\pi^2}}\right)^{1/5} K^{2/5} \quad (5)$$

and

$$\hat{K} = \sum_{j=1}^{H} b_j \log I_j \quad (6)$$

In this model b_3 is the third row of matrix *(Y'Y).1Y'*, where matrix Y has the columns (1,log|2sin(.3/2)|, . ^2_j/2), *(j = 1,2,...,L), L= AN*$^\delta$, for some arbitrary constant *A,* and 0 < δ < 1. To minimize the mean square error, we set δ = 6/7 as suggested by Hurvich and Deo(1999). *13* is the periodogram of the j-th Fourier frequency given by

$$I_j = \frac{1}{2\pi N} \left| \sum_{t=1}^{N} x_t e^{(-i\omega_j t)} \right|^2 \quad (7)$$

The regression estimator of *d* is given by

$$\hat{d}_m = -0.5 \frac{\sum_{j=1}^{m} (a_j - \bar{a}) \log I_j}{\sum_{j=1}^{m} (a_j - \bar{a})^2} \quad (8)$$

where $a = \log|2\sin(. _3/2)|$, $\bar{a} = \frac{1}{m} \sum_{j=1}^{m} a_j$, and m is the Fourier frequencies obtained in formula (4). We find the estimates of *d* are sensitive to the constant *A* occurring in L_An^{δ}. $A = 0.2, 0.25,$ ǝ, and 0.3 which are based on an initial simulation study by Hurvich and Deo (1998) are also used in this study.

According to Theorem 2 of Hurvich and Deo (1999)$Var(d_{hd}) = \frac{\pi^2}{24 \hat{m}_{opt}}$

Henece, the asymptotic standard errors are given by $SD(d_{hd}) = \frac{\pi}{\sqrt{24\hat{m}_{opt}}}$

Hurvich, Deo and Brodsky (1998) gives the variance of long-memory estimator, $\mathrm{Var}(\hat{d}_{gph})$ for the GPH method which, simliar to the $\mathrm{Var}(d_{hd})$, is inversely related to the m:

$$Var(\hat{d}_{gph}) = \frac{\pi}{\sqrt{24m_{gph}}}$$

Because $\hat{m}_{opt} > \hat{m}_{gph}$ for the data used in this study, the $Var(\hat{d}_{hd}) < Var(\hat{d}_{gph})$, resulting in a larger confidence interval for the GPH method. It should be noted that the asymptotic normality of both GPH and HD Plug-in estimators are established (see, Hurvich, Doe, and Brodsky, 1998). For the differences between the empirical results for major daily dollar exchange rates based on the GPH and the Plug-in methods, see Soofi and Payesteh (2002).

According to Hosking (1981), when $0 < d \leq 0.5$ the series is a long memory process, and when $0.5 < d < 1$ it is short memory. For $-0.5 < d < 0.5$, a fractionally integrated series is stationary and ergodic. For $d \geq 0.5$ the process is non-stationary, however, it can be reduced to case $-0.5 < d \leq 0.5$ by taking appropriate differences.

3 Data and empirical results

In this study, the memory property of the daily exchange rates for Bahrain (dinar, BD), Kuwait (dinar, KD), Oman (rial, RO), Qatar (riyal, QR), Saudi Arabia (riyal, SRls), and the United Arab Emirates with respect to Euro and British pound are examined. These data are obtained from DataStream, and also from the web site at the University of British Columbia: http://pacific.commerce.ubc.ca/xr/.

The sample sizes vary with data spanning from 3 May 1999 to 31 March 2003 for Bahrain, Kuwait, and the United Arab Emirate. The sample size for S. Arabia is 1 April 1999 to 31 March 2003, and the number of observations for Oman and Qatar ranges from 15 January 1990 to 31 March 2003. The selection of the currencies and the sample sizes are based on data availability.

It is well-known that most financial time series are non-stationary, hence, before estimating *d*, we first preprocess the data by substituting the original exchange rate series by their corresponding to the first-differenced series to obtain a stationary series.

Table 1 reports the results of estimating the fractionally differencing parameter *d* based on the GPH and the plug-in methods. We also provide 95% confidence intervals for the estimated differencing parameters for each currency based on different p~ and *A* values.

The estimators based on the GPH method indicate that the Bahrain Dinar/Pound, the Oman Rial (both for Euro and Pound), and the Qatar Riyal/Euro fall in the long memory interval with the 95% confidence level. However, based on the optimal estimators of the HD plug-in method, one can not confirm the GPH results. Accordingly, based on the HD estimators all of which fall in $-0.5 < \hat{d}_{hd} \leq 0.50$, we conclude that these series are stationary and ergodic, hence, the exchange rates at level are nonstationary.

Table 1: Estimated Differencing Parameter by the GPH and Hurvich &Deo Methods

Currency	GPH				H&D			
	m^{gph}	$\hat{d}$	$\hat{d}-1.96\,\sigma$	$\hat{d}+1.96\,\sigma$	m^{opt}	$\hat{d}$	$\hat{d}-1.96\,\sigma$	$\hat{d}+1.96\,\sigma$
Bahrain	30	0.0255	-0.2038	0.2548	130	-0.0970	-0.2071	0.0131
Dinar!	43	-0.0851	-0.2768	0.1064	149	-0.1065	-0.2094	-0.0035
Pound	60	-0.0663	0.0827	0.0958	160	-0.0972	-0.1965	0.0021
Kuwait-	30	-0.024	-0.2533	0.2053	119	-0.0887	-0.2038	0.0264
Dinar/	43	-0.1278	-0.3193	0.0637	167	-0.1111	-0.2083	-0.0138
Pound	60	-0.1194	-0.2815	0.0427	147	-0.1181	-0.2217	-0.0144
Oman	33	0.0616	-0.1570	0.2802	259	-0.0054	-0.0834	0.0726
Riyal/	47	0.0893	-0.0938	0.2726	326	-0.0263	-0.0958	0.0432
Pound	67	0.1911	0.0376	0.3445	686	-0.0257	-0.0736	0.0222
Oman	33	0.2296	0.0109	0.4482	385	-0.007	-0.0710	0.0570
Riyal/	47	0.0768	-0.1064	0.2600	237	-0.0242	-0.1058	0.0574
Euro	67	0.0256	-0.1278	0.1790	283	-0.0172	-0.0918	0.0574
Qatar	33	0.0924	-0.1278	0.1790	284	-0.0247	-0.0992	0.0498
Riyal/	47	0.0029	-0.1803	0.1861	356	-0.0220	-0.0885	0.0445
Pound	67	0.0521	-0.1013	0.2055	1246	-0.0768	-0.1123	-0.0412
Qatar	33	0.2231	0.0044	0.4417	662	0.0006	-0.0482	0.0494
Riyal/	47	0.0735	-0.1097	0.2567	253	-0.0151	-0.0940	0.0638
Euro	67	0.0215	-0.1319	0.1749	294	-0.0061	-0.0793	0.0671
S. Arabia	30	0.0613	-0.1680	0.2906	91	-0.1547	-0.2863	-0.0230
Riyal/	43	-0.0268	-0.2183	0.1647	148	-0.0958	-0.1990	0.0074
Pound	60	0.0331	-0.1290	0.1952	160	-0.1003	-0.1996	-0.0009
UAE	30	0.0378	-0.1915	0.2671	130	-0.0837	-0.1938	0.0264
Dirham/	43	-0.0746	-0.2661	0.1169	149	-0.0953	-0.1982	0.0076
Pound	60	-0.0152	-0.1773	0.1469	150	-0.0888	-0.1913	0.0137

m^{gph} *s are* based on $\mu =$ 0.5,0.55, and 0.6. m^{opt} *s* are based on A =0.2,0.25, and 0.30.

4 Conclusions and remarks

Due to policy implications of long memory exchange rate time series, it is important to assess the memory property of nominal exchange rates. I use two methods to estimate the long-memory parameter of the several currencies of the Gulf states. I use the traditional GPH as well as the Plug-in method of optimal selection of the periodogram ordinate for inclusion in the spectral regression of the differencing parameter of the ARFIMA model.

The results based on sub-optimal GPH estimators indicate that the Bahrain Dinar/Pound, the Oman Rial, (both for Euro and Pound), and the Qatar Riyal/Euro are long memory processes. However, these results can not be confirmed with the optimal estimators of Hurvich and Deo Plug-in method. Finally, based on the results obtained by the optimal method, we conclude that the first differenced exchange rate series are stationary and ergodic, implying that the exchange rates at level are non-stationary.

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