189

Long Memory and Forecasting in Euroyen Deposit Rates [*]

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Abstract. We test for long memory in 3- and 6-month daily returns series on Eurocurrency deposits denominated in Japanese yen (Euroyen). The fractional differencing parameter is estimated using the spectral regression method. The conflicting evidence obtained from the application of tests against a unit root as well as tests against stationarity provides the motivation for testing for fractional roots. Significant evidence of positive long-range dependence is found in the Euroyen returns series. The estimated fractional models result in dramatic out-of-sample forecasting improvements over longer horizons compared to benchmark linear models, thus providing strong evidence against the martingale model.

Key words: ARFIMA processes, forecasting, long memory, spectral regression, unit roots.

1. Introduction

The long memory, or long term dependence, property describes the high-order correlation structure of a series. If a series exhibits long memory, there is persistent temporal dependence even between distant observations. Such series are characterized by distinct but nonperiodic cyclical patterns. The presence of long memory dynamics causes nonlinear dependence in the first moment of the distribution and hence a potentially predictable component in the series dynamics. Fractionally integrated processes can give rise to long memory (Mandelbrot (1977), Granger and Joyeux (1980), Hosking (1981)). On the other hand, the short memory, or short term dependence, property describes the low order correlation structure of a series. For short memory series, correlations among observations at long lags become negligible. Standard autoregressive moving average processes cannot exhibit long term (low frequency) dependence as they can only describe the short run (high frequency) behavior of a time series. The presence of fractional structure in asset prices raises issues regarding theoretical and econometric modeling of asset prices, statistical testing of pricing models, and pricing efficiency and rationality.

Because nonzero values of the fractional differencing parameter imply strong dependence between distant observations, considerable attention has been directed to the analysis of fractional dynamics in asset returns. Long memory analysis has

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been conducted for stock prices (Greene and Fielitz (1977), Aydogan and Booth (1988), Lo (1991), Cheung, Lai, and Lai (1993), Cheung and Lai (1995), Barkoulas and Baum (1996/1997)), spot and futures currency rates (Booth, Kaen, and Koveos (1982a), Cheung (1993a), Cheung and Lai (1993), Bhar (1994), Fang, Lai, and Lai (1994), Barkoulas, Labys, and Onochie (1997a)), gold prices (Booth, Kaen, and Koveos (1982b), Cheung and Lai (1993)), international spot commodity prices (Barkoulas, Labys, and Onochie (1997b)), and commodity and stock index futures (Helms, Kaen, and Koveos (1984), Barkoulas, Labys, and Onochie (1997a)).

In this study we investigate the presence of fractional dynamics in the returns series (yield changes) of Eurocurrency deposits denominated in Japanese yen, referred to as Euroyen rates hereafter. We pay particular emphasis on the implications of long memory for market efficiency. According to the market efficiency hypothesis in its weak form, asset prices incorporate all relevant information, rendering asset returns unpredictable. The price of an asset determined in an efficient market should follow a martingale process in which each price change is unaffected by its predecessor and has no memory. If the Euroyen returns series exhibit long memory, they display significant autocorrelation between distant observations. Therefore, the series realizations are not independent over time and past returns can help predict future returns, thus violating the market efficiency hypothesis. The testing methodology employed is the spectral regression method. We find that fractional structure with long memory dynamics is a pervasive feature of the Euroyen returns series. A forecasting experiment clearly demonstrates that long memory forecasts are superior to those of benchmark linear models over longer forecasting horizons.

The plan of the paper is as follows. Section 2 presents the spectral regression method. Data and empirical estimates are discussed in Section 3, while section 4 presents a forecasting experiment using long memory and linear forecasting generating models. We conclude in Section 5 with a summary of our results.

2. The Spectral Regression Method

The model of an autoregressive fractionally integrated moving average process of order (p, d, q), denoted by ARFIMA (p, d, q), with mean μ, may be written using operator notation as

$$\Phi(L)(1 - L)^d(y_t - \mu) = \Theta(L)u_t, \quad u_t \sim \text{i.i.d.}(0, \sigma_u^2), \tag{1}$$

where L is the backward-shift operator, $\Phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p$, $\Theta(L) = 1 + \vartheta_1 L + \cdots + \vartheta_q L^q$, and $(1 - L)^d$ is the fractional differencing operator defined by

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

with $\Gamma(\cdot)$ denoting the gamma, or generalized factorial, function. The parameter d is allowed to assume any real value. The arbitrary restriction of d to integer values gives rise to the standard autoregressive integrated moving average (ARIMA) model. The stochastic process y_t is both stationary and invertible if all roots of $\Phi(L)$ and $\Theta(L)$ lie outside the unit circle and $|d| < 0.5$. The process is non-stationary for $d \geqslant 0.5$, as it possesses infinite variance, i.e. see Granger and Joyeux (1980). Assuming that $-0.5 < d < 0.5$ and $d \neq 0$, Hosking (1981) showed that the correlation function, $\rho(\cdot)$, of an ARFIMA process is proportional to k^{2d-1} as $k \to \infty$. Consequently, the autocorrelations of the ARFIMA process decay hyperbolically to zero as $k \to \infty$ which is contrary to the faster, geometric decay of a stationary ARMA process. For $0 < d < 0.5$, $\sum_{k=-n}^{n} |\rho(k)|$ diverges as $n \to \infty$, and the ARFIMA process is said to exhibit long memory. The process exhibits short memory for $d = 0$, and intermediate memory or antipersistence for $-0.5 < d < 0$.[1] More specifically, for $0 < d < 0.5$, the process exhibits long-range positive dependence while for $-0.5 < d < 0.5$ the process exhibits long-range negative dependence.

Geweke and Porter–Hudak (1983) suggested a semi-parametric procedure to obtain an estimate of the fractional differencing parameter d based on the slope of the spectral density function around the angular frequency $\xi = 0$. More specifically, let $I(\xi)$ be the periodogram of y at frequency ξ defined by

$$I(\xi) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} e^{it\xi} (y_t - \bar{y}) \right|_2 \tag{3}$$

Then the spectral regression is defined by

$$\ln\{I(\xi_{y,\lambda})\} = \beta_0 + \beta_1 \ln \left\{ 4 \sin^2 \left(\frac{\xi_\lambda}{2} \right) \right\} + \eta_\lambda, \quad \lambda = 1, \ldots, v \tag{4}$$

where $\xi_\lambda = (2\pi\lambda/T), (\lambda = 0, \ldots, T - 1)$ denotes the harmonic ordinates of the sample, $\eta_\lambda = \ln\{I(\xi_\lambda)/f(\xi_\lambda)\}$ is the normalized periodogram with $f(\cdot)$ defined as the spectrum of the ARMA component in (1). T is the number of observations, and $v = g(T) \ll T$ is the number of harmonic ordinates included in the spectral regression.

Assuming that $\lim_{T \to \infty} g(T) = \infty$, $\lim_{T \to \infty} \{g(T)/T\} = 0$, and $\lim_{T \to \infty} \ln(T)^2/g(T) = 0$, the negative of the OLS estimate of the slope coefficient in (4) provides an estimate of d. The properties of the regression method depend on the asymptotic distribution of the normalized periodogram η_λ, the derivation of which is not straightforward (Robinson (1995b), Hurvich and Beltrao (1993)). Geweke and Porter–Hudak (1983) prove consistency and asymptotic normality for $d < 0$, while Robinson (1990) proves consistency for $d \in (0, 0.5)$. Hassler (1993) proves consistency and asymptotic normality in the case of Gaussian ARMA innovations in (1). The spectral regression estimator is not $T^{1/2}$ consistent and will converge at a slower rate.

To ensure that stationarity and invertibility conditions are met, we apply the spectral regression test to the returns series (yield changes) of the Euroyen deposits. The estimated differencing parameter for the returns series is denoted by d and the hypothesis $d = 0$ can be tested against fractional order alternatives.

3. Data and Empirical Estimates

The data set consists of daily rates for Eurocurrency deposits denominated in Japanese yen (Euroyen) for maturities of 3 and 6 months. These rates represent bid rates at the close of trading in the London market and were obtained from Data Resources, Inc. The total sample spans the period from 01/02/85 to 02/08/94 for a total of 2300 observations. The period from 01/02/85 to 07/29/92 (1912 observations) is used for in-sample estimation with the remainder of the sample (388 observations) being reserved for out-of-sample forecasting.

We proceed as follows. For each deposit rate series, we initially investigate their low frequency properties by subjecting the series to unit-root tests which only allow for integer orders of integration, but differ in how they establish the null hypothesis. Then we estimate the fractional differencing parameter for each series using the spectral regression method.

We test for integer integration orders by means of the Phillips–Perron (PP: Phillips (1987), Phillips and Perron (1988)) and KPSS: Kwiatkowski, Phillips, Schmidt, and Shin (1992) unit-root tests. In the PP test the unit-root null hypothesis is tested against the alternative of trend stationarity. In the KPSS test, however, trend stationarity is the null hypothesis to be tested against the alternative of a unit root. This test serves as a complement to the PP tests. The combined use of the PP and the KPSS tests for a particular series produces the following alternatives:

(i) Rejection by the PP test and failure to reject by the KPSS test provides evidence in favor of wide-sense stationarity; the series is $I(0)$.

(ii) Failure to reject by the PP test and rejection by the KPSS test supports that the series is integrated of order one; the series is $I(1)$[2].

(iii) Failure to reject by both PP and KPSS tests show that the data are not sufficiently informative with respect to the low-frequency properties of the series; and

(iv) Rejection by both PP and KPSS tests suggests that a series is not well represented as either $I(1)$ or $I(0)$ and alternative parametrizations need to be considered.

Table I reports the $Z(\tilde{\alpha})$ and the $Z(t_{\tilde{\alpha}})$ PP test results for both the levels and first differences (returns) of the Euroyen deposit rates. The unit-room null hypothesis is not rejected for the data in levels form but it is decisively rejected for the first-differenced data in favor of a trend-stationary alternative. This evidence therefore strongly suggests that Euroyen deposit rates at 3- and 6-month maturities are $I(1)$ processes with the corresponding returns series being $I(0)$.

Table I. Phillips Perron (PP) unit root test results for the euroyen rates

Series	$Z(t_\alpha)$		$Z(t_\alpha)$	
	$l = 12$	$l = 24$	$l = 12$	$l = 24$
Levels				
3-Month	-1.152	-1.633	-0.503	-0.656
6-Month	-0.907	-1.398	-0.406	-0.572
First Differences				
3-Month	-2138.3^{***}	-2337.0^{***}	-46.13^{***}	-46.31^{***}
6-Month	-2178.8^{***}	-2393.5^{***}	-47.20^{***}	-47.30^{***}

Notes: The sample period for the Euroyen deposit rate series is 01/02/85 to 07/29/92 for a total of 1912 observations. The Phillips–Perron test statistics are $Z(\tilde{\alpha})$ and $Z(t_{\tilde{\alpha}})$, which are obtained from regressing the time series on an intercept. time trend. and its lagged value. See Perron (1987) and Phillips and Perron (1988) for details on the tests. l stands for the order of serial correlation allowed in constructing the test statistics. We used the lag window suggested by Newey and West (1987) to ensure positive semidefiniteness. The critical values for the $Z(\tilde{\alpha})(Z(t_\alpha))$ tests are -29.5 (-3.96), -21.8 (-3.41), and -18.3 (-3.12) at the 1, 5 and 10 percent significance levels, respectively (Fuller (1976)). The superscript *** indicates statistical significance at the 1 percent significance level.

A different conclusion is reached when the KPSS test is applied to the series. As Table II reports, the trend-stationarity null hypothesis is strongly rejected for both 3- and 6-months Euroyen rates in both their levels and returns forms. Therefore, the returns series cannot be characterized as $I(0)$ processes, conflicting with the inference based on the PP tests. The combined evidence based on the PP and KPSS test results indicates that for the Euroyen returns series neither an $I(1)$ nor an $I(0)$ process is a good representation of the data generating process, which suggests that a fractionally differenced process may be an appropriate representation for these series.

Table III presents the spectral regression estimates of the fractional differencing parameter d for the returns series. A choice has to be made with respect to the number of low frequency periodogram ordinates used in the spectral regression. Improper inclusion of medium or high frequency periodogram ordinates will contaminate the estimate of d; at the same time too small a regression sample will lead to imprecise estimates. We report fractional differencing estimates for $v = T^{0.50}, T^{0.55}$, and $T^{0.60}$ to check the sensitivity of our results to the choice of the sample size of the spectral regression. To test the statistical significance of the d estimates, two-sided ($d = 0$ versus $d \neq 0$) as well as one-sided ($d = 0$ versus $d > 0$) tests are performed.

As Table III reports, there is strong, robust evidence that the 3- and 6-month Euroyen returns series exhibit fractional dynamics with long memory features.[3] The fractional differencing parameters are similar in value across the two maturities

Table II. Kwiatkowski–Phillips–Schmidt–Shin (KPSS)
test results for the euroyen rates

Eurocurrency Deposit Rate	η_τ	
	$l = 12$	$l = 24$
Levels		
3-Month	1.781***	0.935***
6-Month	1.719***	0.902***
First Differences		
3-Month	0.351***	0.298***
6-Month	0.377***	0.316***

Notes: The sample period for the Euroyen deposit rate
series is 01/02/85 to 07/29/92 for a total of 1912 obser-
vations. $\eta_\tau = T^{-2} \sum_{t=1}^{T} S_t^2 / s^2(l)$ is the test statis-
tic for the null hypothesis of trend stationarity, where
$S_t = \sum_{i=1}^{t} e_i, t = 1, 2, \ldots, T$ (partial sum process of
the residuals) with $\{e_t\}_1^T$ being the residuals form the
regression of the series on an intercept and a linear time
trend, and $s^2(l)$ is a consistent estimate of the 'long-run
variance'. The estimator used here is of the form

$$s^2(l) = T^{-1} \sum_{t=1}^{T} e_t^2 + 2T^{-1} \sum_{s=1}^{l} w(s, l) \sum_{t=s+1}^{T} e_t e_{t-s}$$

where $w(s, l)$ is an optimal lag window and l is the order
of serial correlation allowed. We used the lag window
suggested by Newey and West (1987) to ensure positive
semidefiniteness of $s^2(l)$. The test is an upper-tail test
and the critical values are 0.216, 0.146, and 0.119 at
the 1, 5, and 10 percent significance levels, respectively
(Kwiatkowski, Phillips, Schmidt, and Shin (1992)). The
superscript *** indicates statistical significance at the 1
percent significance level.

considered for each of the Euroyen returns series. These series are not $I(0)$ but
they are clearly covariance stationary ($0 < d < 0.5$). The implications of the long
memory evidence in the Euroyen returns series can be seen in both the time and
frequency domains. In the time domain, long memory is indicated by the fact that
the returns series eventually exhibit strong positive dependence between distant
observations. A shock to the series persists for a long time span even though it
eventually dissipates. In the frequency domain, long memory is indicated by the
fact that the spectral density becomes unbounded as the frequency approaches zero.

We now address the issue of robustness of the fractional structure in the 3-
and 6-month Euroyen returns series to nonstationarities in the mean and short
term dependencies. Through extensive Monte Carlo simulations, Cheung (1993b)

Table III Estimates of the fractional-differencing parameter d for euroyen returns series

Maturity	$d(0.50)$	$d(0.55)$	$d(0.60)$
3-Month	0.213	0.289	0.206
	$(2.189)^{***}, \ddagger\ddagger$	$(3.468)^{***}, \ddagger\ddagger\ddagger$	$(2.911)^{***}, \ddagger\ddagger\ddagger$
6-Month	0.160	0.268	0.219
	$(1.973)^{**}, \ddagger\ddagger$	$(3.364)^{***}, \ddagger\ddagger\ddagger$	$(3.375)^{***}, \ddagger\ddagger\ddagger$

Notes: The Japanese-yen denominated Eurocurrency deposit rate series are first differences of the original series for the period 01/02/85 to 07/29/ 92 for a total of 1912 observations. $d(0.50)$, $d(0.55)$, and $d(0.60)$ give the d estimates corresponding to the spectral regression of sample size $v - T^{0.50}, v - T^{0.55}$, and $v - T^{0.60}$. t-statistics are given in parentheses. The superscripts ***, **, * indicate statistical significance for the null hypothesis $d = 0$ against the alternative $d \neq 0$ at the 1, 5, and 10 percent levels, respectively. The superscripts $\ddagger\ddagger\ddagger, \ddagger\ddagger, \ddagger$ indicate statistical significance for the null hypothesis $d = 0$ against the one-sided alternative $d > 0$ at the 1, 5, and 10 percent levels, respectively.

showed that the spectral regression test is robust to moderate ARMA components, ARCH effects. and shifts in the variance. However, possible biases of the spectral regression test against the no long memory null hypothesis were discovered. In particular, the spectral regression test was found to be biased toward finding long memory ($d > 0$) in the presence of infrequent shifts in the mean of the process and large AR parameters (0.7 and higher). A similar point has also been observed by Agiakloglou, Newbold, and Wohar (1993). We now investigate the presence of these bias-inducing features of the data in our sample series.

Graphs of the Euroyen returns series do not indicate that the data generating process for the series in question underwent a shift in the mean. Therefore the evidence of long memory for these series should not be a spurious artifact of changes in the mean of the series. To examine the possibility of spurious inference in favor of long term persistence due to strong dependencies in the data, an autoregressive (AR) model is fit to each of the series in question. An AR(1) model is found to adequately describe dependence in the conditional mean of both series. The coefficient values are −0.056 and −0.080 for the 3- and 6-month Euroyen returns series. respectively. These AR parameters are very small in value suggesting the absence of strong short term dependencies. Neither shift in mean nor strong dependence are therefore responsible for finding long memory in the Euroyen returns series.

4. Evaluation of Forecasting Performance

The discovery of fractional orders of integration suggests possibilities for constructing nonlinear econometric models for improved price forecasting performance, especially over longer forecasting horizons. The nonlinear model construction

Table IV. Out of sample forecasting performance of alternative modeling strategies: 3-Month curoyen rate

Forecasting Model	k-Step Ahead Prediction (Number of Point Forecasts)							
	1 (388)	5 (384)	10 (379)	24 (365)	72 (317)	144 (245)	216 (173)	288 (101)
Long Memory								
$d = 0.213$, AR(4)	0.0625	0.1049	0.1230	0.1943	0.3296	0.3491	0.4047	0.4794
	0.0406	0.0721	0.0912	0.1492	0.2756	0.2664	0.3319	0.4462
$d = 0.289$, AR(6)	0.0619	0.1034	0.1241	0.2008	0.3457	0.3666	0.4308	0.4265
	0.0404	0.0718	0.0927	0.1543	0.2879	0.2845	0.3320	0.3688
$d = 0.206$, AR(4)	0.0625	0.1046	0.1227	0.1935	0.3267	0.3413	0.3949	0.4597
	0.0406	0.0720	0.0910	0.1489	0.2736	0.2599	0.3230	0.4272
AR(1)	0.0619	0.1017	0.1214	0.1951	0.4061	0.6282	0.8711	1.2560
	0.0392	0.0678	0.0863	0.1428	0.3269	0.5884	0.8289	1.2464
RW	0.0632	0.1024	0.1220	0.1954	0.4063	0.6287	0.8716	1.2569
	0.0396	0.0682	0.0868	0.1433	0.3273	0.5887	0.8392	1.2471

Notes: The first entry of each cell is the root mean squared error (RMSE), while the second is the mean absolute deviation (MAD). AR(k) stands for an autoregressive model of order k. RW stands for random walk (with drift). The long memory model consists of the fractional differencing parameter d and the order of the AR polynomial. Those RMSEs and MADs obtained from the long memory models which are lower than the ones obtained from the RW model are underlined.

suggested is that of an ARFIMA process, which represents a flexible and parsimonious way to model both the short and long term dynamical properties of the series. Granger and Joyeux (1980) have discussed the forecasting potential of such nonlinear models and Geweke and Porter–Hudak (1983) have confirmed this by showing that ARFIMA models provide more reliable out-of-sample forecasts than do traditional procedures. The possibility of speculative profits due to superior long memory forecasts would cast serious doubt on the basic tenet of market efficiency, which states unpredictability of future returns. In this section we compare the out-of-sample forecasting performance of an ARFIMA model to that of benchmark linear models.

Concerning the construction of the long memory models and forecasts, we proceed as follows. Given the d estimates, we model the short run series dynamics by fitting an AR model to the fractionally differenced series. An AR representation of low order is found to be an adequate description of short term dependence in the data.[4] The AR orders are selected on the basis of Q statistics for serial dependence; the most parsimonious representation is chosen so as to ensure serial independence for at least 24 lags (approximately a one-month period) in the corresponding residual series (the AR order chosen in each case is given in Tables IV and V).

Table V. Out-of-sample forecasting performance of alternative modeling strategies: 6-Month euroyen rate

Forecasting Model	k-Step Ahead Prediction (Number of Point Forecasts)							
	1 (388)	5 (384)	10 (379)	24 (365)	72 (317)	144 (245)	216 (173)	288 (101)
Long Memory								
$d = 0.160$, AR(2)	0.0537	0.0900	0.1171	0.1881	0.3493	0.4388	0.4695	0.5754
	0.0365	0.0650	0.0873	0.1487	0.2895	0.3112	0.4131	0.5167
$d = 0.268$, AR(4)	0.0537	0.0918	0.1207	0.1989	0.3655	0.4561	0.4955	0.4883
	0.0367	0.0665	0.0905	0.1546	0.2965	0.3643	0.3783	0.4258
$d = 0.219$, AR(3)	0.0537	0.0910	0.1190	0.1936	0.3539	0.4340	0.4570	0.4674
	0.0367	0.0658	0.0890	0.1516	0.2903	0.3337	0.3735	0.4252
AR(1)	0.0532	0.0879	0.1174	0.1952	0.4276	0.6603	0.8704	1.2458
	0.0355	0.0626	0.0889	0.1560	0.3420	0.5774	0.8058	1.2277
RW	0.0546	0.0885	0.1178	0.1950	0.4258	0.6564	0.8640	1.2368
	0.0358	0.0632	0.0892	0.1560	0.3408	0.5726	0.7988	1.2185

See notes in Table IV for explanation.

Then we forecast the Euroyen deposit rates by casting the fitted fractional-AR model in infinite autoregressive form, truncating the infinite autoregression at the beginning of the sample, and applying Wold's chain rule.

The long memory forecasts are compared to those obtained by estimating two standard linear models: an autoregressive model (AR) and a random-walk-with-drift model (RW). The AR model for both Euroyen returns series is of order one as described earlier. The last 388 observations from each series are reserved for forecasting purposes. Therefore, the sample period 01/02/85 to 07/29/92 is the training set and the sample period 07/30/92 to 02/08/94 is the test set. The out-of-sample forecasting horizons considered are 1-, 5-, 10-, 24-, 72-, 144-, 216-, and 288-steps ahead corresponding approximately to 1-day, 1-week, 2-week, 1-month, 3-month, 6-month, and 1-year forecasting horizons. These forecasts are truly ex ante, or dynamic, as they are generated recursively conditioning only on information available at the time the forecast is being made. The criteria for forecasting performance are the root mean square error (RMSE) and mean absolute deviation (MAD).

In generating the out of sample forecasts, the model parameters are not reestimated each time; instead the in-sample estimates are being used. A question arises as to whether the fractional differencing parameter remains stable over the out-of-sample period. To address this issue, we reestimate the fractional differencing parameter over the initial sample of 1912 observations and then on samples generated by adding 25 observations until the total sample is exhausted. Figures 1 and 2 graph the d estimates for the various subsamples. These estimates do not
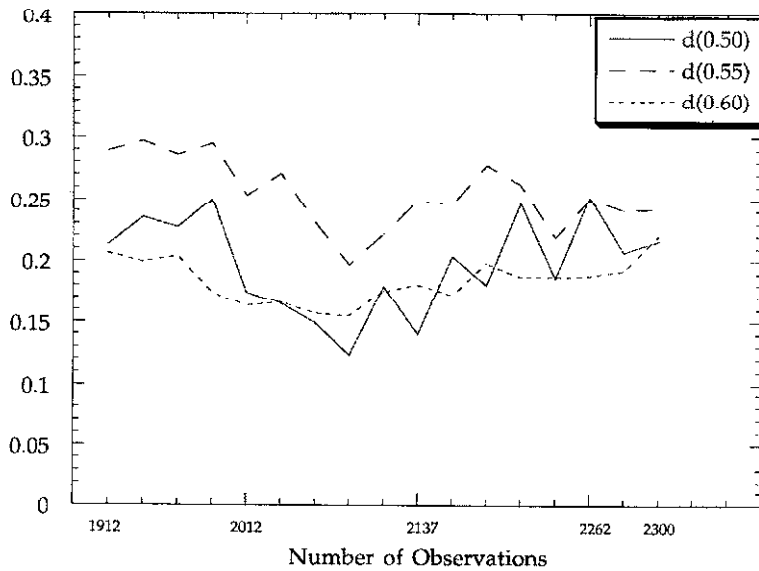
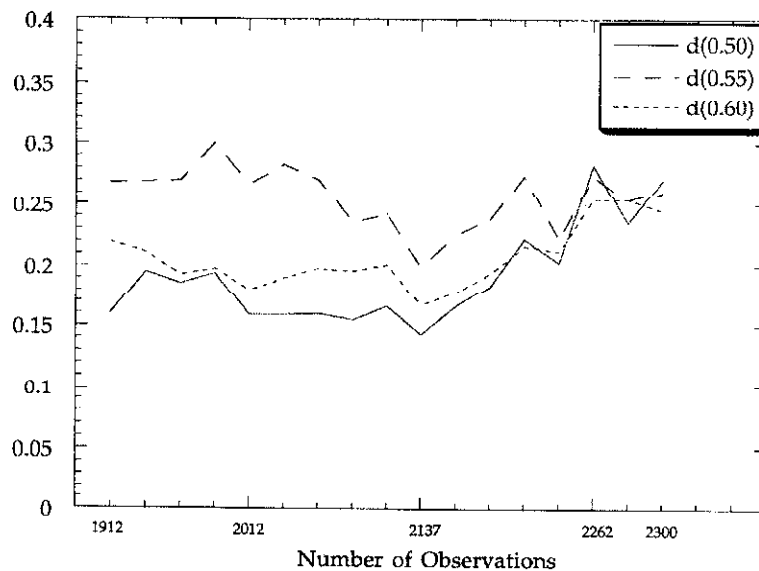*Figure 1.* Fractional differencing Estimates (d) Over Subsamples for the 3-Month Euroyen Returns Series.

Figure 2. Fractional differencing Estimates (d) Over Subsamples for the 6-Month Euroyen Returns Series.

fluctuate noticeably suggesting stability. For each series, there is evidence that the *d* estimates obtained from the various sizes of the spectral regression converge as the sample size increases. Therefore, basing the long memory forecasts on the

fractional differencing parameters estimated from the initial sample is not expected to negatively affect the out-of-sample forecasting performance.

Table IV presents the out-of-sample forecasting performance of the competing models for the 3-month Euroyen returns series. Comparing the forecasting performance between the linear models first, the AR and RW forecasts are very similar with the AR fits having a slight edge. Also, the predictive performance of the long memory forecasts is very similar to those generated by the linear models for short horizons (less than 1 month, or 24 days). However, for longer horizons the long memory forecasts result in substantial improvements in forecasting accuracy compared to those of the AR and RW forecasts. These significant improvements apply to both RMSE and MAD criteria and hold true across the various estimates of d. As an example, for the 288-step ahead (roughly one year) forecasting horizon, the long memory model with $d = 0.289$ results in reductions of 66.06 percent and 70.42 percent over the RW model in terms of RMSE and MAD, respectively. The longer the forecasting horizon, the greater the improvements in forecasting accuracy attained by the long memory models.

A similar picture is obtained for the 6-month Euroyen series as reported in Table V. The AR and RW fits have a similar forecasting performance with the long memory fits dominating their linear counterparts on the basis of both RMSE and MAD forecasting criteria for horizons longer than 10 steps (two weeks) ahead. The percentage reductions in the forecasting criteria attained by the long memory fits are dramatic and increase monotonically with the length of the forecasting horizon. For example, the long memory model with $d = 0.219$ reduces the RMSE and MAD achieved by the RW model by 62.20 and 65.10 percent, respectively.

The forecasting performance of the long memory model is consistent with theory. As the effect of the short memory (AR) parameters dominates over short horizons, the forecasting performance of the long memory and linear models is similar in the short run. In the long run, however, the dynamic effects of the short memory parameters are dominated by the fractional differencing parameter d, which captures the high-order correlation structure of the series, thus resulting in superior long memory forecasts. This evidence accentuates the usefulness of long memory models as forecast generating mechanisms for the Euroyen returns series, and casts doubt on the hypothesis of market efficiency for longer horizons.

5. Conclusions

Using the spectral regression method, we found significant evidence of long memory in the 3- and 6-month returns series (yield changes) on Eurocurrency deposits denominated in Japanese yen. These series appear to be characterized by irregular cyclic fluctuations with long term persistence. They eventually exhibit positive dependence between distant observations. The out-of-sample memory forecasts resulted in dramatic improvements in forecasting accuracy over longer horizons as compared to those obtained from benchmark linear models. This is evidence

against the martingale model, which states that, conditioning on historical returns, futures returns are unpredictable. The weak form of market efficiency hypothesis is therefore violated for the Euroyen returns series. Future research should investigate the sources of long memory in the Euroyen returns series. The analysis should also be extended to rates on Eurocurrency deposits denominated in other major currencies. We are currently investigating these issues.

Notes

[1] Other authors refer to a process as a long memory process if $d \neq 0$.

[2] In interpreting rejection of the $I(0)$ null hypothesis by the KPSS tests, it must be borne in mind that the KPSS tests are consistent against stationary long memory alternatives, that is, they can also be used to distinguish between short memory and stationary long memory processes (Lee and Schmidt (1996)). To distinguish reliably, a sample size in excess of 500 or 1000 observations is required, which is the case in this study.

[3] Estimation of the long memory parameter via smoothed periodogram as well as trimmed periodogram versions of the spectral regression method resulted in fractional exponent estimates broadly consistent with those reported here (these results are available upon request). Our long memory estimates are not altered materially when Robinson's (1992, 1995a) semiparametric method is used. For $v = T^{0.50}, T^{0.55}$, and $T^{0.60}$, respectively, these estimates (standard errors) are 0.180 (0.076), 0.200 (0.063), and 0.110 (0.052) for the 3-month Euroyen returns series, and 0.180 (0.076), 0.180 (0.063), and 0.140 (0.052) for the 6-month Euroyen returns series.

[4] An extension of our approach could also consider moving average (MA) orders in modeling the short run dynamical behavior of the series. However, given the success we had with low-order AR representations, adding a MA component would add complexity to the forecasting experiment while the forecasting improvements are doubtful especially over longer horizons. An AR model with sufficient lag structure can very well approximate the MA components of the series.

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