Time Series Analysis of Settlement Prices for Individual Currency Futures in Singapore

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Abstract This paper investigates the efficiency of the currency futures market in the Singapore International Monetary Exchange. The weak sense of market efficiency is tested, with the random walk model being used as the benchmark for comparing univariate models fitted to the three major currency futures, namely Deutsche Mark, Japanese Yen and British Pound. In weak form tests of the efficient market hypothesis (EMH), security prices reflect fully all available information based on past values of price data. This means that the weak form tests whether all information contained in the historical prices is fully reflected in current prices. A restrictive version of the weak form of the EMH is the random walk model, which assumes that successive returns are independent and identically distributed over time. Thus, evidence supporting the random walk model is evidence supporting the weak form efficiency of the EMH. Univariate modelling of the data involves fitting several moving average (MA), autoregressive (AR), and autoregressive moving average (ARMA) specifications. Using the mean absolute error (MAE), the performances of the estimated models are compared against the random walk model. The three currency futures models consistently outperform the random walk model on the strength of the MAE, which challenges the EMH in the currency futures market in Singapore.

1. INTRODUCTION

Trading in currency futures is relatively new to the capital market in Singapore, with futures contracts on Deutsche Mark and Japanese Yen launched in Autumn 1984. In July 1986, the Singapore International Monetary Exchange (SIMEX) introduced another futures contract, namely the British Pound. Inherent in new and developing markets is the possibility for market inefficiency. In light of this, a time series analysis of the three currency futures traded on SIMEX was conducted. The objective of the paper, therefore, is to analyze the results obtained and their implications for the efficiency of the currency futures market in Singapore.

In Section 2, the processes involved in preparing the data for analysis will be discussed. A graphical analysis of each currency futures series is examined in Section 3, with tests of stationarity conducted in Section 4. Univariate models for each of the series are identified in Section 5, and the forecasting ability of these models is compared with the random walk model in Section 6. Section 7 outlines two main limits to the study. Concluding remarks are given in Section 8.

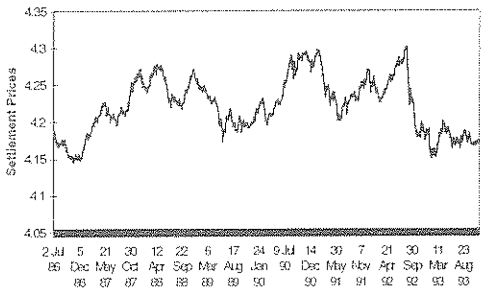
2. DATA COLLECTION

Data on the these currency futures traded in SIMEX, namely the British Pound (BP), the Deutsche Mark (DM) and the Japanese Yen (JY), were obtained from SIMEX. Daily data were obtained for the March, June, September and December contracts on these three currencies between July 1986 and December 1993. The settlement price for the nearest contract was used as the futures price series, with some adjustment for the crossover when the contract is near to maturity. For each contract, there was a noticeable fall in the volume when the contract approaches maturity. At the same time, there is a surge in the volume recorded for the next contract. This point of change will be referred to as the crossover point. At this point, which occurs about 10 days before maturity, the settlement price of the next contract is taken. Following this process, a total of 1877 observations for each currency futures were obtained. The first difference of the logarithmic futures price provides a measure of their daily return. These calculated rates of return need, however, to be adjusted at the appropriate crossover point, when the difference was taken over the same contract. Thus, the price series of the futures contract, as well as the volume series, are extracted from the SIMEX database.

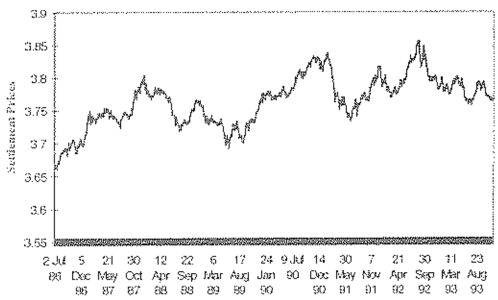
3. GRAPHICAL ANALYSIS

Time plots for the three series, BP, DM, JY, and their first differences, were constructed to observe the movement of the data over the period July

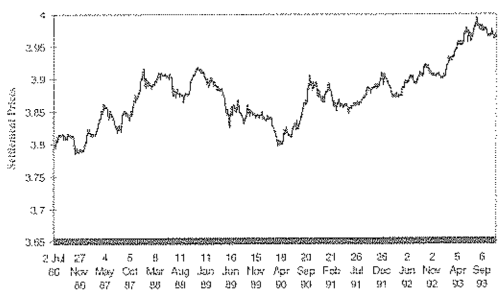
1986 to December 1993. Since the settlement prices of the currency futures are in logarithms, Graphs 1 to 3 represent the time plots for the logarithms of the settlement prices.



Graph 1: BP futures settlement prices

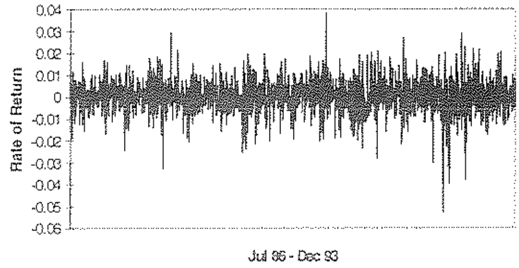


Graph 2: DM futures settlement prices

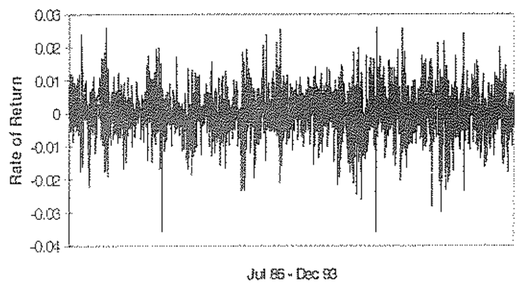


Graph 3: JY futures settlement prices

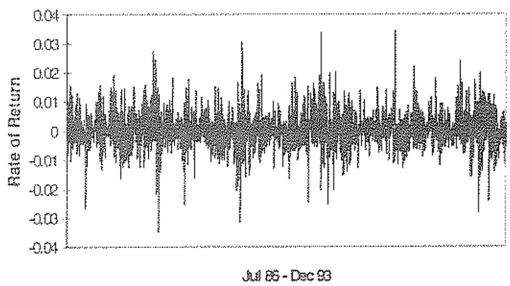
JY settlement prices have the highest coefficient of variation of 0.01159, compared with 0.00089 for BP and 0.00098 for DM. From these graphs, the settlement prices appear to exhibit non-stationarity in all three settlement prices. BP futures settlement prices appear to follow a gradual upward trend, but has taken a noticeable dip from around July 92 to October 92. Following this period, the BP futures settlement prices seemed to fluctuate within a smaller band, up to the last observation noted in December 1993. Similarly, DM and JY settlement prices also appear to follow an upward trend. Graphs 4 to 6 plot the first differences of the logarithms of settlement prices (or rates of return) over time.



Graph 4: BP futures rates of return



Graph 5: DM futures rates of return



Graph 6: JY futures rates of return

Of the three graphs presented, BP rates of return have the highest coefficient of variation of 51.68, compared with 49.28 for DM and 40.32 for JY. Rates of return for all three currency futures appear to be stationary, tending to fluctuate around a zero mean. BP figures show greater variation between the period July 92 to October 92, registering negative rates of return that correspond to a dip in the settlement prices during the same period.

4. TESTS FOR STATIONARITY

Six sets of variables, comprising data on the three settlement prices, and their respective first differences, are tested for unit roots using the ADF test without a time trend. The time trend is not included since an examination of the ADF t-values, with and without a trend, are not substantially different. Thus, the ADF regression (see Campbell and Perron (1991)) is as follows:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + u_t$$

where ΔY_t is the first difference of the variable, α is the constant of the regression, ΔY_{t-i} is the first difference of lagged values, δ_i is the coefficient of the lagged first difference, and u_t is the error term of the regression. The pth order ADF statistic, denoted ADF(p), is given by the t-ratio of the OLS estimate of β in the regression above. Since the asymptotic distribution of the t-ratio is non-standard, the null hypothesis of a unit root is tested using simulated critical values given in MacKinnon (1991). To determine p, an initial lag length of six is used in the ADF regression, and the sixth lag is tested for significance using the asymptotic t-ratio. The sixth lag is insignificant for all six variables, and the lag length is successively reduced until a significant lag was obtained. All lag lengths are found to have insignificant t-values, and the ADF test amounts to a Dickey-Fuller (DF) test for unit roots. Using the SAS (1986) software package, values of the t-statistics of the lagged variables used to select p in six separate regressions are given in Table 1.

Lag	BP		DM		JY	
	Sett Price	Rates	Sett Price	Rates	Sett Price	Rates
1	0.27	-0.89	-1.40	-0.22	-0.07	-0.80
2	1.11	0.73	0.09	1.27	0.58	-0.52
3	-0.46	-1.70	-0.80	-1.55	0.65	1.67
4	1.37	-1.34	1.65	-0.06	-1.50	-0.07
5	1.41	1.06	-0.09	0.61	0.14	0.01
6	-0.26	0.93	-0.57	0.18	-0.29	-0.50

Note: Sett Price refers to the Settlement Price, while Rates refer to the Rates of Return

Table 1: Values of t-statistics of lag lengths

Results of the ADF test are presented in Table 2. DF statistics obtained from the test are compared with critical values at the 5% significance level, with no trend included. DF statistics for the three settlement prices are greater than the critical value of -2.8621, with the most negative DF statistic of -2.786 observed for DM settlement prices. The null hypothesis of a unit root in the settlement prices cannot, therefore, be rejected, which suggests that settlement prices for all three currency futures are non-stationary.

	DF statistic	
Series	Rates of Return	Settlement Prices
BP	-43.463	-1.755
DM	-44.624	-2.786
JY	-43.005	-1.839

Table 2: Result of the DF test for individual series

First differences of the logarithms of the settlement prices, namely, the rates of return, however, yield large negative DF statistics that reject the null hypothesis. The most negative DF statistic of -44.624 is obtained for DM. This suggests that all three futures rates of return are stationary, or integrated of order zero (I(0)).

Individual DF tests conducted for the logarithms of the settlement prices lead to the conclusion that these variables do not follow an I(0) process. The first differences of the logarithms of the settlement prices are, however, I(0), implying that all three settlement prices are I(1) variables.

5. IDENTIFICATION AND SELECTION OF THE CURRENCY FUTURES

Several MA, AR and ARMA models are estimated for the three currency futures to establish whether the data could be effectively described by any of these models. The identification and selection of models for each currency futures series is discussed below.

5.1 BP Currency Futures

The autocorrelation function (ACF) of the BP futures rates of return data looks like a white noise process. Values for the Box and Pierce (1970) Q-statistics obtained from the autocorrelation check for white noise, at lags 6 and 12, are 7.1 and 17.3, respectively. When compared with the chi-squared critical values of 12.59 (with 6 degrees of freedom (df)) and 21.03 (with 12 df), these values mean that the null hypothesis of a white noise process cannot be rejected.

With first differences, however, it is common to find indications of a moving average (MA) term. From the ACF plot, nonzero spikes at lags 4, 5, 9, 10, and 15 are observed, whereas the partial autocorrelation function (PACF) has spikes at lags 4, 5, 9, 10, 15, 19, 22 and

23. Various models are fitted to determine whether the data could be described by an MA process. The Q-statistics of the various models are compared with their chi-squared critical values with the appropriate df. These results indicate that, for all four MA models fitted, the hypothesis of a white noise process is not rejected. The t-statistics of the estimated parameters of these MA models are not significant at the 10% level of significance, which suggests that the BP futures rates of return data are not appropriately described by an MA model.

When the data are fitted to several AR models, results similar to the MA fitting were obtained. All the Q-statistics of the four different AR models, when compared with their respective chi-squared critical values, indicate that the null hypothesis of a white noise process is not rejected. All the t-statistics obtained from these AR models are not significant, with the exception of the t-statistic of the AR lag 4 of the fitted AR(4) model, with a value of 1.72, which is significant at 10%. It is, therefore, unlikely that the data are described by an AR process.

Several ARMA models fitted to the data produce Q-statistics that were not significant, with the exception of the ARMA(3,2) and ARMA(4,2) models. These two ARMA models are consequently rejected as suitable models. The remaining ARMA models registered low values for the t-statistics of the estimated parameters, except for ARMA(2,3) and ARMA(2,4). These two fitted models yield significant t-statistics. Using the Akaike Information Criterion (AIC), the ARMA(2,4) model is selected, namely

$$\underset{[1.83]}{\underset{(0.06)}{(1-0.76L}}+\underset{[13.96]}{\underset{(0.06)}{0.87L^2)}}\,\Delta\log BP_t=\underset{[11.33]}{\underset{(0.07)}{(1-0.77L}}+\underset{[-13.26]}{\underset{(0.07)}{0.9L^2}}\ldots$$

$$\ldots-\underset{[0.53]}{\underset{(0.03)}{0.02L^3}}+\underset{[2.53]}{\underset{(0.03)}{0.06L^4)}}\varepsilon_t$$

where ε_t is independently and identically distributed with zero mean and variance σ_ε^2, L is the lag operator and the numbers in square brackets represent the t-statistics.

5.2 Deutsche Mark Futures

The ACF of the DM futures rates of return data, as with the BP futures, also looks like a white noise process. Since the Q-statistics at lags 6 and 12 are 6.91 and 21.79, compared with a chi-squared value at lag 6 (with 6 df) equal to 12.59, the hypothesis of a white noise process is not rejected. However, at lag 12 (with 12 df), the Q-statistic is 21.03, so this null hypothesis is rejected. Thus, the Deutsche Mark Futures rates of return do not exhibit a white noise process.

From the ACF plot, nonzero spikes were observed at lags 1, 3, 4, 9, 10, 15 and 22, and the PACF has somewhat similar spikes at lags 1, 3, 4, 9, 10, 15, 22 and 23. Several MA models fitted to the Deutsche Mark futures did not result in any suitable model. Although the Q-statistic of all four fitted MA models did not reject the null hypothesis, the t-statistics of the estimated parameters were not significant in all cases. Only one significant t-statistic was obtained at lag 4 of the MA (4) model.

AR models fitted to the data generated Q-statistics that were not significant. Hence, the null hypothesis is not rejected. With t-statistics that were not significant for the estimates of each of the models, the data do not follow an AR process. Three of the ARMA models have Q-statistics that rejected the null hypothesis and, hence, are not suitable models. These models are ARMA(2,4), ARMA(3,3) and ARMA(5,1). Of the remaining ARMA models fitted to the data, only four of these models displayed t-statistics that were significant: namely ARMA(1,1), ARMA(2,3), ARMA(3,2) and ARMA(4,2). Using AIC, ARMA(2,3) was selected, namely

$$\underset{[-28.13]}{\underset{(0.05)}{(1+1.37L}}+\underset{[-18.78]}{\underset{(0.05)}{0.91L^2)}}\,\Delta\log DM_t=\underset{[-25.27]}{\underset{(0.05)}{(1+1.33L}}\ldots$$

$$\ldots+\underset{[-15.27]}{\underset{(0.06)}{0.88L^2}}+\underset{[1.67]}{\underset{(0.02)}{0.04L^3)}}\varepsilon_t$$

5.3 Japanese Yen Futures

As with the ACF plots for both the BP and DM futures, the JY futures also look like a white noise process. With Q-statistics at lags 6 and 12 of 3.68 and 14.33, compared with the chi-squared values at lag 6 of 12.59 (with 6 df) and 21.03 (with 12 df) at lag 12, respectively, the hypothesis of a white noise process is not rejected.

In observing the ACF plot, nonzero spikes at lags 4, 9, 10, 11, 13, 15, 22 and 23 are noted, and the PACF has somewhat similar spikes at lags 4, 9, 10, 11, 13, 15, 20, 22 and 24. For the data fitted to various MA models, all the Q-statistics for all these models are insignificant and, hence, the null hypothesis is not rejected. Furthermore, the t-statistics for all these MA models fitted to the JY Futures are not significant, with an exception for the estimate of the lag 4 parameter of the MA(4) model.

When AR models are fitted to the data, the Q-statistics for all the models are not significant. The t-statistics are not significant, with the exception of the lag 4 parameter of the AR(4) model, which is significant at the 10% level. All ARMA models fitted to the data result in Q-statistics that are not significant and, hence, the null hypothesis is not rejected. However, only three models have significant t-statistics for the estimates of the parameters, namely ARMA(1,1), ARMA(2,2) and ARMA(3,3). Applying the principle of parsimony, that is, the model used should contain the smallest number of parameters that will adequately represent the data, the ARMA(1,1) model is selected, namely

$$\underset{\substack{(0.10)\\ [9.12]}}{(1 - 0.95L)}\, \Delta \log JY_t = \underset{\substack{(0.10)\\ [9.93]}}{(1 - 0.94L)}\varepsilon_t$$

6. MODEL PERFORMANCE

Based on the models identified for each of the three currency futures series, namely BP, DM, and JY, a one-step ahead forecast is conducted. Each data series has a total of 1865 values on the rates of return data. All parameters of each model are estimated using observations 1 to 900, and then recursively re-estimated every 60 periods. At each time period, subsequent to period 900, one-step ahead forecasts are constructed in real time, using Wold's chain rule of forecasting, treating parameters as fixed at their estimated values. The forecasts of ARMA(2,4) for BP futures, ARMA(2,3) for DM futures, and ARMA(1,1) for JY futures, are then compared to the random walk model. These forecasts are evaluated in terms of their mean absolute error (MAE).

Table 3 indicates that the models for each of the three currency futures series consistently outperform the random walk model on the strength of the MAE. This suggests that the various models identified for each of the three currency futures generate forecasts which are consistently superior to the forecasting ability of a random walk model on the strength of its MAE.

START	BP		DM		YEN	
POINT	MODEL	RW	MODEL	RW	MODEL	RW
900	0.0005	0.0007	0.0004	0.0006	0.0004	0.0006
960	0.0004	0.0006	0.0004	0.0006	0.0005	0.0007
1020	0.0081	0.001	0.0006	0.0008	0.0006	0.0008
1080	0.0005	0.0007	0.0006	0.0008	0.0007	0.0011
1140	0.0007	0.001	0.0007	0.0011	0.0006	0.0009
1200	0.0007	0.001	0.0007	0.0011	0.0004	0.0006
1260	0.0006	0.0009	0.0006	0.001	0.0003	0.0004
1320	0.0005	0.0007	0.0006	0.0008	0.0004	0.0005
1380	0.0007	0.0009	0.0007	0.001	0.0005	0.0007
1440	0.0005	0.0008	0.0005	0.0008	0.0004	0.0007
1500	0.0007	0.001	0.0007	0.0011	0.0003	0.0004
1560	0.0009	0.0014	0.0008	0.0011	0.0004	0.0006
1620	0.0008	0.0012	0.0006	0.0009	0.0004	0.0005
1680	0.0006	0.0008	0.0005	0.0008	0.0005	0.0006
1740	0.0006	0.0009	0.0005	0.0071	0.0007	0.001
1800	0.0005	0.0008	0.0006	0.001	0.0004	0.0006

Note: Model refers to the MAE result from the estimated univariate model of each currency futures, while RW refers to the result from the random walk model.

Table 3: Comparison of MAE results from the univariate and random walk model.

7. LIMITS TO THE ANALYSIS

The paper should be viewed in light of two main limits to the results obtained: (i) limits associated with using logarithms to transform the data; and (ii) the inadequacies of the Box-Pierce statistic used in identification tests of the univariate models.

First, a problem with using data in logarithms is that the ADF test is sensitive to non-linear transformations. Essentially, when data are transformed to their logarithmic equivalents, the ADF test of stationarity may be affected. For example, data found to be non-stationary in levels may be found to be stationary in logarithms. Non-linear transformations are, therefore, an important issue that has been strangely neglected in testing for unit roots (see Franses and McAleer (1995)).

Second, identification of the univariate models of the currency futures data requires determination of the parameters p and q in the ARMA(p,q) process. The AIC was used to decide among various models which had satisfied several specification tests. When the order of the process had been decided, regression diagnostics were applied to examine possible inadequacies in the estimated model. The test applied was the modification of the Box and Pierce (1970) Q-statistic given in Ljung and Box (1978). The Q-statistic tests the hypothesis that the residuals of the estimated model are white noise, and is compared with critical values from a chi-squared distribution. If the model is correctly estimated, the residuals should be white noise. Hall and McAleer (1989) demonstrated that, when the errors were normally distributed, the Box-Pierce and Ljung-Box tests were highly unreliable in small samples for testing the adequacy of fitted MA and AR models. In Monte Carlo experiments, the tests were frequently dominated by other tests, suggesting little in favour of using the Q-statistic and its modification for practical purposes. Bearing in mind these limits, the tests are useful insofar as they can be calculated straightforwardly and are widely used.

8. CONCLUSION

All models fitted to the currency futures data are ARMA models. As all settlement prices are in logarithms, their first differences represent rates of return. The MAE calculated for each of the estimated models provide overwhelming support for the time series models as being superior to that of the random walk model. This result indicates the importance of univariate modelling to forecasting future rates of return for each currency series. According to the results above, these models generate forecasts of rates of return which can be computed to yield values of futures settlement prices. Univariate time series modelling of the rates of return, therefore, challenges the efficient market hypothesis. The results must, however, be viewed in light of the limits of applying logarithmic transformations and the inadequacies of the Box-Pierce and Ljung-Box statistics.

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