Econometric Modelling of Long Run Relationships in the Singapore Currency Futures Market

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Abstract The paper investigates the existence of long run relationships among settlement prices of the three major currency futures, namely Duetsche Mark, Japanese Yen and British Pound, in the currency futures market of the Singapore International Monetary Exchange. Tests of cointegration and vector autoregressive relationships among the variables are conducted. The stationarity property of each series is tested using the augmented Dickey-Fuller test, from which it is found that each of the series is non-stationary. A cointegrating relationship among settlement prices is examined for the underlying long run economic relationships. Cointegration tests and vector autoregressive models of the rates of return were unable to establish any long run relationships among the variables. Thus, there is no empirical evidence, in general, indicating that long run relationships exist among the settlement prices for individual currency futures in Singapore.

1. INTRODUCTION

Recent studies of the multivariate behaviour of financial data have produced conflicting empirical evidence regarding the efficiency of the foreign exchange (Forex) markets. Much research in this area has applied cointegration theory to explain the existence of long run relationships apparent among several currencies (Alexander and Johnson (1994), Alexander and Johnson (1992), MacDonald and Taylor (1989), and Coleman (1990)). Other related studies estimate Vector Autoregressive (VAR) models (Diebold et al. (1994)).

Interest is, however, developing in another area of the financial arena: namely, in the currency futures markets. In Singapore, this market is relatively new, having being in existence only since 1984, with little known research being developed in this area. This aim of this paper is to investigate the existence of long run relationships among the settlement prices of three major currency futures in the currency futures market of the Singapore International Monetary Exchange (SIMEX).

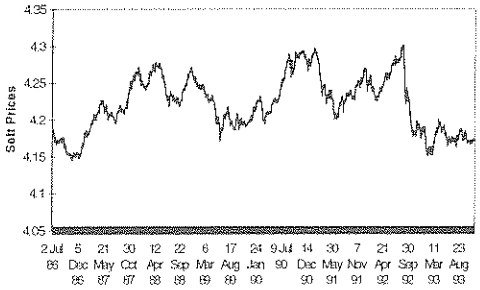
In Section 2, the processes involved in preparing the data for analysis will be highlighted. Before a multivariate analysis can be conducted for the three currency futures series, the stationarity property of an individual series is examined. Section 3 briefly discusses the graphical analysis carried out in Sequeira (1995) for each individual futures prices and their first differences. The stationarity properties of the series are also examined. A theoretical framework of cointegration and VAR models is outlined in Section 4. Section 5 presents the empirical results, with the main findings of the paper discussed in Section 6. The limits to the study are outlined in Section 7, and concluding remarks are given in Section 8.

2. DATA

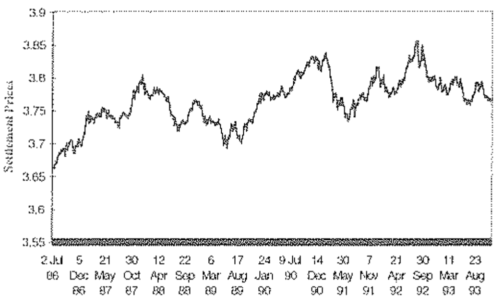
Daily data for the March, June, September and December contracts on British Pound (BP), Deutsche Mark (DM) and Japanese Yen (JY) futures, between July 1986 and December 1993, were obtained from SIMEX. The futures prices series were obtained by using the settlement price for the nearest contract, with 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, a surge in the volume is observed for the next contract. This point of change will be referred to as the crossover point, at which time the settlement price of the next contract is taken. A total of 1877 observations for each currency futures were obtained following this procedure. Rates of return on each futures series are also obtained by taking the first differences of the logarithmic futures prices. These calculated rates of return need, however, to be adjusted at the appropriate crossover point, when the difference was taken over the same contract.

3. GRAPHICAL ANALYSIS AND STATIONARITY

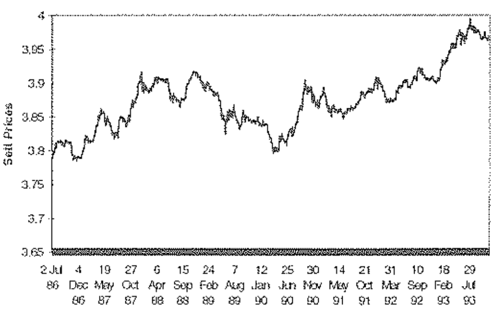
The time plots of the three currency futures series, the BP, DM, and JY, and their first differences given in Graphs 1 to 6, have been reproduced from a paper by Sequeira (1995). As can be seen in the graphs below, the logarithms of the settlement prices of the three currency futures series appear to be trending upwards over time, and appear to exhibit nonstationarity. Their first differences, however, are seen to exhibit stationary behaviour moving around a zero rate of return.



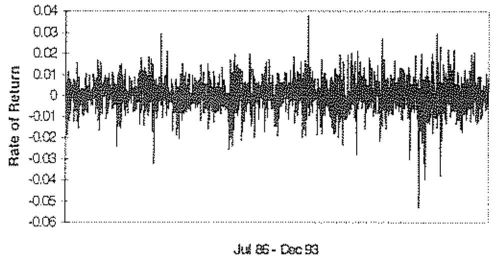
Graph 1: Logarithm of BP futures settlement prices



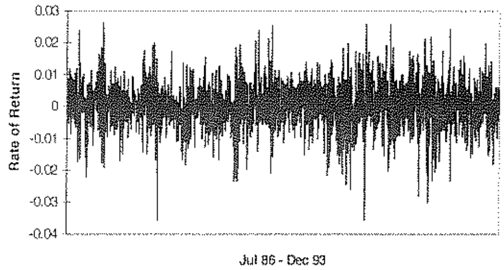
Graph 2: Logarithm of DM futures settlement prices



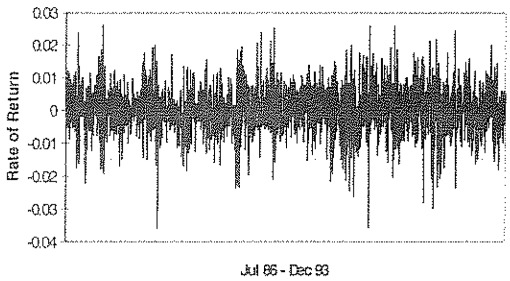
Graph 3: Logarithm of JY futures settlement prices



Graph 4: BP futures rates of return



Graph 5: DM futures rates of return



Graph 6: JY futures rates of return

Sequeira (1995) conducted tests for stationarity using the ADF test for the six sets of variables comprising the three settlement prices and their respective first differences. The null hypothesis of a unit root in the settlement prices was not rejected, suggesting that the logarithms of the settlement prices for all three currency futures are non-stationary. First differences of the logarithms of the settlement prices, namely, the rates of return, however, yielded large ADF statistics that rejected the null hypothesis. Since individual ADF tests on the settlement prices are I(1), and ADF tests on their first differences are I(0), all three settlement prices are I(1) variables.

4. THEORETICAL FRAMEWORK

4.1 Cointegration

When two or more series move closely together in the long run, even though the individual series themselves are stochastically trended, the difference between them will be constant. These series are then regarded as having a long-run equilibrium relationship, that is, the series are said to be cointegrated.

The components of the vector X_t are said to be cointegrated of order (d,b) [denoted CI(d,b)] if:

(i) all components of X_t are I(d), and

(ii) there exists a vector α ($\neq 0$) such that $Z_t = \alpha' X_t \sim I(d-b)$, b>0.

If a set of I(d) variables yields a linear combination that has a lower order of integration, then the vector α is called the cointegrating vector.

Following the Granger representation theorem (Engle and Granger (1987)), if a set of variables is cointegrated of order 1, there exists a valid error-correction representation of the data. If X_t is an n x1 vector such that X_t is cointegrated of order 1, and α is the cointegrating vector, the general error-correction representation is as follows:

$$\Phi(L)(1-L)X_t = -\alpha' X_{t-1} + \Theta(L)\varepsilon_t$$

where both $\Phi(L)$ and $\Theta(L)$ are finite-order polynomials, L is the lag operator, and at least one element in X_t is nonzero. Since the equation given above is a statistical model containing only stationary variables, OLS regression can be applied.

Engle and Granger (1987) demonstrated that if OLS is used to estimate the cointegrating vector, then the other parameters of the error-correction model can be consistently estimated by imposing first-stage estimates of the cointegrating vector in a second-stage regression. This was done simply be including the residuals from the first regression in a general error-correction model. The procedure is referred to as the two-step Engle-Granger estimation procedure. Engle and Granger also demonstrated that the OLS standard errors obtained at the second stage were consistent estimates of the true standard errors. It should be noted that the OLS estimates of cointegrating vectors are superconsistent. If $\hat{\beta}$ is the OLS estimator in a regression model which satisfies the classical assumptions, then $\hat{\beta}$ converges in probability to the true parameter β at the rate $\sqrt{T}$, denoted $O(T^{1/2})$. Stock (1987) demonstrated that, if a set of variables is cointegrated of order (1,1) with cointegrating vector α, and if $\hat{\alpha}$ is the OLS estimator of α, then $\hat{\alpha}$ converges in probability to α at rate T.

If a set of variables is cointegrated of order 1, CI(1,1), then the residuals from the cointegrating regression should be I(0). Cointegration can be tested by subjecting the cointegrating residuals to the DF and ADF tests. There is, however, an additional complication in testing the cointegrating residuals for non-stationarity using the DF and ADF tests, which does not arise when applying the tests to single economic time series. This is because the OLS estimator chooses residuals in the cointegrating regression to have as small a sample variance as possible. Thus, even if the variables are not cointegrated, the OLS estimator will make the residuals look as stationary as possible. Hence, if the DF and ADF tests are used for the residuals, the rejection of the null hypothesis may occur more frequently than the normal significance level would suggest. To correct this bias, the critical values have to be raised slightly. Engle and Yoo (1987) have tabulated critical values for tests of this kind generated by Monte Carlo methods.

4.2 Vector Autoregressive Models

A vector autoregressive model is the unconstrained reduced form of a dynamic simultaneous equation model. The simple VAR model expresses a vector of endogenous variables as linear functions of their own lagged values.

In principle, identification of VAR models is similar to the identification of univariate time series models (Wei (1990)). For a given observed VAR series $\mathbf{z}_1, \mathbf{z}_2, ..., \mathbf{z}_n$, its underlying model is identified from the pattern of its sample correlation and partial correlation matrices after suitable transformations are applied to reduce a non-stationary series to a stationary series.

Estimation of a VAR model often takes multiple stages. Initially, every element of a parameter matrix is estimated. Based on the initial unrestricted model, the restricted model might be considered by retaining only the statistically significant coefficients, with insignificant coefficients being set to zero.

When the parameters have been estimated, the adequacy of the fitted model is evaluated through a careful diagnostic analysis of the residuals. For an adequate model, the residuals should be white noise. Hence, the correlation matrices of the residuals should be insignificant and have no obvious pattern.

5. EMPIRICAL RESULTS

5.1 Cointegration Analysis

Since all three settlement prices are I(1) variables, a linear combination of these variables would be I(0) if they are cointegrated. A cointegrating relationship of one settlement price, normalized as the dependent variable, was regressed against one or two other settlement prices to test any underlying economic relationship among these variables. Nine regression models were estimated, using the SAS (1986) software package, with the normalization on the dependent variable in the particular regression. ADF tests for unit roots, without a time trend, were applied on the residuals of all nine regressions. The time trend is not included since an examination of the ADF t-statistics, with and without a trend, are not substantially different. The ADF(p) statistic without trend is given by the t-ratio of the OLS estimate of ρ in the ADF regression (see Campbell and Perron (1991)) below:

$$\Delta z_t = c + \rho z_{t-1} + \sum_{i=1}^{p} \delta_i \Delta z_{t-p} + \varepsilon_t$$

where Δz_t is the first difference of the residuals of the cointegrating regression, c is the constant of the regression, δ_i is the coefficient of the lagged differences, and ε_t is the error term.

An initial lag of six was applied, and the sixth lag was tested for significance using the asymptotic t-ratio. The six lag was always insignificant and the lag length was subsequently reduced until the test was reduced to a Dickey-Fuller test. The ADF statistic was compared against the critical values given in Engle and Yoo (1987).

Table 3 below summarizes the results obtained. The first column represents the dependent variable in each regression, with the explanatory variables given in the second column. The third, fourth and fifth columns present the ADF t-statistic, critical values and DW statistics, respectively. Comparing these values, the ADF statistics for all nine regressions were insignificant. The most negative ADF statistic of -2.53 was obtained in the regression of DM against BP, which was greater than the critical value of -3.37. The DW statistics of all nine regression models are close to 2, suggesting no significant serial correlation in the regression residuals. Thus, the hypothesis of a unit root in the residuals of the nine cointegrating regressions cannot be rejected, which implies that the three settlement prices are not cointegrated.

Dep Var	Exp Var	ADF Stat	Critical Value	DW Stat
DM	JY	-2.228	-3.37	2.044
DM	BP	-2.530	-3.37	2.041
BP	JY	-1.603	-3.37	1.981
BP	DM	-1.189	-3.37	1.918
JY	DM	-0.241	-3.37	1.937
JY	BP	-1.018	-3.37	1.994
DM	BP, JY	-2.270	-3.78	1.988
BP	DM,JY	-1.575	-3.78	1.915
JY	DM, BP	-0.794	-3.78	1.929

Note: In each of the cointegrating regressions, normalization is on the dependent variable. DW refers to the Durbin-Watson statistic of the ADF test.

Table 3: Results of the cointegration test for Settlement prices using the ADF test

5.2 Vector Autoregressive Modelling of the SIMEX Currency Futures

Estimation of a Vector Autoregressive (VAR) model for a series of variables can only be conducted if all the variables are themselves stationary. Since the settlement prices of the three currency futures were found to be non-stationary, a VAR model for the settlement prices cannot be estimated. The first differences of the settlement prices, namely, the rates of return, are stationary, and a VAR model of the rates of return can, therefore, be estimated.

To estimate a VAR of the rates of return, the value of p, that is, the order of the VAR, is required. A pth-order VAR for the system of futures rates of return was constructed, and is given as follows:

$$F_t = \mu + \sum_{i=1}^{p} \beta_i F_{t-i} + \varepsilon_t$$

where F_t is the 3×1 vector of the rates of return, μ is a 3×1 vector of constants, β_i are the coefficients of lagged terms, and ε_t are 3×3 vectors of error terms. If $p > 0$, there are dynamics in the system, and a VAR model can be formed.

The order of p was determined by minimizing the objective function given by the Schwarz (1978) multivariate SBIC Criterion, which is defined as

$$\text{SBIC}(j) = \ln\left|\hat{\Sigma}_{\varepsilon,j}\right| + g^2 jT^{-1}\ln T, \quad j = 0,1, \ldots,p,$$

where p is the maximum order considered. The SBIC provides a consistent estimate of the correct lag order. Lutkepohl (1985) demonstrated that the SBIC also chooses the correct order most often, with the resulting VAR models providing the best forecasts in a Monte Carlo comparison of objective functions.

Using the TSP (1990) software package, the SBIC and Akaike (1974) Information Criterion (AIC) results are computed for the VAR model for different values of the maximum order, p, from 0 to 4. The results indicate that the highest AIC and SBIC values were obtained for p=0. This suggests the value of p is zero, in which case a VAR of the three rates of return series cannot be formed. Similarly, a VAR system was formulated for two of the three series. The results are similar to the three-variable case above, in that the highest AIC and SBIC values were obtained at p=0. These results are given in Table 4 below, from which it is evident that no VAR model can be formed for the rates of return series of the currency futures data.

	Lag Length				
M	0	1	2	3	4
1	-58164.9	-58160.4	-58145.8	-58136.5	-58135.4
	-31.1939	-31.1632	-31.1287	-31.0961	-31.0682
2	-38036.5	-38050.2	-38043.1	-38038.2	-38039.7
	-20.4078	-20.3934	-20.3783	-20.3634	-20.3520
3	-38358.2	-38356.5	-38350.8	-38346.2	-38341.8
	-20.5715	-20.5576	-20.5423	-20.5269	-20.5117
4	-37672.4	-37671.0	-37664.4	-37659.7	-37664.7
	-20.2035	-20.1899	-20.1751	-20.1603	-20.1511

Note: The first row of figures for each model represents the AIC values, while the second row represents the SBIC values. Model numbers, denoted by M, refer to the variables used for the particular VAR formed, which are as follows: (1)All three rates of return; (2)DM and JY;(3)BP and DM; (4)BPand JY.

Table 4: AIC And SBIC Values for Different Lag Values

6. FINDINGS OF THE MULTIVARIATE ANALYSIS

Some interesting findings were obtained from the analysis of the futures data, namely: (i) identifying the order of integration of the settlement prices of the currency futures; (ii) discovering no cointegrating relationships between the three futures series; and (iii) finding no VAR relationship among the first differences of the logarithms of the three series.

First, individual ADF tests conducted on the logarithms of the settlement prices led to the conclusion that these variables follow a non-stationary I(1) process. It was observed that the logarithms of the first differences of the data series were stationary, that is, I(0), implying that all three settlement prices are I(1) variables.

Second, as each series was I(1), there was scope for establishing a cointegrating relationship among these variables, such that the linear combination between these I(1) variables would be stationary. However, cointegration tests applied to nine regressions could not establish any such relationship between these variables.

Third, following Diebold et al. (1994), an attempt was made to estimate VAR models for the system of currency futures. Since settlement prices are I(1) variables, differenced data were used in the VAR model to estimate a VAR for the rates of return data. SBIC and AIC were used to determine the VAR lag length. The minimum values of the SBIC and AIC were obtained when the value of p, the maximum order, was found to be zero, suggesting that a VAR system could not formed. These results, therefore, could not establish the existence of any VAR relationship.

7. LIMITS TO THE STUDY

VAR analysis involved differencing the logarithms of the settlement prices, since the logarithms of the series were nonstationary. Enders (1995) argues that the issue exists as to whether the variables in a VAR need to be stationary. Sims (1980) and Doan (1992) recommend against differencing data, even if the variables contain a unit root, since differencing eliminates information concerning comovements in the data.

8. CONCLUSION

Multivariate modelling techniques for settlement prices were unable to produce results suggesting any long run relationship existing among the currency futures in SIMEX. The results are, however, generated from data based on a thinly traded market for

BP futures, and a relatively young futures market in SIMEX. Sequeira (1995) showed that univariate models of the currency futures in SIMEX were superior to the random walk model on the basis of their mean absolute error. No such comparison is possible with multivariate models as the study did not find any evidence to suggest the existence of any long run interrelationships among the variables. As this market matures, and with the availability of more data, it is possible that a multivariate model may be formed that could outperform the results from a random walk.

ACKNOWLEDGMENTS

The author wishes to thank Michael McAleer for helpful comments and suggestions, to acknowledge the Department of Employment, Education and Training for an Overseas Postgraduate Research Award, and the C.A. Vargovic Memorial Fund at the University of Western Australia for financial support.

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