A Redetermination of Hedging Strategies Using Foreign Currency Futures Contracts and Forward Markets

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INTRODUCTION

The literature is mixed about the relative hedging effectiveness and pricing efficiency of forward and futures markets in both interest rate and foreign currency markets.

A study by Cornell and Reinganum (1981) failed to find a large difference in the hedging effectiveness of the forward and futures markets for foreign currencies. They found the mean differences between the two markets to be insignificantly different from zero, both statistically and economically.

Hill and Schneeweis (1982) investigated the hedging potential of the foreign currency futures markets. They calculated hedging effectiveness measures and risk-minimizing hedge ratios for five currencies, and found the pound, mark, and Swiss franc futures contracts to have consistently high hedging effectiveness. In addition, hedging effectiveness increased when the length of the hedge period increased. In an earlier study, Hill and Schneeweis (1981) analyzed theoretical and statistical problems arising when price levels, as opposed to price changes, are used as the basis for measuring hedging potential for foreign currency futures. They concluded that price levels cause an overstatement of hedging effectiveness, yield inefficient estimates of hedging ratios, and introduce bias such that standard statistical significance tests are invalid. Pitts (1986) further addressed the issue of nonstationarity, and built a model which explicitly recognized autocorrelation of the error terms in the relationship between the price of the asset to be hedged and the price of the

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hedging vehicle. Testing the OLS regression model with levels and with changes, and applying the Cochrane–Orcutt procedure to levels, he concludes that the autoregressive error structure significantly affects optimal hedging strategies.

Herbst, Kare, and Caples (1989) examined foreign currency futures contracts and concluded that the traditional OLS minimum variance hedge ratio estimates overstated the risk-minimizing hedge ratios because of the presence of autocorrelation. They did not consider the forward currency market. The forward market is far larger than the futures market, and thus studies of currency hedging effectiveness should include the forward market.[1]

The purpose of this article is to extend the hedging literature by measuring hedging efficiency of the interbank forward market and the futures market for those foreign currencies that have corresponding actively traded futures contracts. Prior research employs ordinary least squares (OLS) techniques to estimate minimum-risk hedge ratios. This study adjusts for the serial correlation in the time series data for spot, forward, and futures prices, and employs a larger and more meaningful data set than used in previous work. Box–Jenkins analysis is used to address the serial correlation present in these three exchange rates series. The risk-minimizing hedge ratios are compared to those calculated by ordinary least squares. These ratios are found to be significantly different for the two approaches.

METHODOLOGY

Market Tests

The first test performed on each time series is a check of the residuals for autocorrelation: If the markets (spot, forward, and futures) are free of autocorrelation, the residuals should reduce to white noise.

Next, Box–Jenkins time series tests are used to determine if the regression methodology, as used by Ederington et al., can be properly employed. If the prices within these markets are not independent, then one of the major assumptions of regression analysis has been violated, and the results of the study are open to question.[2]

Regression Model

Initially, the optimal hedge ratios are determined using the methodology of Johnson (1960) and Stein (1961), and extended by Ederington (1979), hereafter JSE. The methodology is an extension of the Markowitz portfolio selection method

[1]Daily foreign exchange market volume reported in the Federal Reserve Bank of New York "Summary of Results of U.S. Foreign Exchange Market Turnover Survey Conducted in March, 1986," was estimated to be $50 billion in *average daily trading volume*. Of that total, 63.2% ($31.6 billion) represented spot transactions, 4.7% ($2.35 billion) represented outright forward transactions, and 29.8% ($14.89 billion) represented swap transactions. On January 23, 1984, the *total* underlying contract value of currency contracts outstanding (i.e., open interest) on U.S. futures exchanges was about $5.2 billion; on November 15, 1990 the total contract value was approximately $20.9 billion. In futures contracts, the daily trading volume is normally much less than the open interest.

[2]When hedge ratios are calculated from the raw price data using the Johnson (1960), Stein (1961), and Ederington (1979) (JSE) methodology, the autocorrelation is more apparent than when first differences are used. It is usual practice to calculate regression-based hedge ratios from the difference. The real test is thus whether or not first differencing is sufficient to remove the autocorrelation.

familiar in financial theory. The primary difference between the traditional model and the model used here is that cash and futures positions are not substitutes for each other. The objective is to minimize risk for a given cash position, and to determine how much of the cash position to hedge. The risk-minimizing hedge ratio is the regression slope coefficient of spot changes regressed against futures/forward changes.

The hedging effectiveness of the minimum-risk hedge is the reduction in variance achieved by maintaining a hedged portfolio over an unhedged portfolio. It is simply the coefficient of determination between the spot and futures/forward price changes (R^2 of the regression).[3] When comparing R^2 for different hedging strategies, however, the comparison is reliable only when the data set of the cash position remains the same. For further discussion of this point, see Lindahl (1989). The higher the correlation, the more effective the hedge.

Box–Jenkins Model

The second methodology employed is a technique developed by Box and Jenkins (1976). The Box–Jenkins method is a three-step approach to model building. The first stage is model identification or specification in which an appropriate structural form is selected to fit the time series data. The second stage is the estimation of the parameters. Finally, the model selected is tested for fit; if the data being tested do not fit the model, the process is repeated. From the Box–Jenkins process, an autoregressive-integrated-moving average model (ARIMA) is obtained.[4]

The tools generally used to identify an appropriate model are the autocorrelation function (ACF) and the partial autocorrelation function (PACF). A stationary stochastic process can be fully determined by its mean, variance, and ACF. Each distinct process has a characteristic ACF; and if an ACF can be estimated from the time series, that information can be used to postulate the process which generates the time series. ACF and PACF are used to describe the process. For a Y_t time series, the ACF $(K) = \mathrm{cov}(Y_t, Y_{t+k})/\mathrm{var}(Y_t)$.

Data

The data employed consist of daily forward and spot prices for 1982, 1983, and the first five months of 1984, as reported in *The Wall Street Journal*. The forward and spot prices are gathered for the five currencies with corresponding actively traded futures contracts: British pound, German mark, Canadian dollar, Swiss franc, and Japanese yen.

In addition, 90-day "perpetual contract" futures prices, are obtained from Commodity Systems, Inc. The rationale for using these futures prices follows. A perpet-

[3]For a discussion of appropriate choices of variables to be used in hedge ratio analysis, see Howard and D'Antonio (1984) and Schwarz, Hill, and Schneeweis (1986).

[4]"Black boxes" (a series of filters) introduce correlation structure or memory into a time series. The Box-Jenkins methodology involves construction of a proper ARIMA (p,d,q) model to describe the time series. The ARIMA model is a series of filters that determine the properties of the output time series. An ARIMA (0, 1, 1) model describes a series in which a random shock passes through a differencing filter ($d = 1$) and a moving average filter ($q = 1$), but not an autoregressive filter ($p = 0$). An ARIMA (1, 0, 1) filter describes a series that passes through a moving average filter and an autoregressive filter, but is not differenced.

ual contract approach provides daily measurements for futures prices[5] that are more comparable to forward prices. This compensates for a problem encountered in any analysis using futures contract data: there are only four delivery months per year, and the contracts continually expire. A particular problem exists when 90-day futures contracts are compared with 90-day forward contracts, because the former are written only four times a year whereas the latter are written daily. In some studies that compare the two contracts [most notably Hill and Schneeweis (1982)], only 13–18 observations are available for each currency even though the study covers several years.

A detailed analysis of the British pound is presented. Similar details for the other currencies are presented in the Appendix because the fundamental method of analysis is the same.

RESULTS

In building univariate ARIMA models for the British pound, heteroscedasticity is indicated when data are first plotted and confirmed by a formal test. A logarithmic transformation is used to stabilize the variance. First differencing of the British pound data is enough to make them stationary.

Optimal hedge ratios are estimated. First, using OLS regression methodology, spot rates for the British pound are regressed against futures rates. The following model is fitted:

$$\text{BPSP}_t = \underset{(0.030)}{0.016} + \underset{(0.018)}{0.989}\ \text{BPFUT}_t \tag{1}$$

with $R^2 = 0.998$ and $\sigma^2 = 0.007$ = mean square error (MSE). The indicated optimal hedge ratio, 0.989, is almost a one-for-one hedge. The hedge ratio is larger than found in some previous studies. Several factors could account for the difference: (1) a statistical problem (such as autocorrelation) might result in overstating the regression coefficients; (2) the use of daily rather than weekly or monthly observations, used in many studies, could also explain it; (3) the way maturing futures contracts are handled could be part of the reason for the divergence; and (4) in this study, 90-day hedges are used, whereas some studies use hedging periods of from one to four weeks.

[5]These rates are purchased from Commodity Systems, Inc., Boca Raton, Florida. The perpetual contract is calculated by taking a near and far futures contract, straddling either side of the day held a fixed distance into the future (in our case 90 days), and calculating a weighted average of the two contracts. The weights are the numbers of days from $t = 0$ to the two futures contracts.

A large hedger could readily create such a perpetual contract, since the weights used for each futures contract are integers. Each day the two actual contract positions would need to be examined and adjusted as necessary to maintain the synthetic perpetual contract.

Perpetual contracts solve several problems, among them the problem of comparing forward contracts (which are written daily for fixed term) to futures (which are not). And, it allows one to compare the two on a daily basis, using many more observations. Daily data are superior to weekly or monthly data comparison because contracts can be traded on any day; banks quote forward rates every business day. If weekly or monthly comparisons are made, a particular day must be arbitrarily selected as the basis for comparison. The day selected might have a considerable impact on the analysis. In some studies, the use of weekly or monthly data very likely influence the hedging ratios as do the small (13–18) number of observations owing to the way futures contracts are included. To avoid this potential problem, daily comparisons are used, and perpetual contracts provide the daily information required.

For additional discussion of perpetual contracts, see Pelletier (1983).

The Durbin–Watson test statistic is 0.998, indicating the presence of autocorrelation which, if not accounted for, tends to underestimate the variance and overestimate the R^2 of the model. The estimated degree of first order autocorrelation is 0.499, which is statistically significant at the 0.01 level.

The associated autoregressive parameter estimates are

$$\text{BPSP}_t = \underset{(0.011)}{0.033} + \underset{(0.006)}{0.979}\ \text{BPFUT}_t \tag{2}$$

with $R^2 = 0.974$ and MSE $= 0.00003$. The indicated hedge ratio is 0.979. Failure of the autoregressive terms to die off indicates nonstationarity and the inability of a pure autoregressive technique to model the autocorrelation of the error terms.[6] Thus, a mixed autoregressive-moving average model is likely to be appropriate. Here, the transfer function methodology of the Box–Jenkins analysis provides the needed flexibility for dealing with correlated residuals.

Consider the following regression model:

$$Y_t = B_0 + B_1 X_t + \Omega(B)\epsilon_t$$

where $\Omega(\epsilon_t)$ is an ARIMA model for the correlated error terms. Taking first differences it becomes:

$$(1 - B)Y_t = (1 - B)(B_0 + B_1 X_t) + (1 - B)\Omega(B)\epsilon_t \tag{3}$$

or

$$(1 - B)Y_t = B_1(X_t - X_{t-1}) + (1 - B)\Omega(B)\epsilon_t \tag{4}$$

where $B_1(X_t - X_{t-1})$ is a transfer function and

$$(B) = a + \Omega_1\sigma_{t-1} + \Omega_2\sigma_{t-2} + \ldots = \sum_{i=1}^{\infty} \Omega_i \sigma_{i-1}$$

$(1 - B)\Omega(B)\epsilon_t$ can be estimated using the standard ARIMA models of Box–Jenkins.

In this study the appropriate estimated model is:

$$(1 - B)\text{BPSP}_t = \underset{(0.014)}{0.924}(1 - B)\text{BPFUT}_t + (1 - \underset{(0.026)}{0.768}B)\varepsilon_t \tag{5}$$

with $R^2 = 0.998$ and MSE $= 0.00002$.

The hedge ratio decreased from the previously indicated 0.989 obtained using OLS to 0.924 using Box–Jenkins; and the measure of effectiveness is very close to 1.

The residuals are extremely clean and appear to be free from autocorrelation. A visual check of the residuals gives highly acceptable P-values, indicating a lack of significant autocorrelation.

In the above model, the structure of the error term, $\Omega(B)$, should be noted. Because this model has a pure moving average structure, theoretically, an infinite number of autoregressive coefficients would be required to model the correlation of the error term. Thus, the moving average representation is a more parsimonious formulation than the autoregressive model.

[6]This indicates either a need to difference the time series (i.e., the errors are not stationary), or that the correlation of error terms is not autoregressive in nature, but follows an ARIMA stochastic process. Thus, it is evident that even the use of an autoregressive model does not completely eliminate the problem.

Similar analyses of the forward hedge ratios are conducted. The OLS model gives:

$$\text{BPSP}_t = \underset{(0.003)}{0.191} + \underset{(0.002)}{0.987}\ \text{BPFOR}_t \tag{6}$$

with $R^2 = 0.998$ and MSE $= 0.0004$.

The Durbin–Watson statistic, at 0.611, indicates the probability of significant autocorrelation. The first order autocorrelation statistic is 0.688. The high value of the BPFOR_t coefficient also indicates the optimal hedge ratio is close to 1. Again, this is much higher than reported in previous studies, and the problems cited above are reiterated.

The autoregressive model is indicated to be:

$$\text{BPSP}_t = \underset{(0.012)}{0.036} + \underset{(0.007)}{0.976}\ \text{BPFOR}_t \tag{7}$$

with $R^2 = 0.974$ and MSE $= 0.00002$.

The estimates of autocorrelation do not die off rapidly; hence, the time series needs to be differenced. This indicates that a pure autoregressive model is inappropriate, and a more complex model is needed.

Using the identification procedures of Box–Jenkins, the model is tentatively identified and estimated to be:

$$(1 - B)(1 - 0.196B)\text{BPSP}_t = \underset{(0.013)}{0.942}(1 - B)\text{BPFOR}_t + (1 - B)(1 - \underset{(0.037)}{0.795}B)\varepsilon_t \tag{8}$$

with $R^2 = 0.999$ and MSE $= 0.00002$.

This is a simple moving average filter with a lag of one day. The measure of hedging effectiveness (R^2) indicates a high degree of hedging effectiveness.

Thus, the analysis of the British pound is complete. The methodology for the other currencies is the same as for the British pound, and the results are presented in the Appendix. The hedge ratios are shown to be lower in each case with Box–Jenkins than with OLS and autoregressive analysis.

DISCUSSION

Table I shows the optimal hedge ratios and hedging effectiveness measures generated between spot and futures markets, and between spot and forward markets, for each of the five currencies tested. In the case of the British pound, the Box–Jenkins methodology gives a lower hedge ratio than the OLS regression for the futures and spot markets (0.924 vs. 0.989). The autoregressive procedure (ALS) provides a number between the other two techniques. It indicates the presence of autocorrelation, which tends to overstate the optimal hedge ratio. The spot-forward model for the British pound also shows that the optimal hedge ratio, using both ALS (0.976) and Box–Jenkins (0.942), is lower than with OLS regression.

The optimal Canadian dollar hedges also tend to be much lower using the Box–Jenkins model than OLS or ALS. The optimal hedge for the spot future relationship given by OLS is 0.962 and is reduced to only 0.893 when Box–Jenkins is used. The forward-spot model is likewise reduced from 0.965 for OLS to 0.911 using Box–Jenkins. In this case, however, the future-spot model is a complex AR(1) with a lag at one day and an MA(1) with a lag at one and two days. The forward-spot model is a simple MA(1) model with a lag at one day.

Table I
SUMMARY OF OPTIMAL RATIOS

		Futures		Forward	
Currency	Technique	Hedge Ratio	R^2	Hedge Ratio	R^2
British pound	OLS	0.9893	0.9979	0.9868	0.9979
	ALS	0.9785	0.9739	0.9761	0.9739
	B–J	0.9235	0.9980	0.9419	0.9989
Canadian dollar	OLS	0.9622	0.9658	0.9646	0.9665
	ALS	0.9036	0.7972	0.9203	0.8291
	B–J	0.8928	0.9781	0.9106	0.9849
German mark	OLS	0.9800	0.9945	0.9656	0.9915
	ALS	0.9683	0.9622	0.9491	0.9635
	B–J	0.9450	0.9933	0.7503	0.9933
Swiss franc	OLS	0.9627	0.9918	0.9527	0.9905
	ALS	0.9283	0.9270	0.9301	0.9558
	B–J	0.9180	0.9955	0.9262	0.9967
Japanese yen	OLS	0.9812	0.9834	0.9711	0.9768
	ALS	0.9597	0.8979	0.9279	0.8724
	B–J	0.9740	0.9905	0.9261	0.9845

The German mark shows a pattern similar to the British pound. With the future-spot model, the OLS optimal ratio is 0.980 (almost a one-for-one hedge), while the Box–Jenkins optimal hedge ratio is only 0.945. The forward-spot model for the German mark is quite different. The hedge ratio for OLS regression is very high at 0.966, while Box–Jenkins gives an optimal ratio of only 0.750. In both cases the Box–Jenkins model is not very complex; in fact, it is a simple MA(1) with a lag only at one day.

The optimal hedge for the Swiss franc futures using OLS is 0.963, and is reduced to 0.918 when Box–Jenkins is used. This model is very complex and takes the form of an AR(1) with a lag at two days, and MA(1) with lags at one day and five days. The optimal hedge ratio for the forward-spot relationship using OLS is 0.953 and is reduced to 0.926 when Box–Jenkins is employed. The Box–Jenkins model in this case is also very complex. It is an AR(1) with lags at one and six days and MA(1), with lags of one and five days.

For the Japanese yen futures-spot model, the results are somewhat different than for the other currencies. The optimal hedge ratio using OLS is 0.981, and is reduced to 0.960 using ALS. The Box–Jenkins optimal hedge ratio is 0.974 (an increase over the ALS ratio). The model given by Box–Jenkins is a simple MA(1), with lags at one day and ten days. The forward-spot model developed by Box–Jenkins is the same MA(1) with lags of one and ten days, and yields an optimal hedge ratio of 0.926 which is lower than the 0.971 given by OLS and 0.928 given by ALS.

CONCLUSION AND ECONOMIC IMPLICATIONS

This article presents findings based on futures, forward, and spot foreign exchange rate data for five currencies. The results show that optimal hedging ratios calculated using the methodology common to prior studies are overstated in almost all cases, because the OLS regression methodology used in them does not account for autocorrelation in the residuals of the time series.

Autoregressive and Box–Jenkins methodologies are used to model the data in the presence of autocorrelation. Daily data are used for all the three data sets analyzed, providing realism to the problem, since these contracts can be traded on a daily basis. A priori, more variance in daily than in weekly or monthly prices are expected and, therefore, more variance reduction should be possible. Another advantage of daily data is the increased number of available observations (over 600), while some earlier works have used less than 20.

It is strongly indicated that past studies of futures and forward markets may have been biased by autocorrelation. In several of those studies, the bias may have caused overestimation of the optimal hedge ratios. Both the hedge ratios and the hedging effectiveness terms may have been overstated, leading to calculated hedge ratios that are higher than the true optimum.

Explicit modeling of the autocorrelation in this investigation produces more precise optimal hedge ratios, and potentially reduces the cost of hedging while increasing risk reduction. Using hedge ratios estimated with OLS results in using larger forward or futures positions than necessary, which means paying for protection that is too large and thus potentially harmful.

Appendix

A. GERMAN MARK

Data heteroscedastic; natural log transformation stabilizes the variance; first differencing makes the series stationary.

OLS Model (Futures):

$$\mathrm{GMSP}_t = \underset{(0.001)}{0.004} + \underset{(0.003)}{0.980}\,\mathrm{GMFUT}_t$$

with $R^2 = 0.995$, MSE $= 0.002$, and D–W $= 1.398$.

ALS Model (Futures):

$$\mathrm{GMSP}_t = \underset{(0.003)}{0.009} + \underset{(0.008)}{0.968}\,\mathrm{GMFUT}_t$$

with $R^2 = 0.962$ and MSE $= 0.000002$.

Box–Jenkins Model (Futures) (Simple Moving Average Filter with a Lag of One Period):

$$(1 - B)\,\mathrm{GMSP}_t = \underset{(0.012)}{0.945}(1 - B)\,\mathrm{GMFUT}_t + (1 - \underset{(0.022)}{0.845}B)\,e_t$$

with $R^2 = 0.993$ and MSE $= 0.000002$.

OLS Model (Forward):

$$\mathrm{GMSP}_t = \underset{(0.001)}{0.009} + \underset{(0.004)}{0.966}\,\mathrm{GMFOR}_t$$

with $R^2 = 0.992$, MSE = 0.002, and D–W = 1.557.

ALS Model (Forward):

$$\mathrm{GMSP}_t = \underset{(0.003)}{0.016} + \underset{(0.008)}{0.949}\,\mathrm{GMFOR}_t$$

with $R^2 = 0.964$ and MSE = 0.000003.

Box–Jenkins Model (Forward) (Simple Moving Average Filter with a Lag of One Period):

$$(1 - B)\mathrm{GMSP}_t = \underset{(0.023)}{0.750}(1 - B)\,\mathrm{GMFOR}_t + (1 - \underset{(0.034)}{0.635}B)\,e_t$$

with $R^2 = 0.993$ and MSE = 0.000003.

B. CANADIAN DOLLAR

Data heteroscedastic, natural log transformation stabilizes the variance; first differencing makes the series stationary.

OLS Model (Futures):

$$\mathrm{CDSP}_t = \underset{(0.006)}{0.032} + \underset{(0.074)}{0.962}\,\mathrm{CDFUT}_t$$

with $R^2 = 0.966$, MSE = 0.002, and D–W = 0.668.

ALS Model (Futures):

$$\mathrm{CDSP}_t = \underset{(0.015)}{0.079} + \underset{(0.019)}{0.904}\,\mathrm{CDFUT}_t$$

with $R^2 = 0.797$ and MSE = 0.00006.

Box–Jenkins Model (Futures) (A Differenced Filter—MA2):

$$(1 - B)(1 - \underset{(0.307)}{0.018}B)\mathrm{CDSP}_t = \underset{(0.019)}{0.893}\,\mathrm{CDFUT}_t + (1 - \underset{(0.305)}{0.691}B - \underset{(0.234)}{0.119}B^2)\,e_t$$

with $R^2 = 0.978$ and MSE = 0.000002.

OLS Model (Forward):

$$\mathrm{CDSP}_t = \underset{(0.006)}{0.030} + \underset{(0.007)}{0.965}\,\mathrm{CDFOR}_t$$

with $R^2 = 0.967$, MSE = 0.002, and D–W = 0.495.

ALS Model (Forward):

$$\mathrm{CDSP}_t = \underset{(0.014)}{0.065} + \underset{(0.017)}{0.920}\,\mathrm{CDFOR}_t$$

with $R^2 = 0.829$ and MSE = 0.000002.

Box–Jenkins Model (Forward) (Simple First Difference—MA1)

$$(1 - B)\text{CDSP}_t = \underset{(0.017)}{0.911}\,(1 - B)\text{CDFOR}_t + (1 - \underset{(0.027)}{0.754}B)e_t$$

with $R^2 = 0.985$ and MSE = 0.000002.

C. SWISS FRANC

Data heteroscedastic; natural log transformation stabilizes the variance; first differencing makes the series stationary.

OLS Model (Futures):

$$\text{SFSP}_t = \underset{(0.002)}{0.011} + \underset{(0.004)}{0.963}\,\text{SFFUT}_t$$

with $R^2 = 0.992$, MSE = 0.002, and D–W = 0.845.

ALS Model (Futures):

$$\text{SFSP}_t = \underset{(0.005)}{0.028} + \underset{(0.011)}{0.928}\,\text{SFFUT}_t$$

with $R^2 = 0.927$ and MSE = 0.000002.

Box–Jenkins Model (Futures) (Simple Moving Average Filter with a Lag of One and Five Days):

$$(1 - B)(1 - \underset{(0.049)}{0.155}B^2)\text{SFSP}_t = \underset{(0.012)}{0.918}\,\text{SFFUT}_t + (1 - \underset{(0.031)}{0.849}B + \underset{(0.026)}{0.031}B^5)\,e_t$$

with $R^2 = 0.996$ and MSE = 0.000002.

OLS Model (Forward):

$$\text{SFSP}_t = \underset{(0.002)}{0.015} + \underset{(0.004)}{0.953}\,\text{SFFOR}_t$$

with $R^2 = 0.991$, MSE = 0.002, and D–W = 0.427.

ALS Model (Forward):

$$\text{SFSP}_t = \underset{(0.005)}{0.026} + \underset{(0.011)}{0.930}\,\text{SFFOR}_t$$

with $R^2 = 0.956$ and MSE = 0.000002.

Box–Jenkins Model (Forward) (Simple Moving Average Filter with a Lag of One and Five Days):

$$(1 - B)(1 - \underset{(0.000)}{0.1}B - \underset{(0.041)}{0.145}B^6)\text{SFSP}_t$$
$$= \underset{(0.011)}{0.926}\,(1 - B)\text{SFFOR}_t + (1 - \underset{(0.027)}{0.778}B + \underset{(0.042)}{0.085}B^5)$$

with $R^2 = 0.997$ and MSE = 0.000002.

D. JAPANESE YEN

Data heteroscedastic; natural log transformation stabilizes the variance; first differencing makes the series stationary.

OLS Model (Futures):

$$\mathrm{JYS}P_t = \underset{(0.002)}{0.003} + \underset{(0.005)}{0.981}\,\mathrm{JYFUT}_t$$

with $R^2 = 0.983$, MSE = 0.003, and D–W = 0.972.

ALS Model (Futures):

$$\mathrm{JYSP}_t = \underset{(0.006)}{0.012} + \underset{(0.013)}{0.960}\,\mathrm{JYFUT}_t$$

with $R^2 = 0.898$ and MSE = 0.000003.

Box–Jenkins Model (Futures) (MA1 Model with Lags at One and Ten Periods):

$$(1 - B)\mathrm{JYSP}_t = \underset{(0.012)}{0.974}(1 - B)\,\mathrm{JYFUT}_t + (1 - \underset{(0.019)}{0.893}B + \underset{(0.041)}{0.081}B^{10})e_t$$

with $R^2 = 0.991$ and MSE = 0.000003.

OLS Model (Forward):

$$\mathrm{JYSP}_t = \underset{(0.003)}{0.007} + \underset{(0.006)}{0.971}\,\mathrm{JYFOR}_t$$

with $R^2 = 0.977$, MSE = 0.003, and D–W = 1.130.

ALS Model (Forward):

$$\mathrm{JYSP}_t = \underset{(0.006)}{0.026} + \underset{(0.015)}{0.928}\,\mathrm{JYFOR}_t$$

with $R^2 = 0.872$ and MSE = 0.000005.

Box–Jenkins Model (Forward) (Simple MA1 Model with Lags at One and Ten Periods):

$$(1 - B)\mathrm{JYSP}_t = \underset{(0.017)}{0.926}(1 - B)\,\mathrm{JYFOR}_t + (1 - \underset{(0.021)}{0.879}\mathrm{B} + \underset{(0.041)}{0.138}\mathrm{B}^{10})e_t$$

with $R^2 = 0.985$ and MSE = 0.000005.

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