TESTS OF RATIONAL EXPECTATIONS AND NO RISK PREMIUM
IN FORWARD EXCHANGE MARKETS*

by

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Abstract

This paper tests the simple efficiency hypothesis, i.e., that traders have rational expectations and charge no risk premium in the forward exchange market. It uses a statistical procedure which is consistent under a large class of heteroscedasticity, and a set of data which takes into account the institutional features of the forward exchange market. The results show that this procedure leads to stronger rejections of the simple efficiency hypothesis than do procedures using the standard assumption of homoscedasticity.

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1. Introduction

This paper tests the "simple efficiency" hypothesis in forward exchange markets. "Simple efficiency," as defined in Hansen and Hodrick (1980), means that traders have rational expectations and that there is no risk premium in the forward exchange market. A testable implication of this hypothesis is that the error committed by the forward rate in forecasting the spot rate has a zero mean and is uncorrelated with any known information.

The present work represents an improvement over the existing literature\(^1\) in two respects. One, most researchers have assumed that the aforementioned forecast error is stationary. Their test statistics are not necessarily consistent under nonstationarity.\(^2\) This paper uses a statistical procedure which is consistent for a large class of heteroscedasticity. Inference results using this procedure can be quite different from those using the standard assumption of homoscedasticity. Two, a new set of data is used, which takes into account the institutional features of the forward market in matching the appropriate spot rate to the forward rate.

Using the new statistical procedure and the new data, I found that the forecast error is correlated with variables which are assumed to be in traders' information set, such as past values of spot and forward rates. These results provide the strongest rejection of the simple efficiency hypothesis thus far in the published literature, and are consistent with the findings of most authors. This does not necessarily imply that the forward market is

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\(^2\)The exceptions are Cumby and Obstfeld (1983) and Hansen and Hodrick (1983).
"inefficient." Traders may charge a risk premium, which is correlated with the spot and forward rates.

The paper is in five sections. The next section discusses the "simple efficiency" hypothesis. The test procedure is introduced in section three. The construction of the data is presented in section four. Empirical results and some conclusions are contained in the final two sections.

2. Tests of the Simple Efficiency Hypothesis

The notation of this paper is as follows: s(t) denotes the natural logarithm of the spot exchange rate at date t, and f(t, n), the natural logarithm of the forward exchange rate contracted at date t for delivery date t + n.\(^3\) \(E[s(t + n)|I(t)]\) is the expectation of \(s(t + n)\) conditioned on the information set \(I(t)\), which is assumed to contain all present and past values of spot and forward rates, and the stochastic processes describing these rates.

\(M[s(t + n)|t]\) is the "market's expectation" of \(s(t + n)\) at time t. The hypothesis of rational expectations is that the market's expectation is the true expectation:

\[ H1: \quad M[s(t + n)|t] = E[s(t + n)|I(t)] . \quad (1) \]

The concept of a single expectation for the entire market may be uncomfortable. But all traders are assumed to have the same information set. Under rational expectations, they will have the same expectation.

A second hypothesis is required to relate the forward exchange rate to

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\(^3\) I use logarithms here for two reasons. One, most researchers have used logarithms. To make my results comparable, I shall follow the same convention. Two, if the stochastic processes are log-normal, then using logarithms yield an approximation of the return. This is discussed in Hansen and Hodrick (1980). The results do not change if I use rates of change in discrete time.
expectations. The market is assumed to set the forward rate equal to the expected spot rate on delivery:

\[ f(t, n) = M[s(t + n)|t] \quad (2) \]

Sufficient conditions yielding this result are (a) that all traders are risk neutral, and (b) that markets are competitive. However, if traders are risk averse, then it is possible to obtain an equilibrium forward rate which is different from the market expectation, because of the presence of a risk premium. Thus, \( H_2 \) is called the hypothesis of "no risk premium" in the forward rate.

Note that \( H_1 \) and \( H_2 \) are totally independent hypotheses. Traders may have rational expectations, but still require a risk premium for forward contracts. If they are risk averse, they may (rationally) expect a loss, in order not to have to carry any exchange risk themselves.

Also, \( H_1 \) and \( H_2 \) are not separately testable, because \( M[s(t + n)|t] \) cannot be observed. However, they jointly imply:

\[ f(t, n) = E[s(t + n)|I(t)] \quad (3) \]

which is called the "simple efficiency" hypothesis in the literature.

A testable implication of (2.1) is the following. Define the \( n \)-period forecast error \( u(t, n) \) of the forward rate:

\[ u(t, n) = s(t) - f(t - n, n) \quad (4) \]

Then the simple efficiency hypothesis implies that \( u(t, n) \) has zero mean and is uncorrelated with any information in \( I(t - n) \), which is assumed to contain \( \{s(t - n - j), f(t - n - j, n): j = 0, 1, 2, \ldots \} \).

Thus, the simple efficiency hypothesis implies:
T1: \( u(t, n) \) has zero mean and is uncorrelated with \( u(t - n, n) \)

T2: \( u(t, n) \) has zero mean and is uncorrelated with the \( n \)-period holding
yield \( r(t - n, n) \) and the \( n \)-period forward discount \( d(t - n, n) \),
which are defined by:

\[
\begin{align*}
  r(t, n) &= s(t) - s(t - n) \\
  d(t, n) &= s(t) - f(t, n)
\end{align*}
\]  

(5)  

(6)  

T1 was first tested by Geweke and Peiđe (1979). Using quarterly data on
the three month forward rate, i.e., \( n = 1 \), they regressed \( u(t, 1) \) on itself
lagged once and a constant term:

\[
u(t, 1) = a + b u(t - 1, 1) + e(t, 1) .
\]  

(7)  

The null hypothesis is that \( a = 0 = b \) and \( e(t, 1) \) is serially uncorrelated.
Assuming that \( u(t, 1) \), and hence \( e(t, 1) \), is covariance stationary,
they tested \( a = 0 = b \) using the standard F-statistic.

Hansen and Hodrick (1980) tested a more general version of (7). Using
weekly data for the three month forward rate, i.e., \( n = 13 \), they regressed
\( u(t, 13) \) on a constant term and lags of \( u(t - 13, 13) \):

\[
u(t, 13) = a + B(L) u(t - 13, 13) + e(t, 13) ,
\]  

(8)  

where \( B(L) \) is a polynomial in the lag operator \( L \). The null hypothesis is
\( a = 0 = B(L) \), and \( e(t, 13) \) is a moving average of order 12, assuming stationarity.
Hansen and Hodrick noted that ordinary least squares (OLS) yields
consistent estimates of the coefficients in (8). The test of the null hypothesis
\( a = 0 = B(L) \) was conducted with a covariance matrix which accounted for
the fact that the error term was a moving average.

This paper differs from the above work in two respects. First, weekly data
on the seven-day forward exchange rate is used. (Note that \( n = 1 \).) This means
I can employ as many observations as Hansen and Hodrick, while retaining serial
uncorrelation of the error term, as in Geweke and Peige. Second, I use a heteroscedasticity-consistent covariance estimate of the OLS coefficients, relaxing the assumption of stationarity made in the previous work. Evidence from Frenkel and Levich (1977) indicate that there are tranquil and turbulent periods in foreign exchange markets, during which the variances of exchange rates change. In addition, the data period in this paper covers the change to the new operating procedure at the Federal Reserve, leading to unprecedented volatility in U.S. interest rates. These are good reasons to use a statistical procedure which relaxes the homoscedasticity assumption often used in OLS regressions.

3. A Heteroscedasticity-Consistent Covariance Estimator of OLS

The heteroscedasticity-consistent covariance estimator for OLS is described in Hsieh (1983), which is an extension of Hansen (1982) and White (1980). The estimator is stated in the general regression model:

\[ y(t) = x(t)'\beta + \varepsilon(t), \quad t = 1, \ldots, T \quad (9) \]

where \( x(t)' = [x_1(t) \ldots x_k(t)] \).

It is assumed that:

(i) \( E[\varepsilon(t)|x(t), x(t-1), \ldots, \varepsilon(t-1), \ldots] = 0, \) with probability 1,

(ii) \( E[x(t) x(t)'] = V_t \)

(iii) \( \sum_{t} V_t/T \rightarrow V, \) as \( T \rightarrow \infty, \) where \( V \) is a positive definite matrix.

(iv) \( \sum_{t} E[\varepsilon(t)^2 x(t) x(t)']/T \rightarrow M, \) as \( T \rightarrow \infty, \) where \( M \) is a positive definite matrix.
(v) There exists $B > 0$, such that

$$E[|\varepsilon(t)x_i(t)x_j(t)x_k(t)|^2] \leq B,$$

for all $i, j, k,$ and $t$.

$$E[|x_i(t)x_j(t)x_k(t)x_m(t)|^2] \leq B,$$

for all $i, j, k, m$ and $t$.

(vi) For all $\{a_{ij} : i = 1, \ldots, k, j = 1, \ldots, k\},$

$$\sum_{i=1}^{k} \sum_{j=1}^{k} \sum_{t} E[|E[\varepsilon(t)^2 x_i(t)x_j(t)a_{ij}]|
- E[\varepsilon(t)^2 x_i(t)x_j(t)a_{ij}|x(t-1), \ldots, \varepsilon(t-1), \ldots)|]
= 0 \left( \sum_{i=1}^{k} \sum_{j=1}^{k} a_{ij} E[\varepsilon(t)^2 x_i(t)x_j(t)] \right).$$

Conditions (i)-(iv) are standard assumptions for time series models. They guarantee that the OLS estimator is consistent, i.e., $b_{OLS} = (X'X)^{-1}(X'Y) + \beta$ in probability. Conditions (v) and (vi) assure that $b_{OLS}$ is asymptotically normal, i.e., $T^{1/2}(b_{OLS} - \beta)$ has an asymptotic normal distribution, with mean zero and covariance $V^{-1}M V^{-1}'$, and that $V^{-1}M V^{-1}'$ can be consistently estimated by:

$$V_{HC} = \left(\frac{X'X}{T}\right)^{-1} \left(\sum_{t} u(t)^2 x(t)x(t)'/T\right)\left(\frac{X'X}{T}\right)^{-1} \quad (10)$$

where $u(t) = y(t) - x(t)b_{OLS}$. 
Note that if \( \varepsilon(t) \) is conditionally (and unconditionally) homoscedastic, i.e.,

\[
E[\varepsilon(t)^2 | x(t), x(t-1), \ldots, \varepsilon(t-1), \ldots] = \sigma^2 \quad \text{with probability 1},
\]

then \( V^{-1} M(V^{-1})' = \sigma^2 V^{-1} \), which can be consistently estimated by:

\[
V_{OC} = s^2 \left( \frac{X'X}{T} \right)^{-1},
\]

(11)

where \( s^2 \) is the sum of squared residuals divided by the number of observations. (No adjustment is made for the degrees of freedom lost in estimating the coefficient \( b_{OLS} \) since this is only an asymptotic result.) Under homoscedasticity, \( V_{HC} \) and \( V_{OC} \) tend to be the same matrix asymptotically.

If \( \varepsilon(t) \) is indeed heteroscedastic, then \( V_{OC} \) may not be consistent, but \( V_{HC} \) is always consistent, provided the assumptions (i) through (vi) hold. The difference between \( V_{HC} \) and \( V_{OC} \) is:

\[
V_{HC} - V_{OC} = \left( \frac{X'X}{T} \right)^{-1} \left( \sum \frac{u(t)^2 - s^2}{T} x(t)x(t)' / T \right) \left( \frac{X'X}{T} \right)^{-1}.
\]

(12)

Asymptotically, \( V_{OC} \) and \( V_{HC} \) tend to the same matrix, if \( u(t)^2 \) and \( x(t)x(t)' \) are not correlated. \( V_{OC} \) tends to underestimate (overestimate) the true covariance if \( u(t)^2 \) and \( x(t)x(t)' \) are positively (negatively) correlated. Since homoscedasticity is not implied by the simple efficiency hypothesis, I prefer to conduct T1 and T2 using \( V_{HC} \) rather than \( V_{OC} \), although both sets of results are reported.

Hsieh (1983) also extends White's (1980) test for heteroscedasticity for time series regressions. Monte Carlo results, however, show that this test may have little power to distinguish between homoscedasticity and heteroscedasticity. Therefore the test is not used in this paper.
4. Construction of the Data

Most empirical studies of the forward exchange market ignore the timing of delivery of forward contracts.\(^4\) Forward contracts generally do not have constant lengths. For example, a one-month contract sold on July 18 is due on August 18, assuming that August 18 is a business day.

(See Riehl and Rodriguez (1977) for a detailed discussion.) This institutional feature means that forward rates and spot exchange rates must be properly matched if tests of the simple efficiency hypothesis are to be conducted.

Another interesting feature of forward markets is that the forward contract is delivered two business days (one, in the case of Canadian dollar) after the contract is due. In the above example, delivery will take place on August 20, assuming the 19th and the 20th are both business days. For a hedger, i.e., someone holding a covered position, this means that the one-month forward contract is actually longer than a month. But for a speculator, i.e., someone holding an open position, this is not true. He must purchase foreign exchange on the spot market to cover his position. Since spot transactions are also delivered two business days (one, in the case of Canadian dollar) after the trades are made, a speculator will trade in the spot market at the time when the forward contract is due, i.e., on August 18, and not when the contract is delivered, i.e., August 20.

This paper matches up the forward rates and spot rates for a speculator using a seven-day forward contract. This has several advantages: (i) the length of the contracts are constant, (ii) many non-overlapping observations are available, and (iii) the non-overlapping observations allow the use of the heteroscedastic-consistent covariance estimator for the OLS coefficients.

\(^4\)Meese and Singleton (1980) made the same point.
Covered Interest Arbitrage

Multinational banks frequently deal in one-, two-, and seven-day forward contracts. But data are not publically available. However, using the "covered interest arbitrage" formula, I can construct forward contracts from seven-day eurocurrency rates and the spot exchange rates.

Let me illustrate this for the case of the U.S. dollar/German mark rate. I can buy forward marks for dollars in two ways. I can buy a seven-day forward contract at \( F(t, n) \) marks per dollar. Or, I can borrow from the eurodollar market at the rate \( i(t, l) \), sell the dollars in the spot exchange market for \( S(t) \) marks, and deposit the marks in a eurobank at the rate \( i^*(t, l) \). The two methods should lead to the same number of forward marks for each dollar (aside from brokerage costs.) This equivalence is the "covered interest arbitrage" condition:

\[
F(t, l) = S(t) \frac{1 + i(t, l)}{1 + i^*(t, l)}.
\]  

McCormick (1979), Frenkel and Levich (1979), and Eaker (1980) showed that arbitrage opportunities using ninety-day forward and eurocurrency rates essentially do not exist.

The reader may object to the construction of the forward rate in this manner, because there are brokerage costs. Conversations with a foreign exchange trader revealed that brokerage costs are quite small—about 12 U.S. dollars per million U.S. dollars of transactions.

Data Sources

Seven-day forward rates are constructed in this manner for seven other currencies—the British pound, the French franc, the Swiss franc, the Dutch guilder, the Italian lira, the Canadian dollar, and the Japanese yen—in addition to the German mark. The spot exchange rates and eurocurrency interest
rates are Friday closing rates in London, published by the Financial Times. The data start on June 9, 1978 and end on April 24, 1981, totaling 151 observations per exchange rate. The choice of currencies and dates are limited by the availability of data.\textsuperscript{5}

On several occasions, seven-day eurocurrency interest rates were not available. They were replaced by the one-month rates if available,\textsuperscript{6} and with the rates from the previous day if one-month rates were also not available.\textsuperscript{7} These imperfections may affect the results, particularly if these dates are outliers. (This is not the case.)

5. The Econometric Results

The econometric results are presented in Tables 1 through 4. The first two tables contain the results of T1, which runs the regression:

\[ u(t, 1) = a + B(L) u(t - 1, 1) + e(t, 1) . \] \hspace{1cm}(14)

The null hypothesis is \( a = 0 = B(L) . \)

As discussed in Geweke and Feige (1979), two versions of this test are possible: the single market and the multi-market test. The difference lies in the amount of information available to the trader.

Let superscript \( j \) denote the \( j \)-th currency. The single market test assumes the trader in the \( j \)-th market has the information set \( I^j(t) \)
\[ = \{ r^j(t, 1), r^j(t - 1, 1), ..., d^j(t, 1), d^j(t - 1, 1), ... \} . \] The multi-market test assumes that each trader has the information set \( I(t) \)
\[ = \{ r^j(t, 1), r^j(t - 1, 1), ..., d^j(t, 1), d^j(t - 1, 1), ... : j = 1, ..., 8 \} . \]

\textsuperscript{5}Cumby and Obstfeld (1981) used Eurocurrency rates from the Financial Times, but spot exchange rates from the Harris Bank Weekly Review. Nonsimultaneity in the two sets of data may create some problems.

\textsuperscript{6}This occurred five times in the data period.

\textsuperscript{7}This occurred two times in the data period.
In the single market test, (5.1) is a system of 8 univariate regressions, of the form:

\[(5.2) \quad u_j(t, 1) = a_j + \sum_{k} \sum_{l=1}^{8} b_{jk} u_{k}(t - k - 1, 1) + e_j(t, 1), \quad j = 1, \ldots, 8.\]

The result of testing \( a_j = 0 = b_{jk} \) using 10 lags, are in Table 1. The first column reports the test statistic computed under the standard procedure, which assumes homoskedasticity of \( e_j(t, 1) \). This uses the OC covariance in (11). The second column reports the test statistic using the HC covariance in (10), which is consistent under a large class of heteroscedasticity of \( e_j(t, 1) \). The latter procedure leads to a higher rate of rejection of the null hypothesis. In fact, only the Canadian dollar fails under OC at the five percent significance level, while three out of eight currencies fail under HC.

In the multi-market test, (5.1) is a vector autoregression:

\[(5.3) \quad u_j(t, 1) = a_j + \sum_{k} \sum_{l=1}^{8} b_{jk}^{kl} u_{kl}(t - k - 1, 1) + e_j(t, 1), \quad j = 1, \ldots, 8.\]

The results of testing \( a_j = 0 = b_{jk}^{kl} \) using 2 lags, are in Table 2. The null hypothesis is rejected at the five percent level for five currencies under OC, and six currencies under HC.

In T2, the following regression is run:

\[(5.2) \quad u(t, 1) = a + C(L) x(t - 1, 1) + D(L) d(t - 1, 1) + e(t, 1).\]

As in T1, the test can be done in the single market and multi-market context. In the former case, the one-period forecast error of each currency is regressed on a constant term and a distributed lag of its holding yields and its forward discount. (Five lags are used.) The results, reported in Table 3, show that three of eight currencies are rejected at the five percent level under OC, and six of eight under HC.
In the latter case, each forecast error is regressed on a constant term and one lag of the holding yields and forward discounts of all eight currencies. The results, in Table 4, show that the null hypothesis is rejected in one of eight cases under OC, and all eight cases under HC, at the five percent level.
Table 1

Results of Tl: single market

Regression: \[ u_j^*(t, 1) = a_j + \sum_{k=1}^{10} b_{jk} u_j^*(t - k - 1, 1) + e_j^*(t, 1) \]

Tests of \[ a_j = 0 = b_{jk} \] using

<table>
<thead>
<tr>
<th>Country</th>
<th>( \chi^2 )</th>
<th>( HC/ )</th>
</tr>
</thead>
<tbody>
<tr>
<td>France</td>
<td>15.03</td>
<td>18.28*</td>
</tr>
<tr>
<td>Germany</td>
<td>13.86</td>
<td>24.79***</td>
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<tr>
<td>United Kingdom</td>
<td>7.91</td>
<td>12.91</td>
</tr>
<tr>
<td>Switzerland</td>
<td>11.37</td>
<td>15.38</td>
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<tr>
<td>Netherlands</td>
<td>11.92</td>
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</tr>
<tr>
<td>Canada</td>
<td>18.89*</td>
<td>26.13***</td>
</tr>
<tr>
<td>Italy</td>
<td>16.78</td>
<td>16.31</td>
</tr>
<tr>
<td>Japan</td>
<td>25.36***</td>
<td>31.58***</td>
</tr>
</tbody>
</table>

Period: September 29, 1978 to April 24, 1981 (139 observations)

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

\(^a/\) The statistic is distributed chi-square, with 11 degrees of freedom. Critical values are: 17.2750, 19.6751, and 24.7250 at the 10%, 5% and 1% levels, respectively.
Table 2

Results of T1: multi-market

Regression: \[ u_j(t, 1) = a_j + \sum_{k=1}^{2} \sum_{l=1}^{8} b_{k,l}^j u_i(t-k-l, 1) + e_j(t, 1) \]

Tests of \( a_j = 0 = b_{k,l}^j \) using

<table>
<thead>
<tr>
<th>Country</th>
<th>( OC^{a/} )</th>
<th>( HC^{a/} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>France</td>
<td>31.94***</td>
<td>33.25**</td>
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<tr>
<td>Germany</td>
<td>31.93**</td>
<td>35.18**</td>
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<td>United Kingdom</td>
<td>21.59</td>
<td>24.50</td>
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<tr>
<td>Switzerland</td>
<td>27.78**</td>
<td>31.40**</td>
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<td>20.85</td>
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<tr>
<td>Italy</td>
<td>23.46</td>
<td>28.84**</td>
</tr>
<tr>
<td>Japan</td>
<td>36.23***</td>
<td>33.70***</td>
</tr>
</tbody>
</table>

Period: September 29, 1979 to April 24, 1981 (139 observations)

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

\( a/ \) The statistic is distributed chi-square, with 17 degrees of freedom.
Critical values are: 24.7690, 27.5871, and 33.4087 at the 10%, 5%, and 1% levels, respectively.
Table 3

Results of T2: single market

Regression: \[ u^j(t,1) = \alpha^j + \sum_{k=1}^{5} b^j_k r^j(t-k-1,1) + \sum_{k=1}^{5} c^j_R d^j(t-k-1,1) + e^j(t,1) \]

Tests of \[ \alpha^j = 0 = b^j_k = c^j_R \]

<table>
<thead>
<tr>
<th>j</th>
<th>OC^a/</th>
<th>HC^a/</th>
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<td>16.03</td>
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<td>27.50***</td>
<td>50.09***</td>
</tr>
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<td>Italy</td>
<td>21.63**</td>
<td>19.01**</td>
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<tr>
<td>Japan</td>
<td>21.90**</td>
<td>21.18**</td>
</tr>
</tbody>
</table>

Period: September 29, 1978 to April 24, 1981 (139 observations)

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

^a/ The statistic is distributed chi-square, with 11 degrees of freedom.
Critical values are: 17.2750, 19.6751, and 24.7250 at the 10%, 5%, and 1% levels, respectively.
Table 4
Results of T2: multi-market

Regression:  \[ u^j(t, 1) = a^j + \sum_{\ell=1}^{8} b^j_\ell r^e(t - 1, 1) + \sum_{\ell=1}^{8} c^j_\ell d^e(t - 1, 1) + e^j(t, 1) \]

Tests of  \[ a^j = 0 = b^j_\ell = c^j_\ell \]

<table>
<thead>
<tr>
<th>Country</th>
<th>OC(^a/)</th>
<th>HC(^a/)</th>
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<tbody>
<tr>
<td>France</td>
<td>27.48*</td>
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</tr>
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<td>Germany</td>
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<td>40.00***</td>
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<tr>
<td>United Kingdom</td>
<td>17.68</td>
<td>35.58***</td>
</tr>
<tr>
<td>Switzerland</td>
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<td>37.46***</td>
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<tr>
<td>Netherlands</td>
<td>27.54*</td>
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</tr>
<tr>
<td>Canada</td>
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<td>31.91***</td>
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<tr>
<td>Italy</td>
<td>24.34</td>
<td>33.68***</td>
</tr>
<tr>
<td>Japan</td>
<td>24.86*</td>
<td>28.57**</td>
</tr>
</tbody>
</table>

Period: September 29, 1978 to April 24, 1981 (139 observations)

\(^a/\) Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

The statistic is distributed chi-square, with 17 degrees of freedom. Critical values are: 24.7690, 27.5871, and 33.4087 at the 10%, 5%, and 1% levels, respectively.
6. Conclusion

The empirical results are interesting for two reasons. First, they show that there is a large difference in inference between using the OC covariance (which assumes homoscedasticity) and the HC covariance (which allows for a large class of heteroscedasticity). This is particularly evident in the multi-market tests performed in Table 4. These results suggest that the OC covariance often overestimate the standard errors of the OLS coefficients.

Second, the results provide the strongest rejection of the simple efficiency hypothesis thus far in the published literature. However, these results are not strictly comparable to those of Feige and Geweke (1979) and Hansen and Hodrick (1980), because of the differences in forecast horizons.

There are at least three possibilities to account for the rejection of simple efficiency. One, traders may not know the full structural model of exchange rate determination. They may not know the intervention rule of the central banks, or they may not know some parameters of the model. In this case, serial correlation in forecast errors may be observed.

Two, there may be a risk premium in the forward market. This arises from many circumstances, including differences in risk preferences. Theoretical models which demonstrate this point are Solnik (1974), Grauer, Litzenberger, and Stehle (1976), Stockman (1978), Fama and Farber (1979), Frankel (1979), Roll and Solnik (1979), and Stulz (1980).

Three, traders may simply act in an irrational manner. Further study is needed to find out which of these alternative hypotheses is responsible for the failure of simple efficiency in the forward exchange market.
References


