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ABSTRACT

Nominal exchange rates do not move to offset differences in inflation rates on a month to month, quarter to quarter, or even year to year basis, resulting in sizable real exchange rate changes. Are these changes predictable? We address this question in three ways. First, we describe a variety of tests of predictability and explain how the different tests are related. Next, we implement the tests for the U.S. dollar relative to four currencies and find statistically significant evidence that real exchange rate changes are predictable. Finally, we examine whether the predictability is of an economically interesting magnitude.

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After fifteen years of experience with floating exchange rates there is universal agreement that purchasing power parity is a poor description of short-run exchange rate movements. However, whether changes in the observed deviations from purchasing power parity can be predicted ex ante remains an unresolved issue. Put another way, nominal exchange rates do not move to offset differences in inflation rates on a month to month, quarter to quarter, or even year to year basis. As a result, real exchange rates show substantial variation. What remains unresolved is whether these changes in real exchange rates are predictable.

Determining whether changes in real exchange rates are predictable is important primarily because a large number of popular models of exchange rate determination suggest that such predictability should exist. For example, despite the obvious failure of purchasing power parity as a theory of exchange rate determination in the short-run, it remains a popular description of long-run exchange rate movements. For this to be correct, existing deviations from purchasing power parity must be predicted to be reversed in the future. In other words, given the existence of short-run deviations from purchasing power parity, predictable movements in real exchange rates are necessary if long-run purchasing power parity is to be correct.

Predictable movements of real exchange rates are also suggested by models as distinct as the log linear, sticky price model of exchange rates introduced by Dornbusch (1976) and the intertemporal optimizing, flexible price model of Stulz (1987).[1] In flexible price models predictability of

[1] Flood (1981) contains a nice description of the predictability of changes in real exchange rates in flexible and sticky price models of exchange rates.

changes in the real exchange rate can arise from serial correlation in disturbances to tastes and technology, from serial correlation in exogenous real variables, and from costs of adjustment for real variables. In sticky price models there can be the additional predictability which arises from the sluggish reaction of inflation to economic disturbances.

Despite the implications of many theoretical models, most empirical work concerning the predictability of changes in real exchange rates supports the proposition that these changes are unpredictable. Studies by Roll (1979), Adler and Lehman (1983), and Meese and Rogoff (1988) are examples. Very few empirical studies provide statistically significant support for the proposition that changes in real exchange rates can be predicted. The most notable of these is Cumby and Obstfeld (1984).[2]

In this paper, we address the issue of detecting predictable movements in real exchange rates in three ways. First, we describe how the null hypothesis that real exchange rate changes are unpredictable can be tested in a variety ways, and explain how the different tests are related. Several tests are shown to be testing implications of the following simple observation: if changes in real exchange rates are unpredictable, then expected changes in nominal exchange rates must be equal to expected inflation differentials. Other tests are based on an examination of regression residuals to see if they possess the statistical properties of forecast errors.

In the second part of the paper we present the results of applying the

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[2] Huizinga (1987) argues that when investigating the predictability of changes in real exchange rates it is important to distinguish between statistically significant and economically important predictability. He estimates that only 60% of the variance of changes in real exchange rates is attributable to permanent movements, an estimate which is not statistically different from 100% but which is quite far from 100% in terms of its economic significance. See also the recent work of Levine (1988, 1989).

various tests we describe to data for the U.S. dollar relative to the Canadian dollar, British pound, Japanese yen, and West German mark during the period 1974 to 1987. The tests are generally in agreement, there is statistically significant evidence that changes in real exchange rates are predictable. This is true for predicting changes over both one and three month horizons.

In the third part of the paper we present evidence designed to determine whether the statistically significant predictability we find is of an economically interesting magnitude. The economic importance of the predictability of real exchange rate changes we detect is measured in several ways. For a variety of horizons, we estimate both the fraction of the variance of the change in the real exchange rate over various horizons that is predictable and the correlation coefficient between expected inflation differentials and expected changes in nominal exchange rates. The fraction of variance that is predictable is often estimated to be in the range of 15%, and goes as high as 30%. Estimated correlation coefficients are sometimes significantly different from zero, but are generally small and occasionally even negative. These coefficients are a stark contrast to the value of unity implied by the proposition that changes in real exchange rates are unpredictable.

We also present estimates of the permanent component in real exchange rates, which is defined as the infinite horizon forecast of the real exchange rate based on a particular information set. The deviations of observed real exchange rates from their permanent level provide a measure of the extent to which real exchange rate changes are predictable because, by definition, real exchange rates are predicted to return to their permanent level. In some cases we find real exchange rates deviating by as much as twenty or thirty percent from their estimated permanent values, and in the direction one would expect. That is, the U.S. dollar appears to have depreciated below it long run value in the late 1970's and appreciated above its long run value in the early 1980's.

II. Testing For Predictability of Changes in Real Exchange Rates

In this section we describe a number of ways to test the null hypothesis that changes in real exchange rates are unpredictable and discuss how these tests are related. We begin by introducing notation. Let s_t be the spot exchange rate in period t, expressed as units of foreign currency per unit of domestic currency, and $\Delta s_{t,k} = \ln(s_t/s_{t-k})$ measure its rate of change from time t-k to time t. Let P_t^* be the period-t price level in the foreign country, P_t be the period-t price level in the domestic country, and $\pi_{t,k} = \ln(P_t^*/P_{t-k}^*) - \ln(P_t/P_{t-k})$ measure the inflation differential between the foreign and domestic country from time t-k to time t. Finally, let $r_t = s_t P_t/P_t^*$ be the real exchange rate and $\Delta r_{t,k} = \ln(r_t/r_{t-k})$ measure its rate of change.

The hypothesis to be tested is that the expected value of $\Delta r_{t,k}$ conditional on Φ_{t-k} equals zero, i.e. $E(\Delta r_{t,k}|\Phi_{t-k}) = 0$, where Φ_{t-k} represents the information set economic agents have available to them at time t-k. We define $\Delta s_{t,k}^e = E(\Delta s_{t,k}|\Phi_{t-k})$, $\pi_{t,k}^e = E(\pi_{t,k}|\Phi_{t-k})$, and the k-step-ahead forecast errors $\nu_{t,k} = \Delta s_{t,k} - \Delta s_{t,k}^e$ and $\eta_{t,k} = \pi_{t,k} - \pi_{t,k}^e$. We assume that Φ_{t-k} includes at least $\Delta s_{t-j,k}$ and $\pi_{t-j,k}$ for all $j \geq k$. This implies that $\eta_{t,k}$ and $\nu_{t,k}$ are uncorrelated with $\eta_{s,k}$ and $\nu_{s,k}$ for $s \leq t-k$, and thus that $\eta_{t,k}$ and $\nu_{t,k}$ are moving averages of order at most k-1. We assume that Φ_{t-k}

is not observable to us, but that a subset X_{t-k} of Φ_{t-k} is observable. Because X_{t-k} is a subset of Φ_{t-k}, it will be uncorrelated with the forecast errors $\nu_{t,k}$ and $\eta_{t,k}$.

The first test we examine is,[3]

(T1) Test whether $\mathrm{cov}(\Delta r_{t,k}, X_{t-k}) = 0$.

The motivation for this test is quite simple. By the law of iterated expectations, $E(\Delta r_{t,k}|\Phi_{t-k}) = 0$ implies $E(\Delta r_{t,k}|X_{t-k}) = 0$, which implies $\mathrm{cov}(\Delta r_{t,k}, X_{t-k}) = 0$. If $\mathrm{cov}(\Delta r_{t,k}, X_{t-k}) \neq 0$, real exchange rate changes are predictable given X_{t-k}, the observable part of the information set. Implementation of the test is also quite simple. Testing can be done by using ordinary least squares to estimate the regression equation,

$$\Delta r_{t,k} = X_{t-k}\,\beta + e_t \tag{1}$$

and testing the hypothesis $\beta = 0$.[4] It should be pointed out that in some situations ordinary least squares estimates will not be the most efficient way to test $\mathrm{cov}(\Delta r_{t,k}, X_{t-k}) = 0$. For example, when data on several different real exchange rates are available, and different information sets X_{t-k} are selected for each exchange rate, estimation with the seemingly unrelated

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[3] Throughout this paper we use cov(x,y) to represent the covariance of x with y and var(x) to represent the variance of x.

[4] Even when the null hypothesis is true, there is no guarantee that the regression error e_t will be serially uncorrelated when $k > 1$. Thus, in conducting a test of $\beta = 0$ it may be necessary to account for serially correlated regression errors. Heteroscedastic errors are also a possibility.

regression method of Zellner (1962) can be expected to provide better tests.[5] Assuming there are data for n distinct real exchange rates, this would involve jointly estimating the system of equations $\Delta r^j_{t,k} = X^j_{t-k} \beta^j + e^j_t$ for $j=1,\ldots,n$ and testing $\beta^j = 0$ as a test of the hypothesis that changes in the j^{th} real exchange rate are unpredictable.

The next test we examine is,

(T2) Test whether $\mathrm{cov}(\pi^e_{t,k}, \Delta s^e_{t,k}) = \mathrm{var}(\Delta s^e_{t,k})$.

To understand this test just recall that $E(\Delta r_{t,k} | \Phi_{t-k}) = 0$ implies $E(\Delta s_{t,k} | \Phi_{t-k}) = E(\pi_{t,k} | \Phi_{t-k})$, i.e. $\Delta s^e_{t,k} = \pi^e_{t,k}$. This obviously is sufficient to imply $\mathrm{cov}(\pi^e_{t,k}, \Delta s^e_{t,k}) = \mathrm{var}(\Delta s^e_{t,k})$.

To see how test T2 can be implemented, note that it is always possible to write $\pi^e_{t,k} = \alpha_1 \Delta s^e_{t,k} + u_{t,k}$, where $\alpha_1 = \mathrm{cov}(\Delta s^e_{t,k}, \pi^e_{t,k})/\mathrm{var}(\Delta s^e_{t,k})$ and $\mathrm{cov}(\Delta s^e_{t,k}, u_{t,k}) = 0$. Since $\pi^e_{t,k}$ and $\Delta s^e_{t,k}$ are unobservable, a more useful formulation of this equation is,

$$\pi_{t,k} = \alpha_1 \Delta s_{t,k} + \varepsilon_{t,k} \tag{2}$$

where $\varepsilon_{t,k} = u_{t,k}, + \eta_{t,k} - \alpha_1 \nu_{t,k}$. The null hypothesis that changes in real exchange rates are unpredictable implies not only that $\alpha_1 = 1$, but also that $u_{t,k} = 0$. In this case, X_{t-k} will be uncorrelated with $\varepsilon_{t,k}$, and estimating equation (2) by two-stage least squares using X_{t-k} as instruments will yield a consistent estimate of α_1. It follows that testing whether the two-stage

[5] The improvement is due to the seemingly unrelated regression procedure accounting for correlation between unanticipated changes in the different real exchange rates. Such correlation can reasonably be expected to exist.

least squares estimate of α_1 equals one is a valid way to implement test T2. Intuitively, when the null hypothesis is true, α_1 measures the correlation coefficient between $\pi^e_{t,k}$ and $\Delta s^e_{t,k}$, which is equal to unity and can be consistently estimated by two-stage least squares.[6]

Before proceeding to discuss other tests, it is useful to note that when ε_t is conditionally heteroscedastic and/or serially correlated (which will happen if $k > 1$), the two-stage least squares estimate of α_1 is not efficient. In particular, the two-step two-stage least squares estimator described in Cumby, Huizinga, and Obstfeld (1983) can be used to correct for the serial correlation and/or heteroscedasticity in ε_t and thereby deliver a more efficient estimate of α_1.

The next two tests we examine are closely related to test T2. They are,

(T3) Test whether the autocorrelations of the regression error ε_t in equation (2) are zero at lags greater than k-1.

(T4) Test whether the regression error ε_t in equation (2) is uncorrelated with X_{t-k}.

The motivation for test T3 is that if the null hypothesis is true, the error term ε_t is made up entirely of forecast errors, while if the null hypothesis is false, ε_t will contain not only forecast errors but also u_t. As previously described, the forecast errors will be a moving average of order

[6] Using an instrumental variables regression to estimate equation (2) and test for a unit coefficient was originally suggested by Krugman (1973) as a test of relative purchasing power parity. The relation of that test to this one is that relative purchasing power parity implies not only $E(\Delta r_{t,k}) = 0$ but also $var(\Delta r_{t,k}) = 0$. Cumby and Obstfeld (1984) were the first to use this test as a way of testing the hypothesis that changes in real exchange rates are unpredictable.

at most k-1, but there are no restrictions on the serial correlation properties of u_t. Hence, if we find that ε_t is correlated with itself at lag k or greater this serial correlation must come from serial correlation in u_t, implying u_t cannot be identically zero, and thus that the null hypothesis is false. Rejection of the null hypothesis in this case can be interpreted as indicating that $\pi^e_{t,k}$ differs from $\Delta s^e_{t,k}$ by a serially correlated random variable.

Cumby and Huizinga (1988) describe a way to implement test T3. Specifically, they describe how to test the hypothesis that a regression error has zero autocorrelation at lags greater than $q \geq 0$. The test statistic, called the ℓ statistic, is constructed from autocorrelations of the regression residuals at lags q+1 through q+s, for any s>0. The test is general enough to allow for conditionally heteroskedastic errors and to allow equations to be estimated using ordinary least squares, two-stage least squares, or two-step two-stage least squares.

The motivation for test T4 is quite similar to that for test T3. If the null hypothesis is true, the error term ε_t is made up entirely of forecast errors and must be uncorrelated with information available at time t-k. If the null hypothesis is false, ε_t will contain u_t which may be correlated with information at time t-k.

Hansen (1982) describes how to implement test T4. The statistic he proposes, called the J statistic, can be used when the equation is estimated by two-step two-stage least squares and X_{t-k} includes more than one variable. Rejection of the null hypothesis in this case indicates that $\pi^e_{t,k}$ differs from $\Delta s^e_{t,k}$ by a term that is correlated with X_{t-k}.

Before proceeding it is useful to note an important difference between tests T1 and T2 on the one hand and tests T3 and T4 on the other hand. Rejection of the null hypothesis using tests T3 and T4 is not only evidence that $\Delta s^e_{t,k}$ and $\pi^e_{t,k}$ not equal, it is evidence that they are not proportional to one another. This is easy to see because if $\Delta s^e_{t,k} = \theta\ \pi^e_{t,k}$ for any constant θ, then $u_{t,k} = 0$ and tests T3 and T4 will not reject the null hypothesis.

The next test to be examined in this section, merely reverses the roles of $\Delta s_{t,k}$ and $\pi_{t,k}$ in test T2. Namely,

(T2′) Test whether $\mathrm{cov}(\pi^e_{t,k},\Delta s^e_{t,k}) = \mathrm{var}(\pi^e_{t,k})$.

As might be expected, the motivation for this test comes from our ability to write $\Delta s^e_{t,k} = \alpha_1'\ \pi^e_{t,k} + u'_{t,k}$, where $\alpha_1' = \mathrm{cov}(\Delta s^e_{t,k},\pi^e_{t,k})/\mathrm{var}(\pi^e_{t,k})$ and $\mathrm{cov}(\pi^e_{t,k},u'_{t,k}) = 0$. Replacing the unobservable $\pi^e_{t,k}$ and $\Delta s^e_{t,k}$ then yields the formulation,

$$\Delta s_{t,k} = \alpha_1'\ \pi_{t,k} + \varepsilon'_{t,k}, \tag{2'}$$

where $\varepsilon'_{t,k} = u'_{t,k} + \nu_{t,k} - \alpha_1'\ \eta_{t,k}$. The null hypothesis that changes in real exchange rates are unpredictable obviously implies the restrictions $\alpha_1' = 1$ and $u'_{t,k} = 0$, implying that estimation of equation (2′) by two-stage least squares will give a consistent estimate of α_1'.

Is there any a prior reason for preferring test T2 to test T2′ or vice versa? We believe that in the present circumstance the answer is yes. This stems from our a priori belief that the null hypothesis is most likely to fail because $\mathrm{cov}(\Delta s^e_{t,k},\pi^e_{t,k}) = 0$. In this case, $\alpha_1 = \alpha_1' = 0$ and with a large enough sample both test T2 and test T2′ would reject the null hypothesis. But note that when $\alpha_1 = \alpha_1' = 0$, $\varepsilon_{t,k} = u_{t,k} + \eta_{t,k} = \pi_{t,k}$ while $\varepsilon_{t,k}' = u_{t,k}' + \nu_{t,k} = \Delta s_{t,k}$. Since $\Delta s_{t,k}$ is well known to have more variance than $\pi_{t,k}$, α_1 will be estimated more precisely than α_1' when the both are zero, and for any finite sample T2 should give a more powerful test than T2′.[7]

The final test we discuss is a combination of tests T2 and T2′. It is,

(T5) Test whether $\mathrm{cov}^2(\pi^e_{t,k}, \Delta s^e_{t,k})/\mathrm{var}(\pi^e_{t,k})\ \mathrm{var}(\Delta s^e_{t,k}) = 1$.

The intuition behind this test is straightforward. If two variables are equal, their squared correlation coefficient is one.

The natural way to implement this test would be to test if $\hat{\alpha}_1\ \hat{\alpha}_1' = 1$ where $\hat{\alpha}_1$ is the two-stage least squares (or two-step two-stage least squares) estimate of α_1 in equation (2) using X_{t-k} as instruments and $\hat{\alpha}_1'$ is the two-stage least squares (or two-step two-stage least squares) estimate of α_1' in equation (2′) using X_{t-k} as instruments. Unfortunately, such a test does not seem possible given standard asymptotic distribution theory. The problem is that when the null hypothesis is true, the error term in equation (2) is minus one times the error term in equation (2′), causing the asymptotic covariance matrix for $\hat{\alpha} = (\hat{\alpha}_1, \hat{\alpha}_1')$ to be singular. This precludes the standard procedure of using a Taylor series expansion to obtain the

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[7] It is also possible to suspect that α_1' may be estimated more precisely than α_1. In particular, the sampling variation for an instrumental variables coefficient depends not only on the variance of the error term but also on the correlation of the instruments with the endogenous regressor. The anticipation of a lower correlation of the instruments with nominal exchange rate changes than with inflation differentials would thus suggest, ceteris paribus, that α_1' would be estimated more precisely than α_1. In practice, the effect described in the text is the dominant one.

asymptotic variance of $\hat{\alpha}_1 \hat{\alpha}_1' - 1$ when the null hypothesis is true and obviously precludes deriving a test of $\hat{\alpha}_1 \hat{\alpha}_1' = 1$.[8] It is not surprising that we have difficulty testing that a correlation coefficient equals one, since there are often problems testing the hypothesis that an unknown parameter is on the boundary of the admissible parameter space.

We close this section with one last observation on how several of the tests we can conduct are related to one another. Specifically, we wish to make the point that test T1 embodies the restrictions of both test T2 and test T2'.

To see this, recall that when test T1 rejects the null hypothesis, $cov(\Delta r_{t,k}, X_{t-k}) \neq 0$. This is equivalent to $cov(\Delta r^e_{t,k}, X_{t-k}) \neq 0$ and provides evidence that $var(\Delta r^e_{t,k}) \neq 0$.[9] Hence, rejecting the null hypothesis with test T1 is evidence that $var(\Delta s^e_{t,k} - \pi^e_{t,k}) \neq 0$, or equivalently, that $var(\Delta s^e_{t,k}) + var(\pi^e_{t,k}) \neq 2\ cov(\Delta s^e_{t,k}, \pi^e_{t,k})$. In contrast, rejecting the null hypothesis with test T2 is evidence of $var(\Delta s^e_{t,k}) \neq cov(\Delta s^e_{t,k}, \pi^e_{t,k})$ while rejecting with test T2' is evidence that $var(\pi^e_{t,k}) \neq cov(\Delta s^e_{t,k}, \pi^e_{t,k})$. Clearly, test T1 embodies the restrictions of both test T2 and test T2'.

The relation between tests T1, T2, and T2' illustrates that when the three tests are applied to a given data set a large number of possible outcomes may occur. For example, it is possible to reject the null hypothesis with T1 but

[8] When the null hypothesis is false, it is possible to obtain the asymptotic variance for estimates of α, and thereby construct a confidence interval for the correlation coefficient between $\Delta s^e_{t,k}$ and $\pi^e_{t,k}$. We return to this issue in section IV of the paper.

[9] In the case of an ordinary least squares regression $\Delta r = X\beta + e$, with e homoscedastic and serially uncorrelated, the standard F-statistic for testing $\beta = 0$ is just the ratio of the estimated variance of Δr^e (calculated as the sample variance of $X\beta$) to the estimated variance of e.

not with either T2 or T2′ because individually tests T2 and T2′ provide weak evidence but taken together provide reasonably strong evidence. On the other hand, if test T2 provides strong evidence against the null hypothesis and test T2′ provides weak evidence, it may be possible to reject the null hypothesis using T2 but not using test T2′ or test T1.

III. Empirical Results

In this section we present the results of performing the tests T1 through T4, using real exchange rates between the U.S. dollar and the British pound, the U.S. dollar and the Canadian dollar, the U.S. dollar and the German mark, and the U.S. dollar and the Japanese yen. We use monthly data from 1974 to 1987 and use consumer price indices to convert nominal exchange rates to real exchange rates.[10] We choose k to equal either one or three, so that we are investigating changes in real exchange rates over one and three month horizons.

Implementation of the tests requires that we choose an information set. When examining the real exchange rate between the U.S. dollar and the British pound we use twelve lags of the one month change in the nominal dollar/pound exchange rate and twelve lags of the one month inflation differential between the U.K and the U.S. We follow a similar procedure when examining the real exchange rate for other currencies. For example, when examining the real exchange rate between the U.S. dollar and the German mark we use twelve lags of the one month change in the nominal dollar/mark exchange rate and twelve

[10] Nominal exchange rates are end of month rates taken from International Financial Statistics. Monthly consumer price indices for Canada, Germany, Japan and the United Kingdom are also taken from this source. The consumer price index we use for the U.S. consistently treats housing costs on a rental equivalence measure.

lags of the one month inflation differential between Germany and the U.S. Using the superscript j to index the particular exchange rate being studied, the timing of these lags is to choose X^j_{t-k} to include both $\Delta S^j_{t-k} = [\Delta s^j_{t-k,1}, \ldots, \Delta s^j_{t-k-11,1}]$ and $\Pi^j_{t-k} = [\pi^j_{t-k,1}, \ldots, \pi^j_{t-k-11,1}]$.

This choice of information set reflects an attempt to find predictable changes in real exchange rates, avoid artificially truncating the dynamics of real exchange rate changes, and avoid overfitting the data. Simply put, the choice of what is contained in X_{t-k} can be broken down into (i) what variables will be used and (ii) how many lags of each variable will be used. In our view it would be a mistake to constrain the dynamics of real exchange rate changes by including only a few short lags in X_{t-k}. We thus include twelve lags. Given our sample size, it seems that at most two variables may be selected without running the risk of overfitting the data. The two variables we have chosen are the ones we expected ex ante to have the most predictive power.

One other issue concerning X_{t-k} needs to be addressed. The inflation rates we use show a distinct seasonal pattern. This is accounted for by including twelve seasonal dummies in X_{t-k}. As we describe throughout the section, these dummies are never part of our testing for predictability of changes in real exchange rates, they are included only as a method of deseasonalizing the data. Our tests are testing for predictability of these "seasonally adjusted" changes.

We begin with the estimation of equation (1) and test T1. Part A of Table 1 presents the correlation matrix of one-month changes in real exchange rates. Given that unexpected changes in real exchange rates are undoubtedly a substantial part of the total change, these estimates suggest that unexpected changes in real exchange rates are correlated across currencies. As a result, we estimate all four bilateral real exchange rate equations jointly using the iterated seemingly unrelated regression method to obtain efficient estimates of the parameters.

Part B of Table 1 presents the probability values associated with a series of Wald tests on the estimated coefficients of equation (1).[11] For each currency pair, the first hypothesis tested is that all twenty-four coefficients on lagged nominal exchange rate changes and lagged inflation differentials are jointly zero ($\beta_s = 0$ and $\beta_\pi = 0$).[12] In three of the four cases we reject the null hypothesis at the five percent level and in the U.K. case, we reject at the ten percent level. The systems estimates provide convincing rejections of the null hypothesis that real exchange rate changes are unpredictable.[13]

We also present the results of several other tests of interest in Table 1. We test the null hypothesis that each of the two coefficient vectors, β_s and β_π are individually zero. In only one of the four cases are we able to reject

[11] The probability value is the probability under the null hypothesis of obtaining a realization of a chi-square random variable at least as large as the chi-square statistic obtained. A probability value of .10 implies rejection of the null hypothesis at the ten percent level.

[12] As described earlier, we have included twelve seasonal dummies in these regressions. However, we do not consider statistically significant coefficients on these variables to be evidence of predictable changes in real exchange rates. Regressions begin with the change in the real exchange rate from January 1975 to February 1975 as the first observation of the dependent variable and end with the change from March 1987 to April 1987 as the last observation.

[13] Examination of the individual coefficients in these regression reveals that the significant coefficients which give rise to the predictability of real exchange rate changes do not primarily occur at the seasonal lags of 3, 6 and 12. We are therefore confident that these regressions are not detecting seasonal predictability of inflation.

at the ten percent level the null hypothesis that lagged values of exchange rate changes do not predict real exchange rate changes (β_s=0). In two of the remaining three cases we can reject the null hypothesis at significance levels between ten and twenty percent. The results from testing the null hypothesis that lagged inflation differentials do not provide useful information for forecasting real exchange rate changes (β_π=0) provide much stronger evidence of rejections. In all four cases we reject the null hypothesis at the ten percent level and reject at the five percent level in two of those.

The final set of tests reported in Table 1 regards the usefulness of the decomposition of real exchange rate changes into nominal exchange rate changes and inflation differentials. Specifically, we test whether the two components taken separately provide different information for forecasting real exchange rate changes than is contained in lagged real exchange rate changes. If only lagged real exchange rate changes enter the regression, rather than the two components individually, we would find that $\beta_s = -\beta_\pi$. The results of tests of this hypothesis are found in the fourth line of part B of Table 1. We reject the null hypothesis at the ten percent level in all four cases, and at the five percent level in two cases.

In Table 2 we present the results of applying tests T2 through T4, using forecast horizons of both one month and three months.[14] We use the two-step two-stage least squares estimator to estimate the coefficient α_1 from

[14] In these regressions we include the twelve monthly seasonals both as instruments and as regressors. For the one month horizon the sample period is the change from January 1975 to February 1975 as the first observation of the dependent variable and the change from March 1987 to April 1987 as the last observation. For the three month horizon the sample period is the change from January 1975 to April 1975 as the first observation of the dependent variable and the change from January 1987 to April 1987 as the last observation.

equation (2). Both the standard errors of the estimates of α_1 and the J statistics we report allow for conditionally heteroscedastic forecast errors, serially uncorrelated forecast errors for the one month horizon, and second-order moving average forecast errors for the three month horizon. The ℓ statistics we report are formed with the two-step two-stage least squares residuals and also allow for conditional heteroscedasticity. For the one month horizon the ℓ statistic tests the hypothesis that the regression error has zero autocorrelation at lags one through three. For the three month horizon the ℓ statistic tests the hypothesis that the regression error has zero autocorrelation at lags three through five.

All four estimates of α_1 using a one-month horizon are small in magnitude and are estimated sufficiently precisely to reject the null hypothesis $\alpha_1 = 1$ at any reasonable significance level. The findings thus corroborate the results of test T1 in rejecting the hypothesis that changes in real exchange rates are unpredictable. The fact that α_1 is estimated to be significantly different from zero in most cases indicates that the covariance between the expected change in the nominal exchange rate and the expected inflation differential is not equal to zero. Interestingly, for Canada and Japan the estimated α_1 is less than zero, indicating a negative covariance between the expected change in the nominal exchange rate and the expected inflation differential.

The J statistics reported in Table 2 for the one-month horizon also provide evidence that the null hypothesis of unpredictable changes in real exchange rates is suspect. The J statistics are distributed as χ^2 random variable with twenty three degrees of freedom if the null hypothesis is true.[15] In two of the four cases (the U.K. and Germany), the J statistic is larger than the 95% critical value for this distribution and in a third (Japan) it is larger than the 90% value. These tests thus indicate that the regression errors from equation (2) do not appear to be orthogonal to the instruments X_{t-k}, which they would be if the null hypothesis were true and they were purely forecast errors.

The ℓ statistics for the one month horizon provide essentially the same information as the J statistics. The statistics are distributed as χ^2 random variables with three degrees of freedom when the null hypothesis is true.[16] In two of the four cases (once again the U.K. and Germany) the ℓ statistic is above the 95% critical value for this distribution, indicating that in these two cases the errors from equation (2) exhibit statistically significant serial correlation. This would not be the case if the null hypothesis were true so that they were purely forecast errors.

The results presented in Table 2 for a three-month horizon also cast doubt on the null hypothesis that changes in real exchange rates are unpredictable. For all four currencies the point estimates of α_1 are statistically significantly different from one at any reasonable significance level. This is true despite the slight loss of precision in estimating α_1 for the three month horizon vis a vis the one month horizon, a loss of precision which is to be expected given that our data set clearly has less information about three month changes than it does about one month changes. The estimates

[15] The 23 degrees of freedom come from estimating thirteen parameters, the twelve dummy variables and α_1, with thirty six instruments. Critical value for the statistic are 32.007 at the 90% level and 35.173 at the 95% level.

[16] This is a result of testing three autocorrelations equal to zero. Critical values are 6.25 at the 90% level and 7.81 at the 95% level.

of α_1 for Canada and Japan are still negative for the three month horizon, once again indicating a negative correlation between expected nominal exchange rate changes and expected inflation differentials.

The J statistics for the three month horizon do not indicate a rejection of the null hypothesis for any of the four currencies at the 10% level. The ℓ statistics indicate rejection at the 5% level in all cases and at the 1% level for Germany and Japan. Thus, we are not able to detect a significant correlation between the regression errors of equation (2) and lagged values of either nominal exchange rate changes or inflation differentials but are able to detect evidence of significant serial correlation beyond lag two for the regression error. This serial correlation is additional evidence against the null hypothesis.

Taken together, the results presented in Tables 1 and 2 provide strong evidence against the null hypothesis the changes in real exchange rates are unpredictable. For the one month horizon we used four different tests. For the U.S. dollar-British pound and U.S. dollar-German mark all four tests rejected the null hypothesis. For the U.S. dollar-Japanese yen three of the four tests rejected and for the U.S. dollar-Canadian dollar two of the four tests rejected. For the three month horizon we used three different tests and for all currency pairs two of the three tests rejected the null hypothesis.

How should one interpret the rejections of the null hypothesis? We prefer the following interpretation. First, the strongest rejections come from test T2, with the estimated α_1 statistically different from one. Thus our rejections are indicating that expected changes in nominal exchange rates are not perfectly correlated with expected inflation differentials, rather they appear to be weakly correlated and sometimes even negatively correlated. We pursue this issue further in the next section by providing estimates of exactly how much correlation there is.[17]

Second, the rejections reported in Table 1 are rejections based on test T1 which, as described in section II, can be interpreted as evidence that the variance of $\Delta r^e_{t,k}$ is non-zero. Thus, our rejections are indicating that is enough variation in $\Delta r^e_{t,k}$ that we can detect statistically significant movement in this variable over time. In the next section we provide estimates of how much movement there is. In particular, how much movement is there in $\Delta r^e_{t,k}$ compared to $\Delta r_{t,k}$?

IV. Characterizing the Predictability of Real Exchange Rate Changes

In this section we discuss whether our statistically significant rejections of the hypothesis that changes in real exchange rates are unpredictable translate into rejections that are economically interesting. What we have in mind is analogous to looking at point estimates instead of t-statistics. For example, using a t-statistic one might be able to statistically reject the hypothesis $\beta = \beta_0$ in a linear regression even though the estimate of β is so close to β_0 that for most economic questions the estimated deviation of β from β_0 is uninteresting.

We use three approaches to measure whether our rejections are economically interesting. The first is to estimate the correlation coefficient between expected changes in nominal exchange rates and expected inflation differentials. Obviously, the correlation coefficient must be between minus

[17] Recall that α_1, the covariance of Δs^e with π^e divided by the variance of Δs^e, is the correlation coefficient between Δs^e and π^e only when the correlation coefficient is one. In the next section we provide estimates of the covariance of Δs^e with π^e divided by the square root of the product of the variance of Δs^e and the variance of π^e.

one and one, with a value of one only if real exchange rate changes are unpredictable. Rejecting a correlation coefficient of one when the point estimate is close to one, say .95, might be taken as evidence that the data does not differ much from the null hypothesis in an economically interesting way even though it does differ in a statistical sense. However, if the correlation coefficient is close to zero or negative, this can reasonably be taken as evidence that the null hypothesis does not accurately reflect what is to be found in the data.

The second way we measure whether our rejections are economically interesting is to compute the ratio of the variance of expected changes in real exchange rates to the variance of actual changes in real exchange rates. We do this for horizons of from one to thirty six months. Finding that this fraction is estimated to be near zero is evidence that although expected changes do exist in a statistical sense they are economically uninteresting. On the other hand, if the fraction is large, the variation of changes in real exchange rates may be worthy of notice.

The final way we measure how important predictable movements in real exchange rates are is to estimate the "permanent component" of the four real exchange rates we examine, where the permanent component is defined as the infinite horizon forecast of the real exchange rate conditional on the information set we have selected. Large deviations of actual real exchange rates from their estimated permanent levels indicates that the predictable movements of real exchange rates may be of interest. Continually small deviations indicate that the predictability is presumably uninteresting.

In order to estimate the correlation coefficient between expected changes in nominal exchange rates and expected inflation differentials we jointly estimate equations (2) and (2') by two-stage least squares, using X_{t-k} as instruments, and take the square root of the product of the resulting estimates of α_1 and α_1'. This can be shown to be numerically equivalent to calculating the sample correlation coefficient of the fitted values from an ordinary least squares regression of $\Delta s_{t,k}$ on X_{t-k} with the fitted values from an ordinary least squares regression of $\pi_{t,k}$ on X_{t-k}. The benefit of doing the joint two-stage least squares estimation is that we can get the joint distribution of the estimates of α_1 and α_1' and thereby obtain an estimate of the standard error for our estimate of the correlation coefficient.[18]

Table 3 presents estimates of the correlation coefficient of expected nominal exchange rate changes and expected inflation differentials for horizons of one and three months. For the one month horizon the highest correlation is .249 for Germany. This estimate is significantly positive but quite a bit less than one. The upper bound on the 95% confidence interval for this estimate is about one-half. For Canada and Japan the correlation coefficient is estimated to be negative, statistically significantly so for Canada. These estimates suggest that the previously reported statistical rejections are of an economically interesting magnitude. Rather than a correlation coefficient of unity between expected changes in nominal exchange

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[18] As described in section II, when the correlation coefficient is equal to one, it is not possible to obtain an estimate of the standard error for this estimate of the correlation coefficient. Since we have rejected a unit correlation coefficient when the J statistic and ℓ statistic rejected the hypothesis that $\Delta s^e_{t,k}$ is proportional to $\pi^e_{t,k}$, the procedure we follow is valid. In calculating the standard errors for the estimated correlation coefficients we continue to allow the errors in equations (2) and (2') to be conditionally heteroscedastic. In addition, we must make some assumption about the amount of serial correlation in the error terms. We have allowed nonzero autocorrelations of the error terms at lags one through twelve, downweighted according to the procedure described in Newey and West (1985).

rates and expected inflation differentials, the correlation coefficients appear to lie in the range of -.5 to .5 (the 95% lower bound for Canada to the 95% upper bound for Germany).

The estimated correlation coefficients for the three month horizon are estimated less precisely than those for the one month horizon. So imprecisely, in fact, that none of the estimated correlation coefficients is significantly different from zero. However, only for the case of the U.K. does there appear to be possibility of a substantial correlation between expected changes in nominal exchange rates and expected inflation differentials, with the upper bound of the 95% confidence interval approaching .8. For the remaining cases the upper bound on the 95% confidence intervals are .5 or below.

A variety of procedures exist for measuring the extent to which changes in real exchange rates are predictable. One procedure is to calculate the simple R^2 from the regressions used in Table 1. Another procedure would be to calculate the R^2 adjusted for degrees of freedom. We see problems with both of these procedures. As is well known, the problem with the simple R^2 is that it can be made arbitrarily large by adding more and more regressors. The problem we see with the adjusted R^2 is the it can be shown to give a downward biased estimate of the ratio explained variance to unexplained variance.[19]

Given these problems, we have estimated the amount of predictive power for changes in real exchange rates using the following procedure. First, for each currency, fit a twelfth-order bivariate vector autoregression to monthly

[19] See Theil (1971) page 179.

changes in real exchange rates and inflation differentials.[20] Second, invert the estimated autoregressive representation to obtain an estimated moving average representation. Third, use the moving average representation to calculate $\sigma^2_{u,k}$, the variance of the k month ahead forecast error for changes in the real exchange rates, $\sigma^2_{a,k}$, the variance of the actual change in the real exchange rate over k months, and $\tilde{R}^2_k = 1 - (\sigma^2_{u,k}/\sigma^2_{a,k})$.[21]

Table 5 contains the values of $\tilde{R}^2_k$ for horizons from one to thirty-six months for all four currencies examined. At the one month horizon there is substantial predictability, with $\tilde{R}^2_1$ ranging from .30 for the case of Canada to .16 for the case of Japan. The statistical rejection of unpredictable movements in real exchange rates is accompanied by economically interesting magnitudes. Moving to a horizon of one year, the predictability drops considerably in some cases, e.g. from .30 to .19 for changes in the U.S. dollar-Canadian dollar rate and from .14 to .03 and for changes in the U.S. dollar-British pound rate, but remains relatively constant in others, e.g. remaining at .23 for changes in the U.S. dollar-German mark rate and dropping only from .16 to .13 for changes in the U.S. dollar-Japanese yen rate. At a horizon of thirty-six months noticeable predictability exists only for changes in the U.S. dollar-German mark and U.S. dollar-Japanese yen rates.

As the forecast horizon k approaches infinity, $\tilde{R}^2_k$ will approach zero

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[20] Because regressing changes in real exchange rates on twelve lagged changes in real exchange rates and twelve lagged inflation differentials is equivalent to regressing changes in real exchange rates on twelve lagged changes in nominal exchange rates and twelve lagged inflation differentials, the real exchange rate equation in this bivariate system is equivalent to the real exchange rate equation used in the tests of Table 1.

[21] The bivariate vector autoregression also includes the twelve seasonal dummy variables discussed earlier. We do not use the dummy variables either in the calculation of $\sigma^2_{u,k}$ or $\sigma^2_{a,k}$.

regardless of which stationary process that changes in the real exchange rates follow. Thus, another measure of predictability is needed for truly long-run forecasts. The measure we choose applies the procedure described by Beveridge and Nelson (1981) to create a decomposition of real exchange rates into permanent and transitory components.

The permanent component of the real exchange rate is defined as the infinite horizon forecast of the real exchange rate from our bivariate vector autoregression. This definition corresponds to the value of the real exchange rate that would arise if all shocks that have been realized to date have exerted their full dynamic effect, and obviously changes through time. The permanent component ignores the effect of the yet unrealized (and by definition, unpredictable) future shocks.

The transitory component of the real exchange rate is the deviation of the actual real exchange rate from its permanent value. Since by definition the transitory component of the real exchange rate is forecasted to go to zero as time goes on, it follows that a large transitory component can be associated with predicitabilty of changes in real exchange rates.[22]

For each of the four currencies examined, we plot the log of the actual real exchange rate, with the average value for 1980 normalized to 1.0, along with its estimated permanent component. When the real exchange rate falls short its permanent component, an "undervaluation" of the U.S. dollar relative to its long run value is indicated. When the real exchange rate

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[22] The reason that this procedure can suggest the presence of predictability even though the R_k^2 approaches zero as k approaches infinity is that this procedure is examining the absolute amount of predictability, not the amount of predictability relative to the expected total change. Unfortunately, this procedure cannot be used to isolate what the source of predictability is, e.g. predictability due to costs of adjustment or predictability due to serially correlated forcing variables.

exceeds its permanent component, an "overvaluation" is indicated.

Figure 1 shows that the deviations of the dollar-DM real exchange rate from its permanent component are large in magnitude and correspond quite closely to popular discussions of overvaluation and undervaluation of the dollar. In real terms the U.S. dollar is estimated to have been above its permanent value by approximately 10% from 1975 to 1977 but to have been below its permanent level from the end of 1978 to 1980 by as much as 20%. The rise of the dollar in the early 1980's is estimated to have coincided with a real exchange rate that exceeded its permanent component by 10%, while the depreciation of the dollar since early 1985 is estimated to have brought the dollar below its permanent level by the early 1987, the end of our sample.

The difference between the real exchange rate and its permanent component is not due simply to changes in real exchange rates around a constant permanent level. The permanent value of the real U.S. dollar-DM exchange rate varies substantially over the time period.[23] Nonetheless, the permanent value of the real exchange rate does appear somewhat more stable than the actual. For example, despite showing some fluctuations, the permanent component of the dollar-DM rate in 1980 is about where it was in 1976. During that time the dollar depreciated by about 30%. The finding of a permanent component of the real exchange rate which is more stable than the actual exchange rate is consistent with the findings reported by Huizinga (1987) using univariate techniques.

Figure 2 presents evidence that suggests that the real dollar-yen exchange rate exhibits several similarities to the real dollar-DM exchange rate.

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[23] The finding that the Beveridge-Nelson permanent component of a series shows substantial variation over time is not unique to our application. See Watson (1986).

Deviations of the log of the actual real dollar-yen rate from its permanent component are often large, and in fact at times are even larger than those for Germany. In the early part of out sample, the real dollar - yen exchange rate is estimated to exceed its long run value by as much as 30% This is reversed in the late seventies, when the dollar - yen exchange rate is below its permanent level by as much as 20% in real terms. The major difference between the figures for Japan and Germany is in the later part of our sample, when the dollar - yen exchange rate fluctuates on either side of its permanent level. The permanent component of the real dollar-yen rate is estimated to be more stable than the actual in the early part of the sample, but not in the later part.

Figures 3 and 4 present similar evidence for the real dollar-sterling exchange rate and the real U.S. dollar - Canadian dollar exchange rate. These figures differ in a quite obvious ways from those for Japan and Germany. The deviations of actual real exchange rates from their permanent components for the U.S. dollar-sterling and the U.S. dollar-Canadian dollar are considerably smaller, with deviations never exceeding 8% in either direction in for either currency. The deviations for the U.S. dollar-sterling real exchange rate also differ from the deviations for other currencies by showing substantially less serial correlation. The relatively small variations in actual rates from the permanent component obvious means that the actual and permanent component show nearly the same amount of variability.

V. Conclusions

In this paper we describe a number of tests of the hypothesis that changes in real exchange rates are unpredictable. We provide some insight into what each testing and discuss how the various tests are related to one another. We also present the results of applying several of the tests to data from Canada, Germany, Japan, the U.K. and the U.S.. The tests lead to convincing rejections of the null hypothesis that real exchange rate changes are unpredictable.

In addition, we ask the natural question of whether the statistically significant rejections are economically meaningful and conclude that they are. The conclusion is based on several facts. First, estimates of the correlation coefficient between expected changes in nominal exchange rates and expected inflation differentials are almost always small in magnitude and are sometimes negative. The correlation between expected changes in nominal exchange rates and expected inflation differentials are too small to be consistent with the hypothesis that changes in real exchange rates are unpredictable.

Second, measures of the fraction of changes in real exchange rates that can be predicted with lagged values of nominal exchange rate changes and inflation differentials are substantial. This is true for all currencies at a one month horizon and for the U.S. dollar-German mark and U.S. dollar-Japanese yen real exchange rates at a thirty six-month horizon.

Third, after decomposing real exchange rates into permanent and transitory components, we find large and sustained deviations of observed real exchange rates from their permanent components. The deviations are largest vis a vis the German mark and the Japanese yen, with the U.S. dollar below its permanent level in the late 1970s and above its permanent level in the early 1980s. By the end of our sample, early 1987, the dollar is estimated to be substantially below its permanent value vis a vis the yen and only slightly below its permanent value vis a vis the mark.

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Table 1: Tests of Predictability of Real Exchange Rate Changes

A. Correlation Matrix of Monthly Real Exchange Rate Changes

	U.K.	Germany	Canada	Japan
U.K.	1.00			
Germany	.587	1.00		
Canada	.236	.269	1.00	
Japan	.448	.591	.175	1.00

B. Probability Values for Chi-Square Tests of Predictability

$$\Delta r_{t,1} = \Delta S_{t-1,1}\beta_s + \Pi_{t-1,1}\beta_\pi + e_t.$$

	U.K.	Germany	Canada	Japan
$\beta_s = 0,\ \beta_\pi = 0$	.087	.014	.1x10-4	.016
$\beta_s = 0$	.328	.173	.7x10-3	.120
$\beta_\pi = 0$	.067	.083	.013	.025
$\beta_s = -\beta_\pi$	.093	.079	.002	.025

Note: All real exchange rate changes are one month changes in bilateral rates vis a vis the U.S. dollar. The sample period is January 1975 to April 1987.

Table 2: Nominal Exchange Rate Changes and Inflation Differentials

$$\pi_{t,k} = \alpha_1 \Delta s_{t,k} + \varepsilon_t$$

A. One-Month Changes (k=1)

	U.K.	Germany	Canada	Japan
α_1 (St. Error)	.058 (.025)	.028 (.012)	-.067 (.034)	-.066 (.023)
J statistic	39.999	35.914	22.592	30.425
ℓ statistic	7.943	10.980	5.863	1.046

B. Three-Month Changes (k=3)

	U.K.	Germany	Canada	Japan
α_1 (St. Error)	.080 (.049)	.014 (.017)	-.059 (.033)	-.061 (.026)
J statistic	20.573	22.507	18.607	23.802
ℓ statistic	11.038	14.316	10.918	14.995

Table 3: Estimated Correlation Coefficients for Expected Nominal Exchange Rate Changes and Expected Inflation Differentials

A. One-Month Changes

	U.K.	Germany	Canada	Japan
$\hat{\rho}$	.180	.249	-.315	-.194
(St. Error)	(.153)	(.128)	(.088)	(.119)

B. Three-Month Changes

	U.K.	Germany	Canada	Japan
$\hat{\rho}$	.310	.098	-.107	-.201
(St. Error)	(.232)	(.200)	(.107)	(.170)

Table 4: Amount of Predictability in Real Exchange Rate Changes

	U.K.	Germany	Canada	Japan
$\bar{R}_{1}^{2}$	.14	.23	.30	.16
$\bar{R}_{3}^{2}$	.10	.21	.23	.18
$\bar{R}_{6}^{2}$	.05	.25	.23	.13
$\bar{R}_{9}^{2}$	.04	.24	.23	.11
$\bar{R}_{12}^{2}$	.03	.23	.19	.13
$\bar{R}_{18}^{2}$	.02	.22	.15	.14
$\bar{R}_{24}^{2}$	.01	.21	.11	.15
$\bar{R}_{30}^{2}$	.01	.19	.08	.15
$\bar{R}_{36}^{2}$	.01	.17	.07	.14

Figure 1:

The Real Dollar-DM Exchange Rate and its Permanent Component

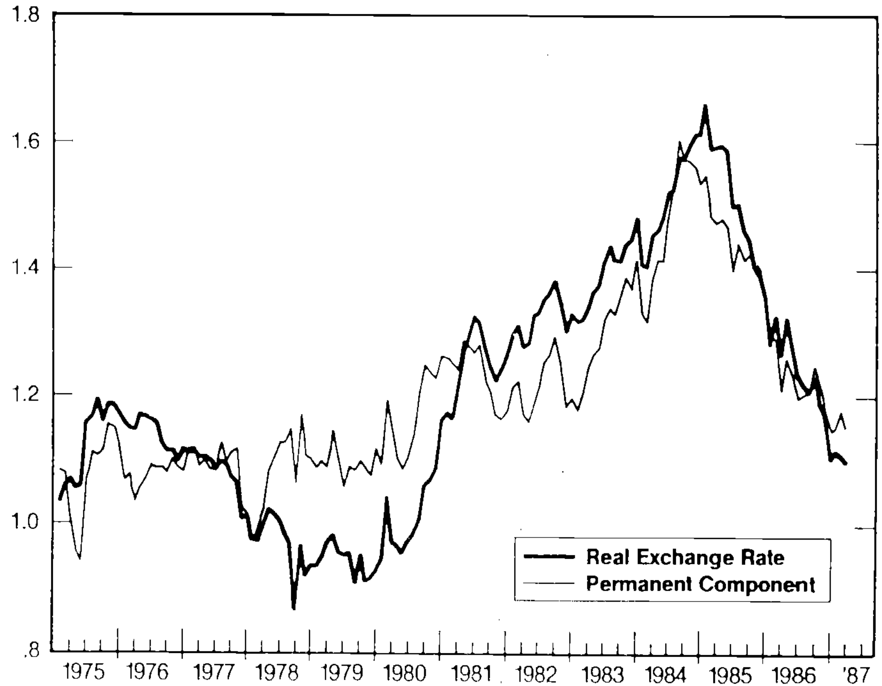

Figure 2:

The Real Dollar-Yen Exchange Rate and its Permanent Component

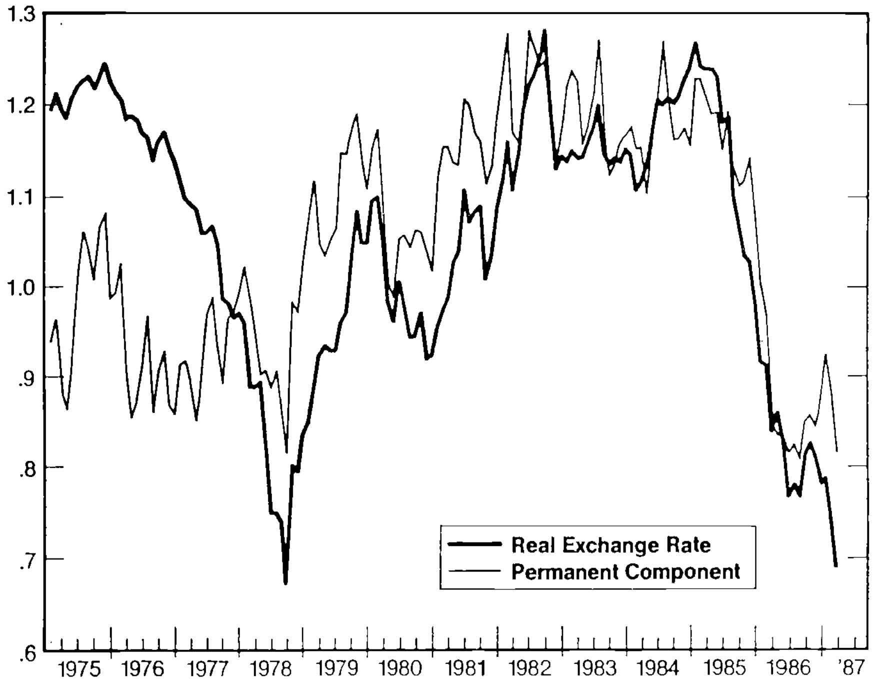

Figure 3:

The Real Dollar-Sterling Exchange Rate and its Permanent Component

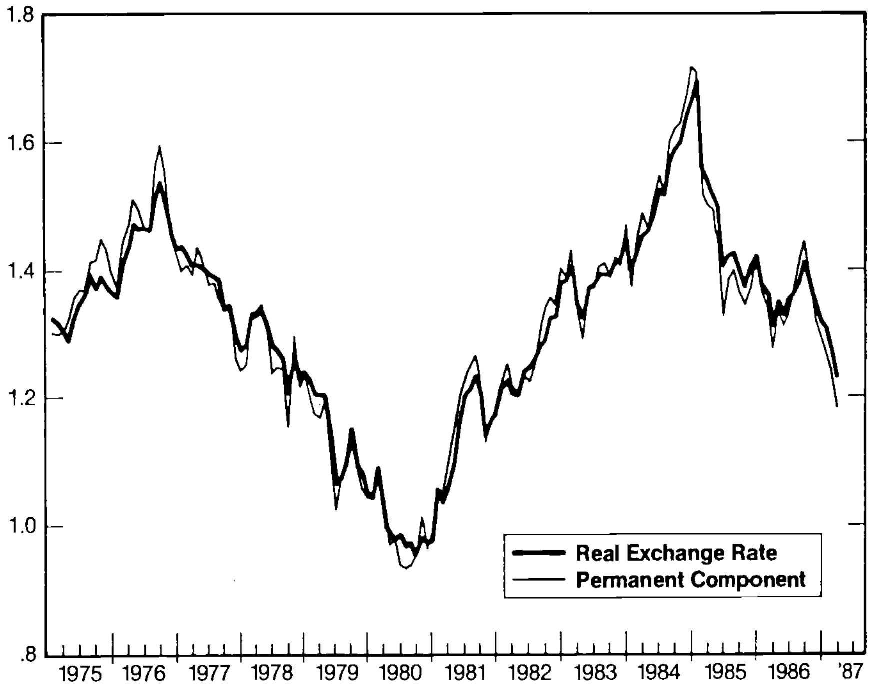

Figure 4:

The Real U.S. Dollar–Canadian Dollar Exchange Rate and its Permanent Component